Unemployment Experience of Demographic Groups*

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Introduction

Longitudinal data following a sample of individuals over time makes it possible to relate individual labor market experience to individual and general background factors. The purpose of this paper is to study the probability of being hit by unemployment and the amount of unemployment for those who are hit using a subsample of a 5 % representative sample of the adult Danish population followed over the period 1979–80. The probability of being hit and the amount of unemployment for those hit by unemployment are related to the degree of compensation offered by unemployment insurance, to lagged unemployment experience and to a number of other background variables.

Most studies on insurance-induced unemployment have been based on aggregate time series.[1] Many of these studies have used the degree of compensation defined as the benefit-wage ratio as the central insurance variable. The predominant result in this tradition has been the finding of a significantly positive coefficient to the degree of compensation in relations with the rate of unemployment as dependent variable.[2] Studies using this approach suffer from a number of methodological problems, especially the testing of theories of individual behavior with highly aggregate data.

Another approach is based on cross-section data on individuals testing for the effects of insurance variables and background factors on the duration of unemployment. Well known studies using this approach are S. J. Nickell (1979) and T. Lancaster (1979). The data used are single spell durations for a cross-section of individuals. This approach represents a major advance compared to aggregate time-series models. However, statistical problems remain as it is difficult to distinguish between duration dependence and unobserved individual factors when only one observation is available for each individual.

Recently panel data or longitudinal data following a sample of individuals over time have made it possible to overcome some of the problems in the single spell approach. Recent studies using this approach are J. J. Heckman and G. J. Borjas (1980), K. Burdett et al. (1984), S. Weiner (1984) and C. Flinn and J. J. Heckman (1982).

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[1] See e.g. H. G. Grubel and M. A. Walker (1970), H. G. Grubel and D. R. Maki (1976) and D. R. Maki and Z. A. Spindler (1975).

[2] This is also found in a recent Danish study in this tradition, P. J. Pedersen (1982). In an aggregate time series approach the rate of unemployment is found to have an elasticity of 1.4 with respect to the degree of compensation for the years 1963–78.

In the next section we present the method used in the paper and discuss the presently imperfect nature of our unemployment variable. Further a short survey of our data base and the principles used in selecting the subsample for the empirical analysis is presented. Empirical results on how the probability of being hit and the amount of unemployment experienced during a year depends on individual background variables, the degree of compensation and lagged unemployment experience are presented. A number of conclusions are found in the last section.

Method

As explained in the introduction longitudinal data ideally contain a dating of transitions between labor market states, i.e. unemployed, employed and non-participation. From this dating of transitions it is straightforward to calculate durations of spells in different states. In this paper our data are of a more crude nature as we use the share of the year spent in unemployment, called the degree of unemployment, instead of the duration of unemployment spells. Technically the degree of unemployment is calculated on a weekly basis as the ratio between benefit hours and potential working hours. The annual degree of unemployment is simply calculated as the average weekly degree during the year. An obvious problem in using this variable is that an infinite number of pairs of frequency and average duration of unemployment spells could produce the same annual degree of unemployment.[3] One spell lasting 3 months would e.g. produce the same degree of unemployment as 9 spells lasting on average 1/3 of a month.

Consequently the methods used are of an explorative nature regressing the unemployment variable on a number of background variables. One approach in an explorative analysis would be to regress the degree of unemployment for all individuals in the sample on their respective background variables. This method would cause an aggregation bias as it is not random which persons are hit by unemployment. Restricting regressions to the subsample of individuals actually hit by unemployment will also cause a bias due to sample selection. The selectivity problem is presumably severe in our case as about 65 % of the sample are not hit by unemployment at all.

Instead of the biased approaches outlined above Heckman's (1979) method of correcting for a selectivity bias has been used. This is a two-step procedure resulting in consistent estimates for which asymptotic standard errors can be computed. The selectivity problem is treated as an omitted variable problem. The omitted variable in the present context is a decreasing function λ of the probability of being hit by unemployment. The first step in the procedure is to estimate the parameters of the probability function for being hit by unemployment using probit analysis for the whole sample. From this an estimated $\hat{\lambda}_i$ can be calculated for individuals hit by unemployment. Finally $\hat{\lambda}_i$ is inserted in a relation explaining the amount of unemployment for those who are hit. The estimation of this relation with OLS results in consistent estimates of the parameters.

Data[4]

The data used in the estimation in the Results-section are a subsample from our data-base consisting of a random 5 % sample of the adult Danish population.

[3] As the degree of unemployment corresponds to an individually calculated rate of unemployment the standard result on decomposing the rate of unemployment in duration and inflow rate applies. Preliminary results from related work on the determinants of the average duration of unemployment spells and the annual number of spells are reported in P. J. Pedersen and N. Westergård-Nielsen (1984).

[4] A more detailed description of our data-base is found in N. Westergård-Nielsen (1984).

For individuals in the unemployment insurance register observations are available on the quarterly degree of unemployment in 1976–78 for those hit by unemployment at some time during this period. For the years 1979–80 weekly observations on the degree of unemployment are available for all persons in the insurance register. The estimations below cover only the 1979–80 period. Besides the degree of unemployment, observations are available on a number of demographic variables, on income subdivided in wages, unemployment benefits, income from independent business, etc., on wealth, on sector of employment, on status in the labor force and on education. Based on these observations implicit hourly wages are calculated for individuals as the ratio between annual wage-income and an estimated number of working hours. For individuals who are classified as wage-earners but who have no wage-income or for whom the number of working hours cannot be estimated an hourly wage rate is calculated from an estimated wage function. Benefits per unemployment hour are calculated in two different ways. The first method consists in using the relavant rules for the calculation of benefits on the implicit hourly wage rate[5]. The benefit-wage ratio is calculated in this way both for individuals hit by unemployment and for those who are not hit as it is a potential measure. The other method utilizes the information on actual benefits paid out to those who are hit by unemployment. For this group hourly benefits are calculated by dividing annual benefits paid out with the product of the degree of unemployment and the standard annual number of working hours. Benefits per hour calculated in this way is then divided by the calculated hourly wage.

The preliminary results in the section below apply to a sample of 9.275 cases of which 2.735 are observations with a positive degree of unemployment. The indirect ways in which we have to calculate wages and benefits makes it necessary to restrict the sample to full-time insured workers. Consequently married women having the highest frequency of part-time jobs are underrepresented in the sample. The size of the sample is small compared to a potential maximum of about 150.000 cases if our data base was fully utilized. The preliminary sample size used is determined in the light of computational costs rising steeply with the number of cases.

Results

In Table 1 probit estimates are shown for four different age groups for the probability of having an annual degree of unemployment $\alpha > .05$. The choice of $\alpha > .05$ instead of $\alpha > 0$ is motivated by the widespread occurrence of very short spells of temporary lay off unemployment. For analytical reasons we are interested in excluding these very short spells as they depend primarily on administrative rules and custom.

Probit estimates are reported in Table 1 for four different age groups. For the insurance variable we use Replac, i.e. the benefit-wage ratio calculated as potential benefits relative to the calculated wage rate. For the two youngest groups the coefficient to Replac is insignificant while significantly positive coefficients are found for the prime age group (33–52) and for the oldest group (53–73). In these groups individuals with low wages (high Replac) are significantly more exposed to unemployment. Lagged unemployment experience, or more generally history dependence, is measured by the variable Palpla set at 1 for individuals hit by unemployment the previous year and at 0 otherwise. For all age

[5] Broadly speaking benefits are calculated as 90 % of a person's wage when employed, but with an absolute maximum. The methods used to calculate wage-rates and benefits are described in Westergård-Nielsen (1984).

Table 1. Probit estimates of the probability function for becoming unemployed with a degree of unemployment $\alpha > .05$. Only full time insured, 1979 and 1980.

	Age 16–23		Age 24–32		Age 33–52		Age 53–73	
	Coef.	Std.dev.	Coef.	Std.dev.	Coef.	Std.dev.	Coef.	Std.dev.
Const.	−1.32*	.89	.78	1.19	−3.92*	1.68	5.45	6.61
Unmarried man	–	–	–	–	–	–	–	–
Married man	.05	.04	−.02	.05	.07	.08	.10	.11
Unmarried woman	.17	.10	.62*	.18	.33	.24	−.01	.27
Married woman	10.15*	1.81	7.50*	1.26	8.46*	1.74	5.85*	1.46
Province	.32*	.08	.12	.09	.11	.09	.27*	.12
Sick	.55*	.10	.25*	.12	.68*	.12	.23	.18
Exper	.01	.09	−.16	.13	.01	.10	−.48*	.22
Exper^2	−.01	.01	.01	.01	−.00	.00	.004	.003
Entrant	−.36*	.10	−.29*	.13	.15	.44	−3.85	273.88
Replac	−.33	.40	−.05	.34	.91*	.38	1.02*	.51
Palpla	1.21*	.15	1.67*	.13	2.03*	.14	2.09*	.18
Apprent	−.09	.11	−.34*	.14	−.24	.25	−.86*	.37
1980	−.23*	.07	−.02	.08	.05	.09	.04	.11
Education:								
None	–	–	–	–	–	–	–	–
Short	.36	.23	.26	.17	−.33	.33	−1.05	.65
Medium	1.26*	.51	.15	.26	−.33	.56	−.98	.69
Long	1.19*	.55	.89*	.36	.87	.52	−.37	.91
Occupation:								
Unskilled	–	–	–	–	–	–	–	–
Skilled	−.09	.15	.36*	.17	−.26	.18	.03	.30
Salaried empl.	−.21	.13	−.37*	.13	−.15	.15	−.06	.18
Other wage earn.	.01	.10	.21	.16	−.13	.16	.39	.22
Industry:								
Primary	−.27	.25	.71	.40	.56	.41	.17	.39
Constr. Small	.40	.25	.96*	.34	.89*	.30	.82	.57
Constr. Large	.40*	.17	.41*	.17	.57*	.17	.54*	.23
Manufacturing	–	–	–	–	–	–	–	–
Commerce	−.18	.11	−.15	.14	.01	.14	−.31	.19
Restaurant etc.	.96*	.27	.24	.26	.45	.32	.73*	.37
Transport	−.26	.17	−.41*	.18	−.06	.18	−.12	.26
Finance	−.04	.18	.03	.18	−.22	.30	−.21	.30
Service	−.16	.17	.04	.21	−.24	.27	−.12	.31
Public sector	−.07	.10	−.17	.12	−.37*	.12	−.41*	.16
Union:								
SiD	–	–	–	–	–	–	–	–
KAD	.20	.16	.08	.21	.18	.19	−.02	.26
Metal workers	.06	.16	−.38*	.19	−.02	.18	−.27	.33
HK	−.26*	.13	−.24	.17	.53*	.21	−.17	.24
Constr. workers	.40*	.19	−.25	.21	.30	.21	.51	.29
Academic	−.66	.45	−.56	.31	−1.80*	.65	−.53	.79
Other unions	−.30*	.10	−.32*	.13	−.28*	.12	−.33*	.16

Notes. Significance at 5 % level is indicated with an asterix.
Legend. Province, living outside the Copenhagen Metropolitan Area. Sick, sickness benefits received for 3 weeks or more. Exper, experience after School. Entrant, education finished during the last two years. Replac, potential unemployment benefits/wage. Palpla, set at 1 for lagged $\alpha > 0$. Apprent, apprentice. Shorter, 10–12 years. Medium, 12–14 years. Long 14–18 years. SiD, unskilled workers. KAD, female workers. HK, clerical workers. Academic, unions for University graduates.

groups we find significantly positive coefficients to Palpla. It is interesting to note that the coefficients for the two oldest groups are significantly higher than for the youngest group. It may be dangerous to conclude on this evidence that the »scar» theory of unemployment is less relevant for the youngest group as the sample contains only full-time insured individuals. Consequently, young people with a weak attachment to the labor market are not included in the sample.

The other variables in the probit analysis fall in a number of groups, i.e. demographic, educational, occupational, industrial and union category.[6] We shall comment only on the most interesting coefficients. Married women have a significantly higher probability of being hit by unemployment whereas it is interesting to note that marriage has no significant effect on the probability of men. The variable Sick is an indicator variable set at 1 for individuals who have received sickness benefits at some time during the year. The three significantly positive coefficients are remarkable because the receipt of sickness benefits introduces a measurement error as the degree of unemployment is set at 0 in weeks for which sickness benefits are paid out. The measurement error should consequently lead to a negative bias in the coefficient to Sick. The significantly positive coefficients found thus indication of a very strong connection between periods of sickness and the risk of unemployment. To be more specific as to the causality would demand knowledge of the frequency and duration of spells of sickness instead of an indicator variable.

For the educational variables a significantly positive coefficient is found to Medium education for the youngest group and to long education for the two youngest groups. This reflects most probably a spell of search unemployment following graduation. For most people this spell seems to be followed by stable employment as we find for the two youngest groups a significantly negative coefficient to Entrant, indicating entry to the labor force after graduation from some vocational education during the previous two years.

Very few of the coefficients to occupational variables are significant. For the age group (24–32) a significantly positive coefficient is found for skilled workers while salaried employees have a significantly lower risk of being hit by unemployment.

For the industry variables a number of significantly positive coefficients are found for workers in construction and in restaurants and hotels. Significantly negative coefficients are, not surprinsingly, found for individuals in the two oldest groups in public service.

Finally, for the union variables, significantly negative coefficients are found to the residual union category Other. This is an uncomfortably large category as it contains about 30 % of all union members.

For each of the age groups the parameters from Table 1 are used to calculate individual probabilities of being hit by unemployment ($\alpha > .05$). From these probabilities Heckman's $\hat{\lambda}_i$ is calculated for each individual with $\alpha > .05$. Finally, the $\hat{\lambda}_i$'s are inserted in regressions explaining the annual amount of unemployment. In these regressions OLS produces consistent estimates as mentioned above.

The results from the 4 OLS regressions are presented in Table 2. Significantly positive coefficients to λ are found for all groups. As λ is a decreasing function of the probability of being hit this means that the probability of being hit and the amount of unemployment are inversely related for those who are hit. This rather surprising result must be seen in combination with the inclusion of the lagged level of unemployment α_{-1}. If α_{-1} is excluded from the regression we have a shift in the sign of λ. This reflects a correlation between α_{-1} and λ with α_{-1} as the dominant

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[6] In principle a person can be insured without being a member of a union. In practice insurance and union membership coincides nearly perfectly.

Table 2. Regressions on the degree of unemployment for individuals with $\alpha > .05$.

	Age 16–23		Age 24–32		Age 33–52		Age 53–73	
	Coef.	Std.dev.	Coef.	Std.dev.	Coef.	Std.dev.	Coef.	Std.dev.
Const.	.19*	.06	.09	.12	.14	.15	.13	.73
Unmarried man	–	–	–	–	–	–	–	–
Married man	.01	.03	–.02	.01	–.02	.02	–.01	.02
Unmarried woman	.05*	.02	–.01	.02	.00	.02	.01	.03
Married woman	.04	.02	–.01	.02	–.01	.02	.02	.03
Province	.03*	.01	.00	.01	.01	.01	.00	.02
Sick	.04*	.01	.02*	.01	.02*	.01	.00	.03
Exper	–.01	.01	.00	.02	.00	.01	.00	.03
Exper^2	.00	.00	.00	.00	.00	.00	.00	.00
Entrant	–.02	.02	.00	.02	.21*	.10	–	–
Apprent	–.02	.02	–.03	.02	.01	.02	–.04	.04
1980	.02	.01	.05*	.01	.05*	.01	.06*	.01
Replac	–.13*	.05	–.09*	.04	–.13*	.05	–.05	.07
λ	.15*	.01	.15*	.01	.12*	.01	.15*	.02
α_{-1}	.82*	.03	.86*	.02	.87*	.03	.92*	.03
Education:								
None	–	–	–	–	–	–	–	–
Shorter	–.01	.04	–.02	.02	.03	.05	–.03	.06
Medium	.00	.07	–.05	.03	.02	.06	.06	.07
Long	.01	.08	–.04	.04	.04	.06	.15	.17
Occupation:								
Unskilled	–	–	–	–	–	–	–	–
Skilled	–.03	.02	.03	.02	–.02	.03	.02	.04
Salaried empl.	.02	.02	–.01	.02	–.01	.02	.02	.03
Other wage earn.	.00	.01	.02	.02	.01	.02	.02	.03
Industry:								
Primary	.01	.03	–.04	.03	.01	.03	–.03	.04
Constr. Small	.07*	.03	.03	.03	.02	.04	.00	.03
Constr. Large	–.01	.02	–.03	.02	.01	.02	.00	.02
Manufacturing	–	–	–	–	–	–	–	–
Commerce	.01	.02	.00	.02	.02	.02	–.04	.03
Restaurant	.06	.03	–.06	.03	–.01	.04	–.08*	.03
Transport	–.02	.02	–.06*	.03	.00	.02	–.02	.03
Finance	.06*	.03	.03	.02	.03	.03	.10*	.05
Service	.10*	.03	–.04	.03	–.01	.04	.13*	.05
Public	–.01	.01	–.05*	.01	.00	.02	–.08*	.02
Union:								
SiD	–.01	.03	.07*	.03	.01	.03	.01	.04
KAD	–.03	.03	.03	.04	.05	.04	–.02	.05
Metal	–	–	–	–	–	–	–	–
HK	–.05	.03	.13*	.03	.01	.04	.00	.05
Constr. w.	.02	.03	.05	.03	.05	.03	.03	.04
Academic	–.06	.08	.09	.05	–.04	.06	–.06	.10
Other	–.04	.03	.05	.03	.03	.03	–.01	.04
R^{-2} (adjusted)	.61		.71		.72		.76	
St. dev.	.15		.14		.13		.13	
N	954		785		601		395	
Mean α	.32		.37		.33		.41	

Notes. Significance on at least a 5 % level indicated with an asterix. Legend, see notes to Table 1.

variable as exclusion of λ means little for the coefficient to α_{-1}. The level and the significance of the coefficients to α_{-1} indicates a very strong history dependence in the amount of unemployment.

For the insurance variable, Replac, we find rather surprisingly significantly negative coefficients except for the oldest group for which the coefficient is insignificant. Together with the result in Table 1 this means that higher wages reduces the risk of being hit but increases the amount of unemployment for those who are hit.

For the demographic variables a significantly negative coefficient is found for married men in the age group 24–32. For married men in the age group 33–52 the coefficient is also negative but not significant at a 5 % level. For the youngest group of unmarried women a significantly positive coefficient is found. For married women no significant coefficients are found in contrast to the result in Table 1. Married women consequently have a higher risk of being hit but not a higher amount if they are hit. Residence outside the Copenhagen Metropolitan area and longer periods of sickness means a significantly higher amount of unemployment for the age groups 16–23, 33–52 and 24–32 (only Sick). Comparing with the results concerning Sick in Table 1 and referring to the measurement problem discussed above we consequently find that periods of sickness are significantly positively related both to the risk and the amount of unemployment. Finally, the significantly positive sign found to 1980 reflects the general increase in unemployment from 1979 to 1980. No significant differences are found between the age groups.

For the educational and occupational variables no significant coefficients are found at all. A small number of significant coefficients are found in the block of industry variables. Especially for the younger groups we find a significantly higher amount of unemployment in a number of industries. Besides this two significantly negative coefficients are found for the public sector. Finally, only few significant coefficients are found in the block of union variables. The overall level of R^{-2} is high but this, of course, is influenced by the inclusion of α_{-1} with t-values in the range 30–45.

Summing up, the main result seems to be the very strong history dependence found in Table 2. In other words the *measured* background factors in Table 2 except α_{-1} do not explain much of the individual variation in the amount of unemployment for those who are hit. We are not able to distinguish between true and spurious history dependence. If *unmeasured* individual factors cause some individuals to have high and other to have a low unemployment risk in each year our results reflect spurious history dependence caused by unobserved heterogeneity. If on the other hand the prospects of an individual in the labor market are influenced by previous unemployment experience we have a situation with true history dependence. It is of relevance to labor market policy to determine whether history dependence is true or spurious. True history dependence demands measures to interrupt spells of unemployment before they become too long while spurious history dependence demands measures to raise the skill level of the weakest part of the labor force.

Next we shall try to interpret the result in Table 2 concerning the insurance variable. The standard result in much of the literature is the finding of significantly positive coefficients to the benefit-wage ratio contrary to the result in Table 2.

Empirical studies using data on individuals fall mainly in the single spell duration approach discussed in the introduction. Typically a positive effect is found for the benefit-wage ratio, see e.g. T. Lancaster (1979) and S. J. Nickell (1979). It should be emphasized that studies in this approach examine exclusively the effect on the duration of one spell of unemployment for each individual in the sample. Our dependent variable, the degree of unemployment, is a composite measure determined as the product of the average duration and frequency of spells of

unemployment over a year. Analytically it may be less satisfactory that it is not split into its components. On the other hand it is a variable of a clear financial interest as the payment of benefits is tied to the degree of unemployment. Further, considering the individual welfare aspects of unemployment, the amount of unemployment experienced over e.g. a year seems to be conceptually more relevant than the duration of a given spell.

Starting in 1979 Danish unemployment statistics were changed from a stock to a flow basis. Based on weekly observations the number of spells and their duration and dating are recorded on an annual basis. For the years 1979–83 we find a clear negative relation between the frequency of spells and their average duration.[7] We further find that the amount of unemployment experienced by the multiple spells group is roughly independent of the number of spells and higher than the amount experienced by the single spell group.

The importance of the first of these observations for our purpose is the following. Suppose we have a random sample of spells, one for each individual in the sample, i.e. the approach used in much of the empirical literature exemplified by Lancaster and Nickell. The longer a duration we observe the higher is the probability that the individual only experiences this one spell over e.g. a year. The shorter the duration the higher is conversely the probability that the individual experiences more than one spell during e.g. a year. Combining this with the second observation above we expect for a single spell sample a negative relationship between the (unobserved annual) degree of unemployment and the observed spell duration, i.e.

$$\alpha_i + X_o\beta_o + \gamma D_i \tag{7}$$

where X_o and β_o are respectively a vector of background variables and a vector of parameters, D_i is the duration of individual No. i's spell in the single spell sample and the coefficient γ is expected to be negative as argued above.[8] As mentioned the standard approach in the single spell literature can be written

$$D_i = X_1\beta_1 + \delta(B/W) \tag{8}$$

where X_1 and β_1 are respectively a vector of background variables and a vector of parameters, B/W is the benefit-wage ratio and δ is expected to be positive. Combining (7) and (8) we find

$$\alpha_i = (X_o\beta_o + \gamma X_1\beta_1) + \gamma\delta(B/W) \tag{9}$$

where $\gamma\delta$ is expected to be negative, i.e. exactly the result found in Table 2. Consequently, we argue that the typical positive effect from the insurance variable on duration in single spell samples and the negative/insignificant effect found on the annual degree of unemployment are not necessarily inconsistent.

Preliminary results from related work on the determinants of the average duration of unemployment and the annual number of spells (P. J. Pedersen and N. Westergård-Nielsen) show a positive but not significant effect from the benefit-wage watio and a significantly positive effect on the annual number of spells. Table 1 shows significantly positive or insignificant effects from the benefit-wage ratio on the probability of being hit by unemployment. Consequently, all components in the degree of unemployment considered partially are either independent of or positively affected by the benefit-wage ratio. The quite reverse effect found on the degree of unemployment calls for caution in drawing policy conclusions from partial analyses of the components of the rate of unemployment.

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[7] See P. J. Pedersen (1983). The same negative relation is reported in G. Akerlof and B. Main (1980) using U.S. data with a much more crude division on number of spells.

[8] For simplicity the relation is assumed to be linear.

Concluding Comments

The main results shall be briefly summarized. A strong positive history dependence is found both in probit estimations for the probability of being hit by unemployment and in selectivity-corrected OLS regressions explaining the amount of unemployment for those who are hit. Further, we find rather few significant coefficients to the different background variables. Consequently, much of the individual variation in the amount of unemployment for those who are hit are either explained by true history dependence or related to unmeasured individual factors.

A positive effect is found from the benefit-wage ratio on the probability of being hit by unemployment for prime age and older workers.

A negative or insignificant effect is found from the benefit-wage ratio on the amount of unemployment. This result is surprising in light of the predominantly positive effects reported in the literature. It is argued that this apparent contradiction may be resolved because the standard result applies to duration analyses in single spell samples while our result applies to the amount of unemployment during a year. Consequently, we conclude that policy recommendation based on results from single spell duration analyses should be viewed with caution.

References

Akerlof, G. A. and Main, B. G. M. (1980). Unemployment spells and unemployment experience. American Economic Review: 885–93.

Burdett, K.; Kiefer, N. M.; Mortensen, D. T. and Neumann, G. R. (1982). Earnings, unemployment, and the allocation of time over time. Mimeo. Cornell University, Cornell University and Economics Research Center/NORC, Nortwestern University, University of Chicago and Economics Research Center, NORC.

Flinn, C. J. and Heckman, J. J. (1982). Models for the analysis of labor force dynamics. In: Advances in Econometrics, Vol. 1, pp. 35–95. JAI Press.

Grubel, H. G. and Maki, D. R. (1976). The effects of unemployment benefits on US unemployment rates. Weltwirtschaftliches Archiv: 274–98.

Grubel, H. G. and Walker, M. A.; eds. (1978). Unemployment insurance. Vancouver.

Heckman, J. J. (1979). Sample selection bias as a specification error. Econometrica: 153–61.

— and Borjas, G. J. (1980). Does unemployment cause future unemployment? Definitions, questions and answers from a continuous time model of heterogeneity and state dependence. Economica: 247–83.

Lancaster, T. (1979). Econometric methods for the duration of unemployment. Econometrica: 939–56.

Maki, D. and Spindler, Z. A. (1975). The effect of unemployment compensation on the rate of unemployment in Great Britain. Oxford Economic Papers: 440–54.

Nickell, S. J. (1979). The effect of unemployment and related benefits on the duration of unemployment. Economic Journal: 34–49.

Pedersen, P. J. (1982). Does unemployment insurance create unemployment? (In Danish). Økonomi og Politik: 75–86.

Pedersen, P. J. (1983). Unemployment spells and duration: a note. Studies in labor market dynamics. Working paper 83–2. Institute of Economics. University of Aarhus.

Pedersen, P. J. and Westergård-Nielsen, N. (1984). Duration and frequency of spells of unemployment in the Danish labor market. (In Danish). Forthcoming, Nationaløkonomisk Tidsskrift.

Weiner, S. E. (1984). A survival analysis of adult male black/white labor market flows. In: Studies in labor market dynamics, edited by G. R. Neumann and N. Westergård-Nielsen. Forthcoming, Springer, Heidelberg.

Westergård-Nielsen, N. (1984). A Danish longitudinal data base. In: Studies in labor market dynamics, edited by G. R. Neumann and N. Westergård-Nielsen. Forthcoming, Springer, Heidelberg.