How Does the Benefit Effect Vary as Unemployment Spells Lengthen?

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No. 375

WARWICK ECONOMIC RESEARCH PAPERS

DEPARTMENT OF ECONOMICS

UNIVERSITY OF WARWICK
COVENTRY

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Revised : July 1991

We are grateful to Peter Mitchell for providing excellent research assistance, Richard Blundell, Costas Meghir, Tony Lancaster, Robert Waldman and Ian Walker for useful comments and helpful discussions and the Leverhulme Trust for financial assistance.

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ABSTRACT

This paper investigates how the effect of income whilst unemployed on the probability of an individual leaving unemployment varies with the length of time that the individual has been unemployed. We examine this question in the context of a variety of alternative econometric models. We extend the Proportional Hazards model with unrestricted baseline hazard to one in which there are unrestricted effects of a subset of the explanatory variables and also consider models that can be estimated as series of binary response models. The proportional hazard restrictions are rejected for the sample of British unemployed men analysed and in the binary sequence framework symmetric models such as the Logit dominate the Extreme Value model implied by extension of the Proportional Hazards formulation. Logit models with a flexible form for the duration dependence which also incorporate unobserved heterogeneity in a flexible way are estimated. The results for all formulations indicate a rapidly declining effect of unemployment income as a spell lengthens, with no significant effect for the long-term unemployed. The preferred specifications which allow for omitted heterogeneity indicate no significant effect after about 5 months and this result is robust to the inclusion or exclusion of previous labour market experience variables.

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1. INTRODUCTION

How does the level of income that an individual receives whilst unemployed, relative to that received whilst employed, affect that individual's probability of leaving unemployment? This question has been the subject of much public debate over many years. Along with the more general question of modelling the determinants of this probability, it has been addressed by a number of empirical studies for Britain based on individual-level data: Lancaster (1979), Nickell (1979), Lancaster and Nickell (1980), Narendranathan et al. (1985), Atkinson et al. (1986) and Narendranathan and Stewart (1989) *inter alia*. The evidence from these studies suggests that the higher the level of benefits that an individual receives, the lower the probability of leaving unemployment and hence the longer the duration of the unemployment spell.

There has also been considerable interest in, and discussion of, how the impact of income while unemployed changes as the spell lengthens. If the long-term unemployed are viewed unfavourably by potential employers and receive very few job offers, they might be expected to accept any job offer that they do get. In which case the level of income they receive while unemployed might be expected to have almost no effect on the probability of their leaving unemployment after some point in the spell.[1] The evidence in Daniel (1990) and elsewhere indicates that the unemployed become very unselective about jobs as their spells of unemployment lengthen. The Daniel study, based on a sample of those entering unemployment in May 1980, finds that of those who had been "particular" about the type of job they were seeking at the first interview (about five weeks into the spell) and who were still unemployed at the third interview (after about ten months), 28% would then "accept anything at all" and a further 29% "anything within limits".[2] The survey also found

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1. See Nickell (1979) and Lancaster and Nickell (1980) for further discussion.
2. Daniel (1990), table A9.2. Change in this direction is however not universal: 13% of those who would accept "anything at all" at the time of the first interview were looking for a "particular type of job" at the time of the third interview.

that "the incidence of turning down job opportunities was tiny among job seekers who went into prolonged unemployment. New jobs were accepted because being in work was better than unemployment rather than because of any positive attraction. The most common reason given for taking new jobs was simply 'it was a job', 'it was better than being out of work' or 'it was the first thing that was offered'." (Daniel, 1990, page 171.)

Some of the studies referred to above have investigated this issue of duration dependence in the benefit effect in a limited way. Nickell (1979) finds that the replacement ratio has no effect on the conditional probability of leaving unemployment after 20 weeks of a spell. Narendranathan et al. (1985) similarly find that, except for teenagers, unemployment income has no effect on the exit probability from unemployment after the first six months of a spell. However both these studies use fairly restrictive specifications for the duration dependence in both the baseline hazard and the benefit effect. Narendranathan and Stewart (1989), using semi-parametric methods that place no restrictions on the baseline hazard, find a similar decline in the effect of income while out of work. They find the effect in the first 13 weeks to be more than twice that in the second 13 weeks and again that after 26 weeks the effect is insignificantly different from zero. They also find that while misspecification of the baseline hazard has little effect on the estimates of covariate effects that are not allowed to vary with elapsed duration, it does bias the pattern of variation in the estimates of those that are allowed to vary.

It is well known that omitted regressors are likely to induce spurious duration dependence in the baseline hazard. As Lancaster and Nickell (1980) point out, such uncontrolled heterogeneity will also potentially induce spurious duration dependence in the effects of included regressors. In fact in the results they present, from Nickell (1979), the finding of a decline in the replacement ratio effect is found to be robust to

controlling for unobserved heterogeneity in a particular way. However, as they point out, "if ... we wish to test the hypothesis that the impact of a particular regressor is attenuated over time ... we must proceed with caution" (Lancaster and Nickell, 1980, page 146). Narendranathan et al. (1985) allow for omitted heterogeneity using the gamma mixing distribution specification employed by Lancaster (1979), but find that it produces implausible results and do not present results based on this specification that allow the effect of income while unemployed to vary over the spell.

The current paper, using very general specifications for the form of any duration dependence in both the baseline hazard and the effect of interest, attempts to (a) estimate the pattern of these effects in more detail and (b) examine how robust the estimated pattern is to the treatment of omitted heterogeneity. In particular the paper seeks to estimate how the income effect on the exit probability varies week by week as the unemployment spell lengthens. The remainder of the paper is arranged as follows. The next section describes the data set used and provides a simple non-parametric graphical preliminary analysis of the question posed. Section 3 presents the formal econometric specifications and estimation methods used, section 4 the results and section 5 some conclusions.

2. PRELIMINAY EXAMINATION OF THE DATA

The data set used in this analysis is the U.K. Department of Health and Social Security (DHSS) Cohort Study of the Unemployed 1978/79. This is a stratified, random sample of unemployed men who registered as unemployed in the autumn of 1978. The selected sample were subsequently interviewed approximately 6, 16 and 52 weeks after entry onto the register.[3] Information on the unemployment and

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3. For further details of the study see Moylan and Davies (1980) and Wood (1982).

supplementary benefits paid to sample members was provided by the DHSS benefit computers and merged with the interview data. The combination provides a longitudinal data set on unemployed men which contains accurate information on actual benefit receipts during the spell, personal characteristics and labour market experience prior to becoming unemployed. The results presented in this paper make use of data from all three interviews and the benefit records.[4]

The variables measuring income in and out of work are both time-varying, being allowed to vary between each quarter. Individuals are assumed to be concerned with total income in and out of work rather than just benefit receipts and expected wages. Unemployment income is measured as net weekly income from all sources and is defined separately for weeks 5-13, 13-26, 26-39, and 39-52. The income from other sources includes benefits such as Family Income Supplement, housing rebates, free school meals and welfare milk. For a married man with a working wife, wife's net earnings are also included in the income variable.[5] Since many of the unemployed receive 'over the counter' cash payments in the first 4 weeks of unemployment which are not recorded by the computer, we omit the period up to the fourth week of unemployment from our analysis and model conditional on the spell reaching this length.

One commonly used measure of expected income in work in unemployment duration analysis of this kind is the individual's net earnings in the last job before becoming unemployed. However this measure has serious disadvantages, including its potential endogeneity. The individuals who are more selective about accepting jobs may well have had higher than average earnings. We assume instead that each individual concentrates his job searching efforts in one particular segment of the labour market.

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4. The sample was constructed using only those individuals who reported at the first interview that they were unemployed and had registered on the date the computer claimed them to have done.
5. See Narendranathan et al. (1985) for further details regarding the construction of this variable.

Following Narendranathan et al. (1985), these labour market segments are defined by five broad occupational groups: (i) Managerial and Professional, (ii) Junior and Intermediate non-manual, (iii) Personal Service, (iv) Skilled manual, and, (v) Semi and Unskilled manual. Wages are assumed to be attached to vacancies rather than to individuals. The expected net earnings for each individual is defined as the mean of the vacancy-wage distribution (adjusted for educational level and age) faced by the individual. This is measured by the fitted values from the relevant earnings regression for each segment of the labour market. Expected income in employment is then measured as the sum of this estimate of expected net earnings and income from other sources with the latter being treated as for unemployment income.

As a prilimary to the specification and estimation of formal models, it is informative to examine non-parametric estimates of the hazard function for appropriate subdivisions of the sample. The Replacement Ratio of income while unemployed to income in work is calculated for each individual in the sample and the sample divided into those with replacement ratio above and below the sample median. Non-parametric estimates of the hazard functions for these two subsamples are plotted in figure 1. These are smoothed versions of the Kaplan-Meier product limit estimates, which are very noisy for these data. Variable kernel estimates of the aggregate hazard are plotted, using a simple triangular kernel weighting function and a band width that increases as the size of the sample at risk decreases.[6] The estimated hazard rate for those with replacement ratio less than the median is initially much greater than that for those for whom the replacement ratio is above the median, but this gap narrows fairly quickly. Figure 2 provides similar estimates for subsamples whose replacement ratio is above the upper quartile and below the lower quartile. There is an even more pronounced initial gap between the estimated hazard functions in this case. Again there is a sharp narrowing, but in this comparison there is some evidence that the gap

6. See Silverman (1986) for discussion of the issues involved in the kernel estimation of density functions.

between the two functions may last somewhat longer. Both figures are consistent with the replacement ratio only having an effect on the conditional exit probability in the early part of the spell and within that early period the effect exhibiting a sharp decline. However since no account is taken of the heterogeneity of the sample, the decline may well be accentuated.

3. ECONOMETRIC SPECIFICATION AND ESTIMATION METHODS

The initial model specified for the conditional probability of leaving the unemployment register is of the Proportional Hazards form (Cox, 1972). The continuous-time hazard is parameterised as

$$\theta_i(t) = \lambda(t).\exp[x_i(t)'\beta] \qquad (1)$$

where $\lambda(t)$ is the baseline hazard at time t, $x_i(t)$ is the vector of (in some cases time-dependent) explanatory variables for individual i (not including a constant) and β is a vector of unknown parameters.

The discrete-time model can be estimated semi-parametrically without restrictions on the baseline hazard, along the lines used by Meyer (1990) and others. If t is measured in weeks and durations only observed in terms of whole weeks completed, then an observed duration of t whole weeks indicates a duration on the continuous time scale of between t and t+1 weeks. The probability of a spell being completed by time t+1 given that it was still continuing at time t, (the discrete-time or grouped hazard) is given by

$$h_i(t) \equiv P[\, T_i < t+1 \mid t \le T_i \,] = 1 - \exp\left[- \int_t^{t+1} \theta_i(u)\, du \right]$$

$$= 1 - \exp[- \int_t^{t+1} \lambda(u) \exp(x_i(u)'\beta)\, du]$$

Assuming that $x_i(u)$ is constant for $t \le u < t+1$, i.e. that the changes in the time-varying variables occur at integer points, the discrete-time hazard can be written as

$$h_i(t) = 1 - \exp [- \exp \{ x_i(t)'\beta + \gamma(t) \}] \qquad (2)$$

where $\gamma(t) = \ln [\int_t^{t+1} \lambda(u)\, du]$.

Thus the discrete-time hazard takes an extreme value distribution form. Note that this follows directly from the proportional hazards specification without any further distributional assumptions. As discussed above, we estimate the parameters of the model only for those who were unemployed for at least 4 weeks. Thus we condition on $T_i \ge 4$. If d_i is the observed duration of the i-th individual (completed or censored) and c_i is an indicator variable equal to 1 if the spell is completed and 0 if it is censored, the contribution of the i-th individual to the log-likelihood is given by

$$\ln L_i = c_i \ln[h_i(d_i)] + \sum_{t=4}^{d_i-1} \ln[1-h_i(t)]$$

$$= c_i \ln\{1 - \exp[- \exp(x_i(d_i)'\beta + \gamma(d_i))]\} - \sum_{t=4}^{d_i-1} \exp[x_i(t)'\beta + \gamma(t)] \qquad (3)$$

The log-likelihood is maximised with respect to β and a full set of γ's to provide Maximum Likelihood estimates. This is the form of model estimated, on the same data set as that used here, by Narendranathan and Stewart (1989). That paper also

estimates a slightly generalised form where the coefficient on the unemployment income variable is allowed to vary between quarters. A further extension of this would allow this coefficient (and perhaps others) to be different for each week. We can write the discrete-time hazard function in this case as

$$h_i(t) = 1 - \exp [- \exp \{ x_i(t)'\beta + z_i(t)'\gamma(t) \}] \qquad (4)$$

The variables and constant have now been divided into two groups: those whose coefficients remain constant, the x's, and those which have a different coefficient for each week, the z's. In the original model described, the z-vector contains only the constant and the x-vector contains all the variables. In the extended model referred to above z would contain (the log of) unemployment income as well as the constant and x would contain the remaining variables. In the limiting case z would contain all the variables and x would drop from the model. In this case we have a series of binary models (one for each week) without parameter restrictions across the models, which can therefore be estimated separately week-by-week.

This provides a useful alternative way of viewing such models (see Kiefer, 1987), each exit or continuation in each week being regarded as an observation. The i-th individual in the sample contributes (d_i - 3) "observations". Define a set of indicator variables, a_{ti} = 1 if individual i has a completed duration of t whole weeks and = 0 else. Thus

$$a_{ti} = \begin{cases} 1 \text{ if } t = d_i \text{ and } c_i = 1 \\ 0 \text{ else} \end{cases}$$

So for example if c_i = 0, a censored spell, a_{ti} = 0 for all t. The log-likelihood of the full sample can be written

$$\ln L = \sum_{t=4}^{51} \sum_{d_i \geq t} \{a_{ti}.\ln h_i(t) + (1-a_{ti})\ln[1-h_i(t)]\} \qquad (5)$$

In the most general case where there are no parameter restrictions across the $h_i(t)$, this partitions into the sum of 48 independent components and in the case where $h_i(t)$ is given by equation (2) can be estimated by a series of 48 binary models with an Extreme Value distribution formulation. Within this framework other binary models, not implied by the Proportional Hazards formulation, can be estimated as alternatives. Probit and Logit formulations are also estimated in this paper, being the most commonly estimated binary response models. Both are symmetric and provide a useful contrast with the skewed Extreme Value formulation.

One of the key assumptions in these formulations is that all the inter-individual heterogeneity is due to observed variables. It is this assumption which enables one to write the likelihood function as a product of independent binary probabilities. In the presence of unobserved characteristics, correlated over time, this independence assumption would be violated resulting in inconsistent parameter estimates. The potential effect of the failure to account for the effects of unobservables on the estimated duration dependence was recognised very early by researchers in the statistical literature (see, for example, Bates and Neyman (1952)). More recently, Lancaster (1979,1985), Lancaster and Nickell (1980), Davies and Pickles (1985), and Ridder (1987) have shown that uncontrolled heterogeneity can also bias the estimated effects of the included explanatory variables. As discussed in the introduction, Lancaster and Nickell (1980) additionally point out that omitted heterogeneity is also likely to induce spurious duration dependence in these effects. We therefore consider next models which explicitly take account of possible omitted heterogeneity.

The model extended for this purpose is that involving a sequence of Logits, since this is generally found to dominate in likelihood terms the corresponding formulation based on the Extreme Value distribution. We follow the conventional procedure and assume that the neglected heterogeneity can be regarded as omitted variables which are then represented by a single zero-mean random disturbance term ε with probability density function $f_\varepsilon(.)$. We incorporate this variable representing a combination of unobserved factors into the model in the same way that observable factors are introduced. Thus, the conditional probability of a spell being completed by week t+1 given that it was still in progress in week t is now given by

$$h_i(t \mid x_i(t), z_i(t), \varepsilon_i) = \{1 + \exp\{-[\, x_i(t)'\beta + z_i(t)'\gamma(t) + \varepsilon_i \,]\}\}^{-1} \qquad (6)$$

An assumption about the parametric form of the density of the disturbance term, ε, is then required to enable us to marginalise the likelihood function with respect to it.[7] The likelihood contribution for the i-th individual is then given by

$$L_i = \int \{\prod_{t=4}^{d_i} h_i(t)^{a_{it}}(1-h_i(t))^{(1-a_{it})}\} f_\varepsilon(\varepsilon_i) d\varepsilon_i \qquad (7)$$

with $h_i(t)$ given by equation (6).[8] We adopt two alternative approachs to the specification. The first approach is non-parametric and follows Heckman and Singer (1984a). A set of mass points is taken as a discrete approximation to $f_\varepsilon(.)$. Mass points are added until the additional one has a probability of close to zero attached to it and produces no improvement in the likelihood. In the results reported in the next section, two mass points were always found to be sufficient. However models with a third

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7. Given the very specific nature of the binary sequences we have in our analysis, the conditional likelihood maximisation where the conditioning in carried out with respect to a set of sufficient statistics to eliminate the unobservables (see Chamberlain (1980)) is not open to us.

8. Note that the omitted heterogeneity term, ε_i, is introduced directly into the discrete-time logit hazard and not into the underlying continuous-time hazard. This has the advantage of avoiding potential problems with the 4-week conditioning. Specification and estimation of the parameters corresponding to the first three weeks of the spell are not required in this case, whereas they would be for the estimation of the parameters of an underlying continuous-time model.

mass point were estimated to check the robustness of the findings.[9] The second approach is parametric. Since a myriad of minor influences are to be captured by this heterogeneity term, we specify a Normal distribution on the basis of a Central Limit Theorem type argument.

4. RESULTS

The formulation given in equation (4) with z containing the logs of income while unemployed and income in work as well as the constant term and x containing the remaining control variables provides the starting point of the empirical analysis. The unemployment rate in the individual's travel-to-work area is used to measure local demand conditions and is time-varying. Controls are also included for age, marital status, ethnicity, health, housing tenure, educational qualifications, receipt of vocational training and completion of an apprenticeship. A number of variables measuring various aspects of labour market experience prior to entering the unemployment spell are also included. In particular we include indicators of whether the individual had any full-time jobs in the 12 months prior to the start of the spell, whether he had been in the last full-time job (if any) less than 12 months, whether he had registered as unemployed in the period and whether or not he voluntarily quit his last job.[10]

The Maximum Likelihood estimates of the $\gamma(t)$ on log-unemployment-income are given in table 1. They are mostly significantly less than zero up to 12 weeks. The

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9. In duration models identification is always an issue. This is particularly so in models of this type where no restrictions are placed on the baseline hazard and a mass point approximation taken to the mixing distribution. However the model can be viewed as a restricted version of a binary sequence as in (5) with each h specified as a logit with mass point mixing. (The correlations between the ε's over time are restricted to all be unity.) The binary logit model with an arbitrary mixing distribution is identifiable if at least one of the regressors is continuous (see Wood and Hinde, 1987). For further discussion of identification in duration models see Ridder (1990).

10. This is a slightly modified version of the control vector used in Narendranathan and Stewart (1989), which in turn was a slightly modified version of that used in Narendranathan et al. (1985).

effect falls sharply from week 4 to week 5 and from 5 to 6, but then remains roughly constant up to week 12.[11] Thereafter there is considerable variation in the coefficient. However only 2 of the 39 subsequent coefficients are significantly different from zero at the 5% level: roughly what one would expect under the null hypothesis of no effect. The joint test of their significance gives a $\chi^2(39)$-statistic of 43.18. Thus the null hypothesis that the income effect is zero in weeks 13 to 51 inclusive is not rejected at conventional levels of significance.[12] In addition it should be pointed out that in the later weeks there are only relatively few exits per week. For example the significant negative effect at week 45 is based on only 9 exits. The maximum likelihood estimates of the β-vector along with the sample means of the x-vector are given in table 2. These coefficients are similar to those found in models without a varying unemployment effect, which are discussed for example in Narendranathan and Stewart (1989).

In this specification the effects of the various control variables are assumed constant over t. When this is relaxed, the formulation given in equation (5) with h( ) taking an Extreme Value form results. This can be estimated by a series of Extreme Value binary response models. The results for weeks 4 to 16 are given in column 1 of table 4. Beyond this point the number of exits per week is starting to get a bit thin. The first column of table 3 gives the corresponding results of grouping into 4-week intervals. Probit and Logit models are estimated as alternative functional form specifications for h( ) and given in columns 2 and 3 respectively of each table. The findings are broadly consistent with those above. The significant negative effects are concentrated in the first 12 weeks, with the effect after 4 weeks being considerably larger and the effect after 5 weeks somewhat larger than those in weeks 6 to 12. The effect after 4 weeks is about three times that in weeks 6 to 12. The symmetric specifications

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11. Note that the effect for week t, $\gamma(t)$, is strictly the effect on the conditional probability of exiting with t complete weeks. Thus it is the probability of exit with duration in the interval [t,t+1), i.e. during the (t+1)-th week.
12. Critical points are: 5%: 54.6, 10%: 50.7, 20%: 46.2.

generally dominate the Extreme Value model in likelihood terms: the Logit and Probit both give higher likelihoods than the Extreme Value model for 10 of the 13 weeks in table 4, while the Extreme Value model gives the highest likelihood in only one of the 13. Overall the Logit and Probit specifications considerably dominate the Extreme Value model in likelihood terms.

Narendranathan et al. (1985) find differences in the unemployment income effect by age. When separate unemployment income coefficients are included for those aged under 20, those aged 20-24 and those aged 25 and over in the Logit models for weeks 4 to 16, the differences are only significant (on a likelihood-ratio test) for week 4.[13] The week 4 coefficients for the three age groups are -2.74 (0.76), -1.90 (0.32) and -1.47 (0.15) respectively. For the purposes of the current paper we therefore do not further divide the unemployment income effect by age.

We turn next to the estimation of the model incorporating allowance for omitted heterogeneity. A related econometric issue here concerns the assumption of independence of the error term and the x_{it} variables.[14] Our model of the probability of leaving unemployment contains variables representing the previous labour market experience of the individual (see table 2). There is a strong possibility that these variables will be correlated with the disturbance term capturing omitted individual-specific factors, and it is sometimes argued on these grounds that such variables should be excluded from the model to avoid a form of endogeneity bias. However this exclusion potentially causes an alternative problem. Previous labour market experience measures clearly influence the exit probablity and are also likely to be correlated with the level of unemployment income. Excluding them may be a more serious misspecification than including them. Since ε is assumed uncorrelated with

13. Week 4 gives a $\chi^2(2)$ likelihood-ratio test statistic of 6.60 as compared with a 5% critical point of 5.99. For all other weeks the statistics are insignificant even at the 10% level.
14. Note that this independence assumption would not be required for the maximisation of the conditional likelihood function.

the regressors, either the influence of the omitted previous labour market experience varaibles will not be captured by ε, leaving an important source of still uncontrolled heterogeneity, or ε will become correlated with the included regressors. Either way consistency of the Maximum Likelihood estimator would be lost. In addition, as discussed in the introduction, this source of uncontrolled heterogeneity may induce spurious duration dependence in the effect of variables such as unemployment income. We therefore present estimates of this model both including and excluding these variables.

The models presented only allow the effects of the unemployment and employment income variables and the intercept to vary week by week. The effects of the other factors in the model are taken to be constant over the spell. Restricting the coefficients on the other factors in this way is required for the tractability of the estimation, since incorporation of omitted heterogeneity means that the log-likelihood can no longer be partitioned by week as in equation in (5). All parameters must be estimated at the same time. However this may mean that restrictions not supported by the data are being imposed on the model. Fortunately, as will be seen below, imposing these restrictions does not distort the unemployment income coefficients of interest.

Results including and excluding the previous labour market experience variables are given in tables 5 and 6 respectively. The models presented have weekly unemployment income effects up to week 7 and effects that change 4-weekly thereafter. The steps in the intercept and the employment income effect are specified equivalently. Estimates are presented for the two heterogeneous models described in the previous section together with the corresponding homogeneous model.[15] The restrictions on the general model with two mass points which has weekly intercepts

15. The models are estimated using the program MIXTURE (see Ezzet and Davies, 1987).

and weekly unemployment income and employment income effects to reduce it to the specification in the two tables are accepted by the data in both cases, the likelihood-ratio tests giving $\chi^2(99)$-statistics of 101.76 in the model with the previuos labour market experience varaiables and 102.13 in that without. (Using the standard transormation this gives approximate standard normal random variates of 0.23 and 0.26 respectively.[16]) The results are also robust to the restriction to two mass points, both in the two models presented in the tables and in the general unrestricted weekly ones. Adding a third mass point to the models here increases the log-likelihood by only 0.78 and 0.11 relative to tables 5 and 6 respectively and in both cases results in no changes in any of the estimated coefficients. The results for the homogeneous model with previous labour market experience variables in column 1 of table 5 are fairly similar to those in the final columns of tables 3 and 4 although the week 4 coefficient here is somewhat lower. Nevertheless the restricting of the effects of the factors other than the two income variables to be constant over the spell does not appear to seriously distort the effects of interest.

Comparing tables 5 and 6 indicates that the previous labour market experience variables are highly significant. A likelihood-ratio test for the mass point model gives a $\chi^2(7)$-statistic of 37.64. Despite this, the estimated unemployment income effects given in the two tables are extremely similar and none of the conclusions depend on which model is prefered. The rate of decline in the unemployment income elasticity is slower in the models with allowance for omitted heterogeneity than in the model without heterogeneity. In the homogeneous models in tables 5 and 6, as in those in atbles 3 and 4, the unemployment income elasticity is insignificantly different from zero after week 12. This is not the case in the models that allow for omitted heterogeneity, where in all four cases the effects are significant up to week 20. In particular the coefficients for weeks 12-16 and 16-20, insignificant in the

16. If X is distributed as $\chi^2(v)$, then for large v, $\sqrt{(2X)}$ is approximately normally distributed with mean $\sqrt{(2v-1)}$ and unit variance.

homogeneous model, are jointly significant in the models that allow for heterogeneity. For example in the mass point models the likelihood-ratio tests give $\chi^2(2)$-statistics of 13.80 in the model with previous labour market experience variables included and 15.03 in that with them excluded. This overstatement of the negative duration dependence in the elasticity when allowance is not made for omitted heterogeneity is in line with theoretical predictions discussed earlier. The omitted heterogeneity accentuates the negative duration dependence in the unemployment income elasticity. The homogeneous model is rejected against the model with allowance for omitted heterogeneity in all four cases on the basis of likelihood-ratio tests. The two models with alternative specifications of the mixing distribution to capture omitted heterogeneity give very similar estimates for the unemployment income elasticities. It is interesting to note that the two mass point mixing distribution model gives higher likelihoods than that using a Normal mixing distribution.

5. CONCLUSIONS

This paper investigates how the effect of income whilst unemployed on the probability of an individual leaving unemployment varies with the length of time that the individual has been unemployed. We started by extending the Proportional Hazards model with unrestricted baseline hazard to one in which there are unrestricted effects of a subset of the explanatory variables; and also considered models that can be estimated as series of binary response models. The results in these models without allowance for omitted heterogeneity suggest no effect past the 12th week of a spell and a declining effect within those 12 weeks. The decline is slightly more gradual when allowance is made for omitted heterogeneity. Both models with heterogeneity indicate no effect of unemployment income on the conditional

probablity of leaving unemployment after the 20th week of a spell and a steady decline in the effect within this period. This result is robust to the inclusion or exclusion of the variables measuring the previous labour market experience of the individuals.

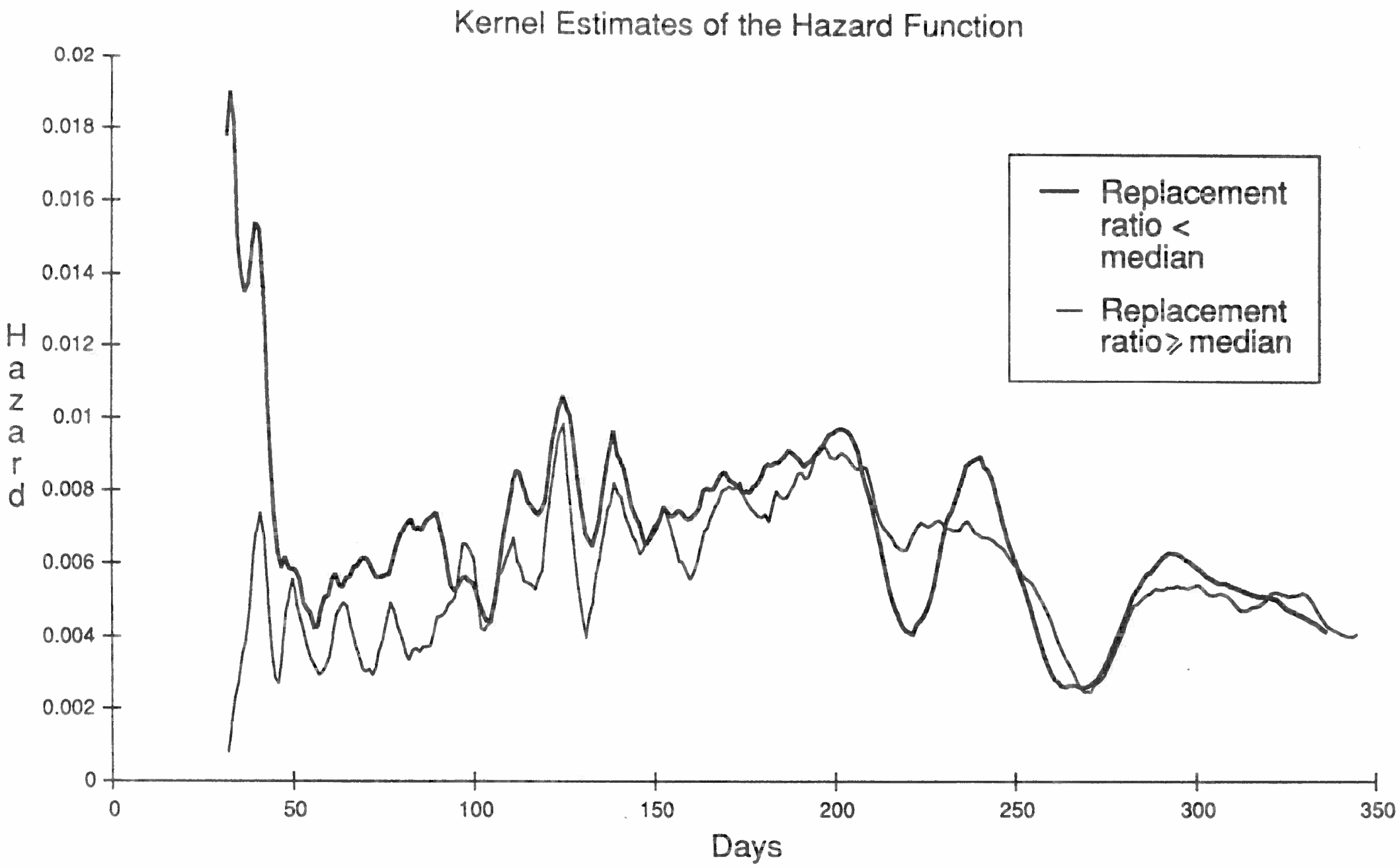
Kernel Estimates of the Hazard Function
Hazard
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
0
50
100
150
200
250
300
350
Days
Replacement ratio < median
Replacement ratio ≥ median

Figure 1

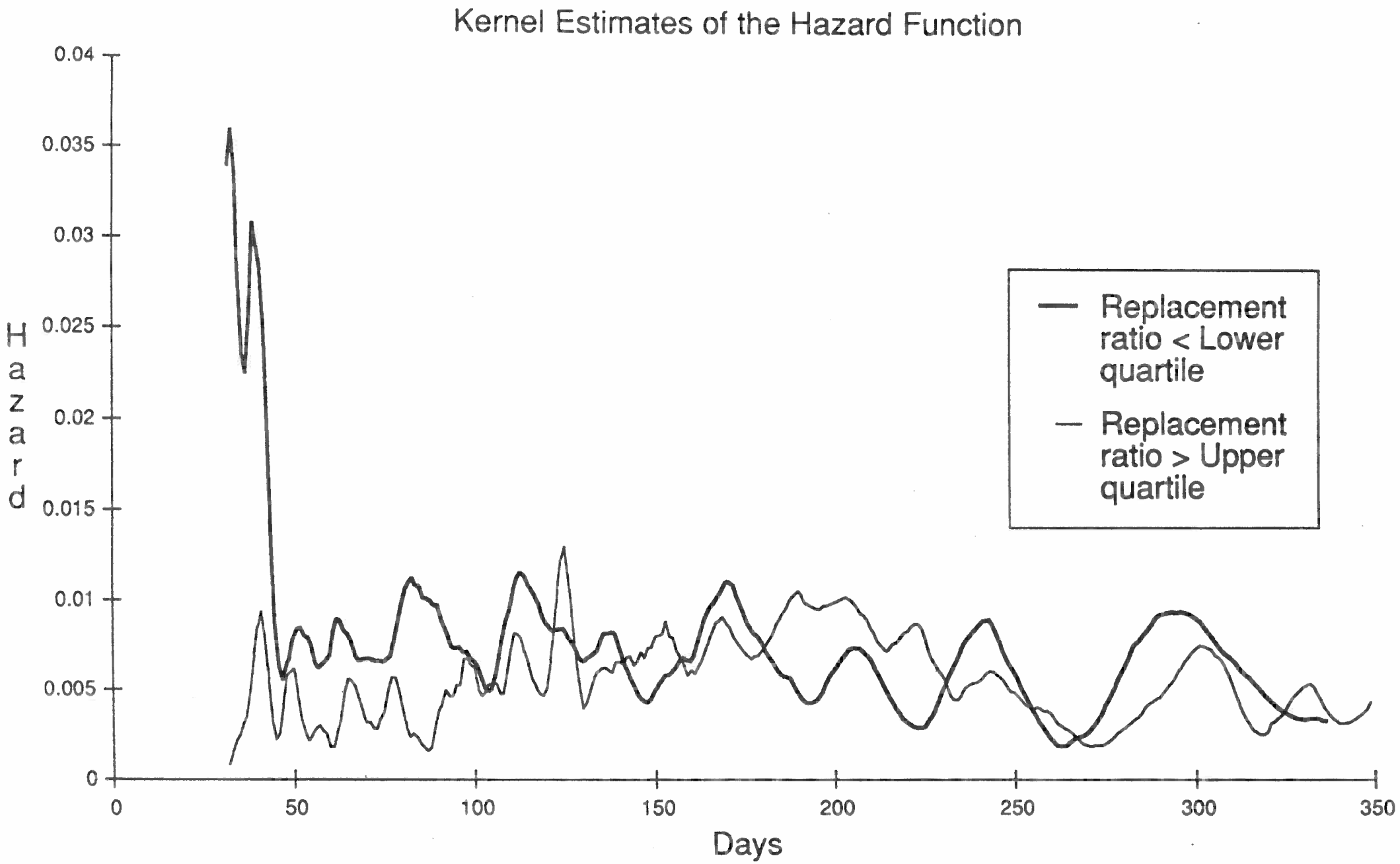
Kernel Estimates of the Hazard Function
Hazard
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
0
50
100
150
200
250
300
350
Days
Replacement ratio < Lower quartile
Replacement ratio > Upper quartile

Figure 2

Table 1

Maximum Likelihood Estimates of Model with Weekly Income Coefficients
γ(t) coefficients on ln(unemployment income)

week [t]	coef (s.e.) [γ(t)]		week [t]	coef (s.e.) [γ(t)]	
4	-1.12 (.07)	*	28	.75 (.41)	
5	-.81 (.08)	*	29	.75 (.44)	
6	-.56 (.13)	*	30	-.18 (.28)	
7	-.45 (.16)	*	31	.15 (.45)	
8	-.40 (.19)	*	32	.42 (.44)	
9	-.31 (.21)		33	.16 (.35)	
10	-.53 (.18)	*	34	-.27 (.21)	
11	-.43 (.18)	*	35	.21 (.48)	
12	-.51 (.18)	*	36	.07 (.41)	
13	.54 (.41)		37	2.25 (1.5)	
14	.03 (.32)		38	1.70 (1.5)	
15	-.17 (.25)		39	-.32 (.70)	
16	-.32 (.21)		40	-.54 (.26)	*
17	.16 (.28)		41	-.44 (.31)	
18	-.20 (.28)		42	1.01 (.84)	
19	-.29 (.20)		43	.24 (.60)	
20	.63 (.45)		44	-.25 (.41)	
21	.44 (.39)		45	-.75 (.32)	*
22	.07 (.37)		46	-.07 (.52)	
23	.13 (.36)		47	.51 (.65)	
24	-.02 (.28)		48	.17 (.75)	
25	-.06 (.30)		49	.49 (1.4)	
26	.32 (.32)		50	.04 (.51)	
27	.72 (.44)		51	.72 (1.2)	

Notes:
1. Asymptotic standard errors in parentheses. An asterisk indicates significantly different from zero at the 5% level
2. Appropriate quarterly values of time-varying variables used.
3. z also contains ln(employment income) and a constant. x contains the variables whose coefficients are given in table 2.

Table 2

Means and Maximum Likelihood Estimates of Other Variables in the Model.

Variable	Mean	ML coefficient*
Age under 20	0.08	.16 (.12)
25 - 34	0.26	-.02 (.09)
35 - 44	0.20	-.11 (.10)
45 - 54	0.13	-.42 (.12)
55 - 59	0.08	-.65 (.14)
60 - 64	0.10	-.80 (.13)
Married	0.76	-.04 (.09)
Non-white	0.07	.12 (.11)
Has a health disability which affects work	0.26	-.07 (.07)
Housing - owner occupier	0.25	.24 (.07)
Any educational qualifications	0.32	.11 (.06)
Vocational training	0.34	.13 (.06)
Apprenticeship completed	0.17	.08 (.07)
Previous labour market experience:		
Trade union member in last full time job	0.32	-.05 (.06)
Less than 12 months in last full time job	0.55	.15 (.08)
Registered unemployment in last 12 months	0.52	-.18 (.07)
Voluntarily quit from last job	0.30	-.13 (.06)
No full time job in last 12 months	0.11	-.32 (.12)
Looked for work while in last job	0.32	.09 (.06)
Was disallowed from receipts of benefits	0.29	.07 (.06)
Unemployment rate in individual's travel-to-work-area (%)	7.73	-.019 (.009)

* Note: Asymptotic standard errors in parentheses.

Other Sample Statistics

Unemployment income in 1st quarter : mean (£)	37.85
Employment income in 1st quarter : mean (£)	63.67
Unemployment income in 1st quarter : mean of log	3.32
Employment income in 1st quarter : mean of log	4.11
Durations completed (%)	87.0
Durations < 26 weeks (%)	63.1
Durations < 13 weeks (%)	30.5
Median duration (weeks)	20
Sample size	1571

Table 3

Binary Response Model Estimates: 4-week steps
Coefficient on ln(unemployment income)

weeks	Extreme Value Model	Probit Model	Logit Model
4- 8	-.81 (.05) *	-.64 (.04) *	-1.12 (.08) *
8-12	-.42 (.10) *	-.28 (.07) *	-.50 (.12) *
12-16	-.13 (.14)	-.10 (.09)	-.16 (.16)
16-20	-.11 (.16)	-.07 (.11)	-.12 (.18)
20-24	.42 (.23)	.24 (.13)	.46 (.25)
24-28	.16 (.18)	.08 (.10)	.17 (.20)
28-32	.31 (.21)	.19 (.12)	.36 (.23)
32-36	-.10 (.16)	-.06 (.10)	-.10 (.18)
36-40	.67 (.43)	.30 (.21)	.69 (.44)
40-44	-.35 (.19)	-.19 (.13)	-.37 (.23)
44-48	-.31 (.23)	-.19 (.16)	-.35 (.27)
48-52	.48 (.52)	.25 (.28)	.50 (.56)

Table 4

Binary Response Model Estimates: Single weeks
Coefficient on ln(unemployment income)

week	Extreme Value Model	Probit Model	Logit Model
4	-1.24 (.10) *	-.84 (.06) *	-1.60 (.14) *
5	-.85 (.09) *	-.53 (.06) *	-1.00 (.12) *
6	-.56 (.14) *	-.29 (.08) *	-.60 (.15) *
7	-.35 (.19)	-.15 (.10)	-.36 (.20)
8	-.35 (.22)	-.19 (.11)	-.37 (.23)
9	-.32 (.22)	-.17 (.11)	-.34 (.23)
10	-.53 (.19) *	-.28 (.10) *	-.57 (.21) *
11	-.40 (.20) *	-.22 (.10) *	-.45 (.21) *
12	-.58 (.21) *	-.33 (.12) *	-.63 (.23) *
13	.43 (.39)	.23 (.20)	.46 (.41)
14	-.02 (.30)	-.02 (.15)	-.02 (.30)
15	-.11 (.29)	-.07 (.14)	-.12 (.30)
16	-.30 (.25)	-.16 (.14)	-.32 (.27)

Notes:
1. Asymptotic standard errors in parentheses. An asterisk indicates significantly different from zero at the 5% level.
2. The x-vector also contains ln(employment income) and all variables in table 2.
3. Appropriate quarterly values of time-varying variables used.

Table 5

Logit models with and without alternative mixing distributions for omitted heterogeneity.

Previous labour market history variables included.

Coefficient on ln(unemployment income)

weeks	Homogeneous model	2 mass point mixing model	Normal mixing model
4	-1.35 (.12) *	-1.49 (.13) *	-1.55 (.17) *
5	-.94 (.10) *	-1.11 (.12) *	-1.18 (.16) *
6	-.60 (.15) *	-.79 (.17) *	-.85 (.20) *
7	-.47 (.16) *	-.67 (.18) *	-.72 (.21) *
8-12	-.44 (.11) *	-.66 (.13) *	-.71 (.17) *
12-16	-.23 (.15)	-.45 (.17) *	-.48 (.20) *
16-20	-.19 (.17)	-.40 (.19) *	-.43 (.22) *
20-24	.30 (.23)	.14 (.25)	.13 (.25)
24-28	.07 (.15)	-.07 (.17)	-.09 (.18)
28-32	.36 (.20)	.28 (.22)	.29 (.22)
32-36	.01 (.16)	-.06 (.18)	-.07 (.18)
36-40	.40 (.43)	.34 (.44)	.34 (.44)
40-44	-.24 (.16)	-.32 (.17)	-.35 (.18)
44-48	-.24 (.25)	-.32 (.25)	-.36 (.26)
48-52	.28 (.65)	.19 (.65)	.11 (.66)
log L	-5318.77	-5310.81	-5312.81
σ			.965 (.27)
mass points		-0.99 (2.32)	
		0.70 (2.28)	
prob. of 1st		0.41 (.26)	
variance of mixing dist.	0	0.69	0.93

Notes:
1. Asymptotic standard errors in parentheses. An asterisk indicates significantly different from zero at the 5% level.
2. Mass points are given relative to the mean of the mixing distribution.
3. Employment income effects are allowed to vary in the same way as those for unemployment income. The x-vector contains the same variables as given in table 2.
4. Appropriate quarterly values of time-varying variables used.

Table 6

Logit models with and without alternative mixing distributions for omitted heterogeneity.

Previous labour market history variables excluded.

Coefficient on ln(unemployment income)

weeks	Homogeneous model	2 mass point mixing model	Normal mixing model
4	-1.34 (.12) *	-1.52 (.13) *	-1.56 (.17) *
5	-.93 (.10) *	-1.15 (.12) *	-1.18 (.17) *
6	-.60 (.15) *	-.82 (.17) *	-.85 (.21) *
7	-.47 (.16) *	-.70 (.18) *	-.73 (.21) *
8-12	-.44 (.11) *	-.71 (.13) *	-.71 (.18) *
12-16	-.22 (.15)	-.48 (.17) *	-.49 (.20) *
16-20	-.18 (.17)	-.42 (.20) *	-.42 (.22) *
20-24	.33 (.23)	.13 (.25)	.15 (.26)
24-28	.09 (.15)	-.09 (.18)	-.07 (.18)
28-32	.37 (.20)	.27 (.23)	.29 (.22)
32-36	.01 (.16)	-.06 (.17)	-.07 (.18)
36-40	.41 (.43)	.33 (.43)	.34 (.43)
40-44	-.24 (.16)	-.31 (.17)	-.36 (.18)
44-48	-.23 (.25)	-.31 (.25)	-.36 (.26)
48-52	.23 (.64)	.14 (.64)	.09 (.66)
log L	-5338.09	-5329.63	-5332.41
σ			.997 (.29)
mass points		-1.05 (2.35)	
		0.82 (2.32)	
prob. of 1st		0.44 (.23)	
variance of mixing dist.	0	0.86	0.99

Notes:
1. Asymptotic standard errors in parentheses. An asterisk indicates significantly different from zero at the 5% level.
2. Mass points are given relative to the mean of the mixing distribution.
3. Employment income effects are allowed to vary in the same way as those for unemployment income. The x-vector contains the same variables as given in table 2.
4. Appropriate quarterly values of time-varying variables used.

REFERENCES

Atkinson, A.B., Gomulka, J., Micklewright, J., and Rau, N. (1984) - "Unemployment benefits, duration, and incentives in Britain: How robust is the evidence?", Journal of Public Economics, 23, 3-26.

Bates, G. and Neyman, J. (1952) - "Contributions to the theory of accident proneness II: True or false contagion", Univ. of California Publications in Statistics, 1, 255-75.

Chamberlain, G. (1980) - "Analysis of covariance with qualitative data", Review of Economic Studies, 47, 225-38.

Cox, D. R. (1972) - "Regression models and Life-Tables" (with discussions) - Journal of the Royal Statistical Society, B, 34, 187-220.

Cox, D.R. and Oakes, D. (1985) - Analysis of Survival Data, London and NY: Chapman & Hall.

Daniel, W.W. (1990) - The Unemployed Flow, London: PSI.

Davies, R.B. and Pickles, A.R. (1985) - "Longitudinal vs. cross-section methods for behavioural research: a first round knockout", Environment and Planning, 17, 1315-29.

Ezzet, F.L. and Davies, R.B. (1987) - A Manual for MIXTURE, Centre for Applied Statistics, University of Lancaster.

Heckman, J.J., and Singer, B.L. (1984a) - "A method for minimizing the distibutional assumptions in econometric models for duration data", Econometrica, 52, 271-320.

Heckman, J.J., and Singer, B.L. (1984b) - "Econometric duration analysis", Journal of Econometrics, 24, 63-132.

Kalbfleisch, J.D., and Prentice, R.L. (1980) - The Statistical Analysis of Failure Time Data, NY: Wiley.

Kiefer, N.M. (1987) - "Analysis of Grouped Duration Data", Cornell CAE Working Paper No. 87-12.

Kiefer, N.M. (1988) - "Economic duration data and hazard functions", Journal of Economic Literature, 26, June, 646-79.

Lancaster, T. (1979) - "Econometric methods for the duration of unemployment", Econometrica, 47, 939-56.

Lancaster, T. (1985) - "Generalised residuals and heterogeneous duration models: with application to the Weibull model", Journal of Econometrics, 28, 155-69.

Lancaster, T., and Nickell, S. (1980) - "The analysis of re-employment probabilities for the unemployed" (with discussions), Journal of Royal Statistical Society, A, 143, 141-65.

Meyer, B.D. (1990) - "Unemployment insurance and unemployment spells", Econometrica, 58, 757-82.

Moylan, S., and Davies, B. (1983) - "The DHSS Cohort Study of the unemployed men: Sample design and representations", Working Paper No. 5, DHSS.

Narendranathan, W., Nickell, S., and Stern, J. (1985) - " Unemployment benefits revisited", Economic Journal, 95, 307-329.

Narendranathan, W. and Stewart, M. (1989) - "Modelling the Probability of Leaving Unemployment: Competing Risks Models with Flexible Baseline Hazards", Warwick Economic Research Paper No. 331.

Nickell, S.J. (1979) - "Estimating the probability of leaving unemployment", Econometrica, 47, 1249-66.

Ridder, G. (1987) - "The sensitivity of duration models to misspecified unobserved heterogeneity and duration dependence", mimeo, University of Amsterdam.

Ridder, G. (1990) - "The Non-parametric Identification of Generalized Accelerated Failure-time Models", Review of Economic Studies, 57, 167-182.

Silverman, B.M. (1986) - Density Estimation for Statistics and Data Analysis, London and NY: Chapman & Hall.

Wood, A. and Hinde, J. (1987) - "Binomial Variance Component Models with a Non-parametric Assumption Concerning Random Effects", in R. Crouchley (ed), Longitudinal Data Analysis, London: Avebury-Gower.

Wood, D. (1982) , Men registering as unemployed in 1978: a longitudinal study, London: Department of Health and Social Security.