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MODELLING THE PROBABILITY OF LEAVING UNEMPLOYMENT: COMPETING RISKS MODELS WITH FLEXIBLE BASELINE HAZARDS.

ABSTRACT

Unemployment durations are generally modelled by specifying the conditional probability of leaving unemployment (the hazard function). Existing studies for Britain all use very restrictive parametric specifications of the hazard function, most commonly Weibull in form. These restrictions potentially bias the estimated effects, particularly those of the time-varying economic variables and the baseline hazard. This paper investigates models for the probability of leaving unemployment with these restrictions removed. We use semi-parametric methods to estimate models with completely unrestricted baseline hazards and a model involving flexible step-function approximations to the baseline hazard. The Weibull is found not to give a satisfactory representation of the baseline hazard and its use is found to distort the pattern of unemployment income effects over the length of the spell. The existing studies for Britain also model the exit probability from unemployment rather than the probability of entering a job, despite generally interpreting the evidence as being about the latter probability. We use a competing risks model to distinguish exit into employment from exit into alternative states. We find that the single risk model of exit understates the effects of income in and out of work on the probability of entering a job.

KEY WORDS: Hazard functions; Survival analysis; Competing risks models; Unemployment durations; Semi-parametric estimation; Heterogeneity.

1. INTRODUCTION

The probability of an unemployed person finding a job after a certain length of time out of work, and the variation in this probability, are currently of great interest in Britain - and elsewhere - to economists, policy makers and the general public alike. Particular attention is often focused on the influences of unemployment benefits and demand conditions in the local labour market, but the impact of demographic characteristics and how an individual's chances change as the spell of unemployment lengthens are also of interest and importance.

There have been a number of interesting empirical studies of these issues for Britain over the last decade. See for example, Lancaster (1979), Nickell (1979), Lancaster and Nickell (1980), Narendranathan et al. (1985) and Atkinson et al. (1986) which between them use widely differing data sets. All model the duration of unemployment by specifying the conditional probability of leaving unemployment (the hazard function). Such hazard function models have been extensively used in the biometrics literature and have over the last decade found increasing use in economics. (See for example, Kalbfleisch and Prentice (1980) and Cox and Oakes (1985) for the statistical background of such models and Heckman and Singer (1984) and Kiefer (1988) for surveys of their use in economics.) The main application in economics has been to the modelling of unemployement durations. More recently the durations of strikes have also been investigated (see Kennan (1985) and Harrison and Stewart (1989)).

The above listed studies of unemployment durations in Britain all use very restrictive parametric specifications of the hazard functions, most commonly Weibull in form. These restrictions potentially bias the estimated effects, particularly those of the time-varying economic variables and the baseline hazard. The first strand of this paper investigates models for the probability of leaving unemployment with these restrictions removed. We start by using semi-parametric methods to estimate models with completely unrestricted baseline hazards on data with unemployment durations measured in weeks. The usefulness of such models has recently been investigated on U.S. unemployment duration data by Moffitt (1985), Han and Hausman (1986), Meyer (1988) and Katz and Meyer (1988), Han and Hausman for example finding the restrictions implied by the Weibull specification to be rejected for their data. We find likewise that the Weibull does not give a satisfactory representation of the basline hazard for our data for Britain. We also utilise daily data and a model involving flexible step-function approximations to the baseline hazard in a continuous time framework.

The individual-level studies for Britain referenced above model the exit probability from unemployment rather than the probability of finding a job, despite generally interpreting the evidence as being about the latter probability. However, some of those who exit the unemployment register do not do so into employment. The second strand of the paper examines the validity of making such inferences about the exit-to-employment probability by estimating competing risks models that distinguish exit into employment from exit into alternative states. Han and Hausman (1986) and Katz and Meyer (1988) use competing risks models of this type on U.S. data to distinguish recalls to the same firm from other exits, but ignore the employment/non-employment distinction.

The third, and final, theme of the paper concerns differences between groups of unemployed individuals, particularly in the shape of their baseline hazards and in the effects on the hazard of the key time-varying economic variables: income in and out of work and local labour market conditions. Attention is focused on differences between age groups and between manual and non-manual workers and some important variation in the key effects between these groups found.

The paper is organised as follows. The hazard models, with both single and competing risks, that we use are presented and discussed in the next section together with appropriate tests. The data set used and the results from the estimation of a range of models are discussed in section 3. Section 4 summarises the main findings and presents our conclusions.

2. MODELS AND ESTIMATION

The models employed for the conditional probability of leaving the unemployment register are all 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 time-dependent and independent explanatory variables for individual i (not including a constant) and β is a vector of unknown parameters.

2.1 Semi-parametric Estimation:

We start by specifying an unrestricted baseline hazard and estimate the model semi-parametrically along the lines used by Meyer (1988) and others. Suppose initially that t is measured in weeks and that durations are 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

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

$$= 1 - \exp[\, - \int_t^{t+1} \lambda(u) \exp(x_i(u)'\beta)\, du] \qquad (2)$$

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

$$h_i(t) = 1 - \exp [\, - \exp \{\, x_i(t)'\beta + \gamma(t) \,\} \,] \qquad (3)$$

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

Note that this follows directly from the proportional hazards specification without any further distributional assumptions.

The probability of observing a completed spell of length d is given by

$$p_i(d) = h_i(d) \prod_{t=0}^{d-1} [\, 1 - h_i(t) \,] = h_i(d)\, S_i(d-1) \qquad (4)$$

S being the discrete survivor function. For reasons set out in the next section, we estimate the parameters of the model only for those men who were unemployed for at least 4 weeks. Thus, we condition on $T_i \geq 4$. The likelihood contribution of a completed spell of length d given $T_i \geq 4$ is given by,

$$L_i = h_i(d) \prod_{t=4}^{d-1} [\, 1 - h_i(t) \,] \qquad (5)$$

and the probability of an incomplete spell of d weeks, given the left-censoring is given by

$$P[\, T_i \geq d \mid T_i \geq 4 \,] = S_i(d-1) \,/\, S_i(3) = \prod_{t=4}^{d-1} [\, 1 - h_i(t) \,] \tag{6}$$

Thus, 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

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

$$= c_i \ln\{\, 1 - \exp[\, - \exp(\, x_i(d_i)'\beta + \gamma(d_i) \,)]\} - \sum_{t=4}^{d_i - 1} \exp[\, x_i(t)'\beta + \gamma(t) \,] \tag{7}$$

The log likelihood, the sum of these contributions, is maximised with respect to β and a full set of γ s to provide maximum likelihood estimates. Maximisation was carried out using the Goldfeld-Quandt quadratic hill-climbing algorithm in GQOPT with analytic first and second derivatives. Estimation is aided by the fact that the γ block of the Hessian of the log-likelihood is diagonal.

2.2 Weibull Specifications:

To enable comparison of the results with those from the model used in most of the existing British literature we also estimate models with a Weibull specification of the baseline hazard:

$$\lambda(t) = \alpha\, t^{\alpha-1} \tag{8}$$

The contribution of the i-th individual to the log-likelihood is given by

$$\ln L_i = c_i \ln \theta_i(d_i) + \ln(\, \overline{F}_i(d_i) \,/\, \overline{F}_i(4) \,) \tag{9}$$

θ being given by equation (1) with equation (8) substituted for λ, and $\overline{F}$ being the corresponding continuous-time survivor function. The model differs from that described in section 2.1 in both the specification of the baseline hazard and in its use of continuous as opposed to discrete time.

To test the restrictions on the unconstrained discrete-time hazard implied by a Weibull specification we can use a minimum χ^2 test similar to that used by Han and Hausman (1986). Define γ to be the vector of discrete-time baseline hazard parameters, $\gamma(t)$, and $\hat{\gamma}$ to be the vector of semi-parametric estimates of these parameters. Then

$$\hat{\gamma} \sim_a N(\gamma, \Omega)$$

where Ω is the appropriate block of the inverse of the information matrix. Under the Weibull specification

$$\gamma(t) = g_t(\alpha,\beta_0) = \ln \left[\int_t^{t+1} \alpha\, u^{\alpha-1} e^{\beta_0}\, du \right] \qquad (\alpha > 0)$$

$$= \beta_0 + \ln \left[(t+1)^{\alpha} - t^{\alpha} \right] \tag{10}$$

Define $g(\alpha,\beta_0)$ to be the vector of such functions over the discrete points t in the γ vector. Then the minimum distance estimates of α and β_0 are given by

$$\min_{\alpha,\beta_0} W = [\hat{\gamma} - g(\alpha,\beta_0)]' \, \hat{\Omega}^{-1} \, [\hat{\gamma} - g(\alpha,\beta_0)]$$

For $\hat{\Omega}$ we use the appropriate block of the estimated asymptotic covariance matrix. Under the null of a Weibull

$$\text{Min } W \sim_a \chi^2(k-2)$$

where k is the number of baseline hazard parameters in the vector γ.

The discrete-time Weibull model is given by equation (3) with the specification in (8) imposed. The contribution of the i-th individual to the log-likelihood in this model is given by equation (7) with equation (10) imposed on the γ-vector. The model is nested within that of section 2.1 and a Likelihood-Ratio test can also be used to test the implied restrictions.

2.3 Continuous-time Models with Step-function Baseline Hazards:

We now consider a continuous-time model with t measured in days and a step-function representation used for the baseline hazard. Define $\gamma^*(t) = \ln[\lambda(t)]$. Then the continuous-time hazard parameterisation in equation (1) becomes

$$\theta_i(t) = \exp [\ x_i(t)'\beta + \gamma^*(t)\ ] \tag{11}$$

The equivalent model to the semi-parametric weekly model of section 2.1 is given by this formulation with γ^* a step function with steps of size 7 days. That is, the γ^* function changes at the beginning of each week. The model can also be generalised to daily steps and to allow steps of varying sizes.

2.4 Competing Risks Models:

The models outlined above specify the determinants of a single risk: that of leaving the unemployment register. Consider now a situation where there are competing risks, where an exit from the unemployment register can result from the finding of a job or be for other reasons, and suppose that we wish to model the determinants of the probability of finding a job. See Cox and Oakes (1985) or Kalbfleisch and Prentice (1980) for surveys of competing risks models. Some recent treatments of such models can be found in Clayton and Cuzick (1985), Han and Hausman (1986), Heckman and Honoré (1989), Meyer (1988).

Denote the jth (j=1, 2,..,J) cause specific hazard for individual i as $h_{ji}(.)$. Then, the contribution of the i-th individual with an observed duration d_i and failure type k to the log-likelihood is given by,

$$\ln L_i = c_i \ln [\ h_{ki}(d_i)\ ] + \sum_{t=4}^{d_i - 1} \{ \sum_{j=1}^{J} \ln [\ 1 - h_{ji}(t)\ ]\ \} \tag{12}$$

This likelihood contribution can be re-written as

$$\ln L_i = c_i \ln [\ h_{ki}(d_i)\ ] + \sum_{t=4}^{d_i - 1} \ln [\ 1 - h_{ki}(t)\ ] + \sum_{j \neq k} \sum_{t=4}^{d_i - 1} \ln [\ 1 - h_{ji}(t)\ ]$$

Thus the log-likelihood can be partitioned into a sum of terms, each of which is a function of the parameters of a single cause-specific hazard only. From this it can be seen that the of the parameters of a single cause-specific hazard only. From this it can be seen that the parameters of a given cause-specific hazard can be estimated as described above by treating durations finishing for other reasons as censored at the point of completion. For example, the determinants of the conditional probability of finding a job can be examined by treating spells which end with exit to a non-employment state as censored at the point of exit. The same line of argument can be applied to the continuous-time models. The same proportional hazards formulation as used above for the single risk model can be used for each of the cause-specific hazards.

2.5 Testing for Proportionality of the Risks:

An interesting question in the competing risks framework is whether exits into different states are behaviourally distinct or whether the state exited into is incidental. One way of formulating this hypothesis is as follows:

$$H_0: \ \theta_{ji}(t) = p_j\, \theta_i(t) \ \text{ for all } i, j \text{ and } t, \text{ with the } p_j \text{ independent of } t,$$

$$\text{where } \theta_i(t) = \Sigma_j\, \theta_{ji}(t) \ \text{ and } \ \Sigma\, p_j = 1.$$

In this case the cause-specific hazards are proportional to one another:

$$\theta_{ji}(t) \,/\, \theta_{ki}(t) \ = \ p_j \,/\, p_k$$

p_j is the conditional probability of exit into state j at time t given an exit at that time. The set of restrictions imposed by this hypothesis in our proportional hazard framework is the equality of the slope coefficients across the risks, and of the baseline hazard coefficeints up to a factor of proportionality. As shown in Narendranathan and Stewart (1989), this test can be carried out very easily using the maximised log-likelihood values of the single risk (L^{SR}_{max}) and competing risks (L^{CR}_{max}) models and the observed proportions of individuals who exit who do so into different states (n_j , j=1,..J). The likelihood ratio statistic for the above test can be written

$$-2\left[\ln L^{CR}_{max} - \ln L^{SR}_{max} - \sum_{j=1}^{J} n_j \ln(\hat{p}_j)\right]$$

where, $\hat{p}_j = n_j / \sum_{k=1}^{J} n_k$, the maximum likelihood estimates.

2.6 Testing for Omitted Heterogeneity:

The above model specifications assume that all the inter-individual heterogeneity is due to observed variables. However, it would be surprising if unobserved, and possible unobservable, variables did not account for a substantial part of population heterogeneity. The potential effect of the failure of this assumption 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), and Ridder (1986) have shown that uncontrolled heterogeneity can also bias the estimated effects of the included explanatory variables. However, this second consequence may not be particularly serious in certain cases. Ridder (1986) shows that, in the absence of censoring, the bias in the maximum likelihood estimates of the parameters in the proportional hazards model is negligible if one has a flexible enough baseline hazard. That is, the misspecification of the distribution of the omitted heterogeneity need not have serious consequences for the maximum likelihood estimates.

We construct a score test for the presence of omitted heterogeneity. The derivation of the test statistic follows the approach of Cox (1983) and Lancaster (1985) (see also Chesher (1984)). Assume that the neglected heterogeneity can be represented by the presence of unobservable random factors in the hazard function and that these random effects can be represented by a single disturbance term ν , with p.d.f. f_{ν} (.). We first respecify the observed hazard as

$$\theta^{*}(t \mid \nu) = \theta(t)\,\nu, \tag{14}$$

and assume ν to be a positive-valued unit-mean unobservable random variable with range of values R_{ν} and variance σ^2. No specific distribution is assumed for ν. The unconditional survivor function is given by

$$\overline{F}(t) = \int_{R_{\nu}} \exp[\, - \varepsilon(t)\, \nu \,]\, f_{\nu}(\nu)\, d\nu \tag{15}$$

where $\varepsilon(t)$ is the integrated hazard function and is also the generalised error in the Cox and Snell (1968) sense. Expanding (15) about the mean of ν to second order gives the unconditional survivor function and corresponding density function as

$$\overline{F}(t) = \exp\{\, - \varepsilon(t) \,\}\, [1 + \varepsilon(t)^2\, \sigma^2 / 2]$$

$$f(t) = \exp\{ - \varepsilon(t) \}\ \theta(t)\ [1 + \sigma^2 \{ \varepsilon(t)^2 - 2\, \varepsilon(t) \} / 2]$$

These combine to give the corresponding (unconditional) likelihood function and thus enable construction of a score test statistic for the null hypothesis $\sigma^2 = 0$. This is distributed asymptotically as a chi-squared variate with one degree of freedom. The version of the above score test we implement uses analytical second derivatives of the likelihood.

3. DATA AND RESULTS

3.1 Data:

The data set used to examine the questions posed in the introduction 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 2332 unemployed men who registered as unemployed in the autumn of 1978. The selected sample were subsequently interviewed approximately 6 weeks, 16 weeks and 52 weeks after entry onto the register. For further details of the study see Moylan and Davies (1980) and Wood (1982). Information on the unemployment and supplementary benefits paid to sample members was provided by the DHSS benefit computers and merged with the interview data. The combination provides a unique longitudinal data set on unemployed men which contains accurate information on actual benefit receipts during the spell, personal characteristics, labour market experience prior to becoming unemployed and, for those who left the register within the given period, information on their subsequent labour market experiences. The results presented in this paper make use of data from all three interviews and the benefit records.

The duration variable is the length of the initial spell of registered unemployment. The explanatory variables in the hazard include both time-varying and time-invariant variables. The time-varying ones are described first. The unemployment rate in the individual's Travel-to Work Area is used to measure local demand conditions. This is allowed to vary between each quarter. The variables measuring income in and out of work are also time-varying. Two basic assumptions regarding the behaviour of unemployed individuals are made in the construction of these income variables. One, is that wages are attached to vacancies and not to individuals and the other is that individuals are 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. See Narendranathan et al. (1985) for further details regarding the construction of this variable. 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. The size of the sample used in our analysis is 1571. 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.

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. 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. 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 estimated mean of the vacancy-wage distribution (see Narendranathan et al. (1985)) and income from other sources with the latter being treated as for unemployment income.

Controls are included for age, marital status, colour, health and housing tenure. Descriptive statistics of these and the other variables used are presented in Table 1. Variables are also included for whether the individual has an educational qualification, has received any vocational training and whether he has completed an apprenticeship. A measure of redundancy and other lump-sum payments received is also included and following Narendranathan et al. (1985) is normalised with respect to unemployment income. Finally 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.

3.2 Flexible baseline hazard models:

Maximum Likelihood estimates of the single risk models with restricted and unrestricted baseline hazards described in the previous section are given in Table 2. Since, there was no justification for the choice of any particular step size and also to keep the models comparable, we only report results of the weekly step function model. Columns 1 and 4 refer to models where the duration variable is measured in days and columns 2 and 3 where it is measured in completed weeks. In the Weibull specifications the estimated value of the duration dependence parameter, α, is not significantly different from 1 in either case: a constant hazard is not rejected within the Weibull specification. In these simple models, which do not allow the effects of the exogenous variables to vary over the spell, the coefficients are very similar across the four columns. The estimated elasticity of the hazard with respect to employment income is around 0.8 in all four specifications, while that with respect to unemployment income is estimated to be -0.43 and the Replacement Ratio restriction is rejected. The local unemployment rate has a significant downward effect on the probability of leaving unemployment. The elasticity evaluated at the mean is about -0.15. There is a strong negative age effect on the probability of leaving unemployment, while having an educational qualification or vocational training has a significant positive effect. The results also indicate that those who had a spell of registered unemployment or no full time job in the 12 months prior to the start of the current spell, and those who voluntarily quit their last job, have a lower conditional probability of exiting out of unemployment.

While the estimated effects of the exogenous variables in the Weibull and flexible baseline hazard models are very similar, the estimated baseline hazards are very different. The minimum distance test of the restrictions on the unconstrained discrete-time hazard implied by a continuous-time Weibull specification strongly rejects the null hypothesis, giving a $\chi^2(46)$ statistic of 110. The likelihood ratio test of the discrete-time Weibull against the unconstrained discrete-time model also strongly rejects the hypothesis, giving a $\chi^2(46)$ statistic of 127.8. Both of these exceed even the 0.1% critical point. The scaled estimated baseline weekly hazards for the semi-parametric and step function models along with the restricted specification of a (continuous) Weibull are plotted in figure 1. The baseline hazards are scaled to the characteristics of a 'standard man', defined by setting all dummy variables to zero and all other variables to their sample means for the base age group. He is therefore, single, white, British, aged 20-24, living with his parents, with no education or training qualification. He lives in an area with a mean unemployment rate of 7.6%, has a sample mean income while unemployed of £28.70 per week and an expected income of £58.00 per week. He was not a union member in his previous job, spent more than 12 months in that job and is in good health. Since the models used are of the proportional hazards type, the set of characteristics chosen acts merely to fix the scale on the vertical axis. It does not alter the shape of the hazard. The semi-parametric and step function hazards in Figure 1 are, not surprisingly, very similar. Both indicate a general underlying upward slope to the hazard between 8 and 29 weeks. There also appears to be an initial sharp fall at around 6 weeks and a general decline between 33 and 39 weeks. The monotonic baseline hazard imposed by the Weibull specification cannot capture these conflicting movements.

There is a lot of noise in the plotted hazards. The picture is simplified by smoothing, although at a cost of accuracy. A 5-period moving average of the scaled baseline hazard is given in figure 2. A general rise between 8 and 27 weeks and a fall between 27 and 37 weeks are the main features. The exit probability at 6 months is roughly double that at 2 months. The equivalent continuous-time step function model with daily steps throughout yielded identical coefficients on explanatory variables to those in column 4 of table 2 and hence the results are not tabulated separately. There was considerable increase in the noise in the scaled baseline hazard without any indication of differences in the underlying shape from that in figure 1. The general shape after weekly smoothing was very similar to that from the weekly step function specification plotted in figure 1.

The score test for omitted heterogeneity, outlined in section 2.6, when conducted on the step-function model (Table 2 column 4), produced a $\chi^2(1)$ test statistic value of 2.80 (the 5% significance level critical point is 3.84). The evidence of significant omitted heterogeneity is weak in this model. This is consistent with the suggestion made by Ridder (1986) that omitted heterogeneity need not have serious consequences providing the baseline hazard is modelled in a sufficiently flexible way.

Evidence that the impact of unemployment income on the hazard varies with elapsed duration has been found by several authors. Estimates for each of the four models with this effect allowed to differ between the four quarters are given in table 3. It can be seen that when there are time-varying coefficients, the estimates of these coefficients differ between the four methods presented. When a Weibull is imposed, the extent of the decline in the unemployment income effect is understated somewhat. This effect varies considerably over the spell. A likelihood-ratio test of the equality of the four coefficients in the step-function model gives a $\chi^2(3)$ statistic of 91. The hypothesis is easily rejected. The unemployment income elasticity is estimated to be -.64 in the first quarter. It falls to -.28 in the second quarter, but is still significant. After six months of unemployment it has no significant effect. When a Weibull is imposed on the baseline hazard, the effect in the first quarter is understated, while that in the remaining quarters is overstated. In particular the effects after the 6 months point are considerably overstated and are found to be significant. The imposition of inappropriate restrictions on the baseline hazard distorts the profile of the time-varying effects.

We next turn to the estimated hazard for the 'standard man' in this model with time-varying coefficients. We consider two versions of this model. In the first, unemployment income is evaluated at the overall sample mean in each of the four quarters. This ignores the fact that typically unemployment income changes with elapsed duration. In the second version, the hazard in each quarter is evaluated at the sample mean for that quarter. This suffers from the fact that each mean is based only on survivors to that quarter. However the plotted hazards are very similar. Figure 3 gives the smoothed versions (5-period moving averages again). The effect of any measurement errors in the scaling with respect to unemployment income does not appear to be a major problem. In comparison with that for the model without time-varying effects given in figure 2, the initial decline lasts longer and the subsequent rise is more short-lived. The hazard is essentially flat between 16 and 33 weeks. After that point the hazards from the two models are very similar. The corresponding hazard for the misspecified Weibull model is also plotted in the same figure. It is apparant from this figure why the estimated Weibull duration dependence parameter, α, is so low when the time-varying effect of unemployment income is allowed for. Significant upward jumps in the hazard imparted by the changes in the unemployment income coefficients must be offset by a declining Weibull baseline hazard, resulting in a value of α considerably below 1.

3.3 Single vs Competing Risks Models:

We now turn to the distinction between the exit hazard and the return-to-employment hazard. We focus here on entry into a full-time job as the risk of interest. The appropriateness of this will be considered shortly. The results for the full-time job hazard using the competing risks framework with the weekly step-function specification for the baseline hazard and time-varying unemployment income effects (corresponding to column 4 of table 3) is given in column 1 of table 4. The general pattern of the estimated effects of most of the variables is similar to the single risk model, although some of the more important effects are more pronounced in the full-time job hazard as one might expect. The age effects are more pronounced. The conditional exit to employment probability for a man over 60 is one fifth that for an equivalent man of under 20. The unemployment income elasticities in the first six months are slightly larger. The employment income elasticity is larger than in the single risk model by about a third. The downward impact on the hazard of not having had a full-time job in the 12 months prior to the start of the current unemployment spell is considerably more marked in the full-time job hazard than in the single risk exit hazard: about three times the size. It is tempting to attribute this in part to those with part-time jobs in the past being more likely to exit into a part-time job when they leave the unemployment register. However examination of this by including part-time jobs in the job exit (column 4) indicates that this is not the cause, the coefficient changing little. The model also indicates that those who were unemployed in the 12 months prior to the start of the current spell and those who voluntarily quit their last job had a considerably lower probability of finding a job. In the case of an individual with all three of these characteristics of his previous labour market experience, the probability of finding a full-time job is reduced by some 83%, i.e. divided by six.

The appropriateness of focusing on entry into a full-time job is examined in the remaining columns of table 4 by estimating alternative formulations within the competing risks framework. As already mentioned the estimates were found to be very similar when exit into a part-time job is included with that into a full-time job. The specification in column 2 excludes those who took the job exited into while looking for something else and without the intention of remaining in the job. No satisfactory (ex ante) job had been found. Column 3 gives the results when exit into self-employment is excluded from the 'job' risk. The main conclusions seem robust to both these modifications to the definition of a 'job'.

We next turn to the test of independence of duration and the exit state (given exit). We concentrate on the step function model in which the duration of unemployment is measured in days and the two exits under consideration are FT job (column 1) and 'other'. The test statistic, distributed as a chi-squared variate with 75 degrees of freedom, is equal to 3448.5 (the 5% critical point is approximately 95). The null hypothesis of independence is strongly rejected.

3.4 Group Differences:

Finally, attention is focused on the differences in the effects on the hazard (both single risk and full-time job hazards), by age and, between manual and non-manual workers. The results are given in tables 5 and 6 respectively. In both cases there are some differences of interest that are worth highlighting.

We first consider the main differences between the effects for the under 45s and the 45-and-over age group within the single risk framework. The unemployment income effects are larger for the under 45s with significant effects only found in the, first two quarters for the under 45s and first quarter for the over 45s. There is also a difference in the impact of employment income between the two age groups with the effect being 50% higher for the under 45s than the older age group. Disallowance from benefits only affects the older age group, where it increases the probability of exit from unemployment by about 34%. Neither possessing an educational qualification nor having completed an apprenticeship has any effect on the exit hazard, whereas vocational training has a significant effect for the under 45s and not for the older men. Marital status has a significant effect only for the older age group and the exit hazard for the owner occupiers who are over 45 is about 30% lower, ceteris paribus. Some of the previous labour market experience variables also show differences between the two age groups. Having voluntarily quit the last job only affects the older age group, reducing the probability of exit by about 25%. In contrast, having had a spell of registered unemployment in the previous 12 months and having had no full-time job in the period have a stronger effect on the younger age group. The combination of the two reduces the probability of exit by more than half for this group. But, having spent less than twelve months in the last full-time job increases the probability of exit for the older age group by about 42% ceteris paribus. The local unemployment rate has a significant negative effect only for the under 45s. The 'standard man' smoothed hazards for the two age groups are given in figure 4. That for the older age group lies entirely beneath that for the younger age group. It can be seen that both exhibit a rise at around 15 to 18 weeks, although that for the younger age group is much steeper. Both then remain at this higher level until experiencing a fall at around 34 to 37 weeks. The hazard for the older age group exhibits less variation than that for the younger group. However, it should be noted that the proportional difference between low and high points is almost as large for the older group as for the younger. Both more than double over a period of about 6 weeks.

We next turn to the full-time job hazard for the two age groups. The age effects are increased, particularly for the over 60s. The conditional probability of exit into a full-time job for someone in this age group is half that for a comparable man aged 45-54. Vocational training now has a significant effect for both age groups and having completed an apprenticeship also has a positive and significant effect but, only for the under 45s. The most important finding here is the increased importance of previous labour market experience variables in the exit to full-time job for the older workers. For example, an older worker who has not had a full-time job in the 12 months prior to entry now has a 80% smaller probability of exiting into a full-time job compared to some one who has. If this man had voluntarily quit his last job and has also had a spell of registered unemployment in the last 12 months, then, the probability of exiting into full-time job is further reduced by about 60%. The income effects are also worth reporting. The expected employment income elasticity for the under 45s is now 1.13: about a third higher than that for the single risk model. The unemployment income elasticity in the first quarter, for both age groups, is also higher here compared to the single risk model. The positive effect of unemployment income after the first quarter for the older men is surprising.

There are also some interesting differences between the effects for manual and non-manual workers in the single risk model. However, the unemployment income effects for the two groups are very similar. In contrast, the employment income effect for manual workers is more than three times that for the non-manual group and is insignificant for the latter. The downward impact of the local unemployment rate is only exhibited for manual workers. For non-manual workers local demand conditions do not appear to bite. In addition, the three main previous labour market experience variables, unemployment in previous 12 months, no full-time job in that period and voluntary quit from last job, only have an effect for manual workers. As in the case of older workers, having spent less than twelve months in the last full-time job increases the probability of exit for non-manual workers. The age effects are also somewhat more pronounced for the non-manual group and marital status and colour only have a significant effect on the exit probability for this group. The 'standard man' hazards for the two groups are given in figure 5. For the first 9 months of a spell that for a non-manual worker is considerably below that for a manual worker.

Although most of the estimated effects in the competing risks model for the manual and non-manual works are very similar to those from the single risk model, there are some differeces that are worth pointing out. The age effects are now more pronounced. Having not had a full-time job in the 12 months prior to this unemployment spell now plays an even bigger role with the effects being significant for both groups. Whereas, for a non-manual worker the full-time job exit probability is 57% lower ceteris paribus, it is 78% lower for a manual worker. Expected employment income elasticity is also now significant for non-manual workers, but is estimated to be some 4 times larger for manual workers. The unemployment income elasticites are only significant in the first two quarters for the manual workers and the first quarter for the non-manual workers. It is estimated to be about 15% higher for the manual workers in the first quarter of the spell.

4. CONCLUSIONS

This paper investigates the determinants of the probability of an unemployed individual finding a job at a particular point in his spell. In particular it considers the robustness of the findings to (a) the specification of the baseline hazard, and (b) allowance for the difference between exit from unemployment and entry into a job.

The fitted exit hazard in the semi-parametric and step-function formulations shows considerable variation and there is some evidence of a rising hazard during the first 6 months of a spell which was concealed in the Weibull specification. The Weibull specification is rejected in likelihood-ratio and minimum χ^2 tests. However the estimated effects of the economic and socio-demographic factors considered are very similar in the two specifications when there are no time-varying coefficients on them. Discrete-time formulations in weeks and continuous-time formulations in days produce equivalent conclusions. The effect of unemployment income is found to decline with the length of the spell when time-varying effects are introduced and there is a tendency for the Weibull model to understate the extent of this decline.

The single risk model of exit is found to understate the effects of income in and out of work on the probability of entering a job. The effects of the key previous labour market experience variables are also understated in the single risk model, particularly that indicating those who had had no full-time job in the 12 months prior to entry onto the register. The effects in the basic model are most suitably viewed as averages and a number of differences in the effects by age and between manual and non-manual workers are found. The income elasticities as estimated in the competing risks model are very much larger for the under 45s than the 45 plus age group. This is also found to be the case for manual workers compared to non-manual workers. The local unemployment rate only has a significant effect for manual workers. The previous labour market experience variable which plays a crucial role again is not having had a full-time job in the 12 months prior to this unemployment spell. This effect is very strong for the manual workers as well as for men aged over 45. Partitions of this type by demographic group thus reveal major differences in the key effects of interest.

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Table 1: Means and Standard Deviations of the Variables Used in the Analyses

Variable	Mean	S.D.
Continuous Variables		
Duration of the current unemployment spell - weeks	23.30	15.7
Unemployment income - £ per week*	36.07	21.4
Employment income - £ per week*	63.61	19.6
Redundancy,severence pay from last job - £ 00's(i)	10.26	16.2
Unemployment rate by travel-to-work-area - %*	7.73	3.1
Dummy Variables		
Age under 20	0.08	
20 - 24	0.15	
25 - 34	0.26	
35 - 44	0.20	
45 - 54	0.13	
55 - 59	0.08	
60 - 64	0.10	
Married	0.76	
Widowed	0.01	
Non-white	0.07	
Has a health disability which affects work	0.26	
Housing - owner occupier	0.25	
Any educational qualifications(ii)	0.32	
Vocational training	0.34	
Apprenticeship completed	0.17	
Previous labour market experience		
Trade union member in last full time job	0.32	
Less than 12 months in last full time job	0.55	
Registered unemployment in last 12 months	0.52	
Voluntarily quit from last job	0.30	
No full time job in last 12 months	0.11	
Looked for work while in last job	0.32	
Was disallowed from receipts of benefits	0.29	
Sample size	1571	

Notes: (i) The mean is calculated over the 162 men who received this.
(ii) Educational qualifications included are dgrees and teacher training, 'A' levels, 'O' levels, CSE, and foreign qualifications.
* Indicate the time-varying variables. The mean is calculated over the spell length.

TABLE 2 - Maximum Likelihood Estimates of Single Risk Hazard Function Parameters (asymptotic standard errors)

Variable	Continuous Weibull Days	Discrete Weibull Weeks	Discrete Semi-param. Weeks	Continuous Step Functions Days with weekly steps
Alpha	1.04 (0.04)	1.03 (0.04)		
Constant	-6.79 (0.57)	-4.81 (0.54)		
Age under 20	0.19 (0.12)	0.18 (0.12)	0.20 (0.13)	0.20 (0.12)
25 - 34	-0.04 (0.01)	-0.04 (0.09)	-0.03 (0.09)	-0.03 (0.09)
35 - 44	-0.16 (0.10)	-0.16 (0.10)	-0.15 (0.10)	-0.15 (0.10)
45 - 54	-0.49 (0.12)	-0.49 (0.12)	-0.48 (0.12)	-0.47 (0.12)
55 - 59	-0.71 (0.14)	-0.72 (0.14)	-0.71 (0.14)	-0.70 (0.14)
60 - 64	-0.83 (0.13)	-0.84 (0.13)	-0.83 (0.13)	-0.82 (0.13)
Married	0.13 (0.09)	0.13 (0.09)	0.12 (0.09)	0.12 (0.09)
Widowed	0.19 (0.46)	0.20 (0.46)	0.23 (0.46)	0.22 (0.46)
Non-white	0.09 (0.11)	0.10 (0.11)	0.10 (0.11)	0.10 (0.11)
Has a health disability	-0.09 (0.07)	-0.09 (0.07)	-0.09 (0.07)	-0.08 (0.07)
Housing - Owner occupier	0.22 (0.07)	0.22 (0.07)	0.22 (0.07)	0.22 (0.07)
Education -				
Any educational qualification(i)	0.12 (0.06)	0.12 (0.06)	0.13 (0.06)	0.12 (0.06)
Vocational training	0.15 (0.06)	0.14 (0.06)	0.14 (0.06)	0.14 (0.06)
Apprenticeship completed	0.05 (0.08)	0.05 (0.07)	0.06 (0.07)	0.05 (0.07)
Previous labour market experience -				
Trade union member in last full time job	-0.10 (0.06)	-0.10 (0.06)	-0.10 (0.06)	-0.10 (0.06)
Less than 12 months in last FT job	0.13 (0.09)	0.13 (0.09)	0.14 (0.08)	0.14 (0.08)
Registered unemployment in last 12 months	-0.21 (0.07)	-0.21 (0.07)	-0.22 (0.07)	-0.21 (0.07)
Voluntarily quit from last job	-0.12 (0.06)	-0.12 (0.06)	-0.13 (0.06)	-0.13 (0.06)
No full time job in last 12 months	-0.37 (0.11)	-0.38 (0.12)	-0.37 (0.12)	-0.36 (0.12)
Looked for work while in last job	0.04 (0.06)	0.04 (0.06)	0.05 (0.06)	0.05 (0.06)
Was disallowed from benefit receipts	0.06 (0.06)	0.07 (0.06)	0.07 (0.06)	0.07 (0.06)
Redundancy, holiday pay etc (ii)	-0.45 (0.21)	-0.45 (0.21)	-0.46 (0.21)	-0.46 (0.22)
Unemployment rate by Travel to work area(iii)	-0.02 (0.01)	-0.02 (0.01)	-0.02 (0.01)	-0.02 (0.01)
Employment income(iii) - log	0.78 (0.14)	0.80 (0.14)	0.77 (0.14)	0.77 (0.14)
Unemployment income(iii) - log	-0.43 (0.03)	-0.43 (0.03)	-0.42 (0.03)	-0.42 (0.03)
Log likelihood	-8136.4	-5467.4	-5403.5	-8052.8

Notes: (i) Educational qualifications included are degrees and teacher training, 'A' levels, 'O' levels, CSE, and foreign qualifications.

(ii) Redundancy payments were normalised by dividing by the level of income while unemployed.

(iii) Unemployment income, employment income and the unemployment rate variables were allowed to take different values for each quarter of Cohort observation period.

TABLE 3 - Maximum Likelihood Estimates: Single Risk Model.
Separate unemployment income coefficients in each quarter.
(asymptotic standard errors)

Variable	Continuous Weibull Days	Discrete Weibull Weeks	Discrete Semi-param. Weeks	Continuous Step Functions Days with weekly steps
Alpha	0.40(0.08)	0.38(0.08)		
Constant	-2.70(0.79)	-1.88(0.69)		
Age under 20	0.15(0.12)	0.14(0.12)	0.11(0.12)	0.14(0.12)
25 - 34	-0.02(0.09)	-0.03(0.09)	-0.02(0.09)	-0.02(0.09)
35 - 44	-0.13(0.10)	-0.13(0.10)	-0.11(0.10)	-0.12(0.10)
45 - 54	-0.45(0.12)	-0.45(0.12)	-0.42(0.12)	-0.43(0.12)
55 - 59	-0.68(0.14)	-0.69(0.14)	-0.67(0.14)	-0.67(0.14)
60 - 64	-0.79(0.13)	-0.80(0.13)	-0.80(0.13)	-0.79(0.13)
Married	0.08(0.09)	0.08(0.09)	0.05(0.09)	0.07(0.09)
Widowed	0.15(0.46)	0.17(0.46)	0.16(0.46)	0.16(0.46)
Non-white	0.10(0.11)	0.10(0.11)	0.11(0.11)	0.10(0.11)
Has a health disability	-0.09(0.07)	-0.09(0.07)	-0.09(0.07)	-0.08(0.07)
Housing - Owner occupier	0.23(0.07)	0.23(0.07)	0.23(0.07)	0.23(0.08)
<u>Education</u> -				
Any educational qualification(i)	0.11(0.06)	0.11(0.06)	0.11(0.06)	0.11(0.06
Vocational training	0.14(0.06)	0.14(0.06)	0.14(0.06)	0.14(0.06)
Apprenticeship completed	0.06(0.07)	0.06(0.07)	0.07(0.07)	0.06(0.07)
<u>Previous labour market experience</u> -				
Trade union member in last full time job	-0.08(0.06)	-0.09(0.06)	-0.08(0.06)	-0.08(0.06)
Less than 12 months in last FT job	0.14(0.08)	0.14(0.08)	0.14(0.08)	0.14(0.08)
Registered unemployment in last 12 months	-0.20(0.07)	-0.21(0.07)	-0.20(0.07)	-0.20(0.07)
Voluntarily quit from last job	-0.14(0.06)	-0.14(0.06)	-0.15(0.06)	-0.15(0.06)
No full time job in last 12 months	-0.36(0.11)	-0.37(0.11)	-0.39(0.12)	-0.37(0.11)
Looked for work while in last job	0.05(0.06)	0.05(0.06)	0.06(0.06)	0.05(0.06)
Was disallowed from benefit receipts	0.08(0.06)	0.08(0.06)	0.08(0.06)	0.08(0.06)
Redundancy, holiday pay etc (ii)	-0.44(0.21)	-0.43(0.21)	-0.44(0.21)	-0.45(0.21)
Unemployment rate by Travel to work area(iii)	-0.02(0.01)	-0.02(0.01)	-0.02(0.01)	-0.02(0.01)
Employment income(iii) - log	0.72(0.14)	0.74(0.14)	0.66(0.14)	0.69(0.14)
Unemployment income(iii) - log				
qtr 1	-0.58(0.04)	-0.59(0.04)	-0.69(0.04)	-0.64(0.04)
qtr 2	-0.32(0.04)	-0.32(0.04)	-0.22(0.07)	-0.28(0.05)
qtr 3	-0.20(0.04)	-0.20(0.04)	0.07(0.09)	-0.06(0.07)
qtr 4	-0.23(0.05)	-0.24(0.06)	-0.13(0.12)	-0.15(0.12)
Log likelihood	-8083.4	-5412.9	-5343.8	-8007.4

Notes: See Table 2 notes.

TABLE 4 - Maximum Likelihood Estimates: Competing Risks Models.
Separate unemployment income coefficients in each quarter.
Continuous step function hazard in days with weekly steps.
(asymptotic standard errors)

Variable	FT job	FT excl. 'temp' jobs	FT excl. self emp.	FT and PT
Age under 20	0.19(0.15)	0.38(0.18)	0.21(0.16)	0.17(0.15)
25 - 34	-0.08(0.12)	-0.01(0.14)	-0.09(0.12)	-0.06(0.11)
35 - 44	-0.18(0.13)	-0.06(0.16)	-0.22(0.14)	-0.15(0.13)
45 - 54	-0.63(0.15)	-0.53(0.17)	-0.61(0.16)	-0.59(0.15)
55 - 59	-0.93(0.19)	-0.85(0.22)	-0.88(0.19)	-0.90(0.18)
60 - 64	-1.43(0.20)	-1.34(0.24)	-1.33(0.20)	-1.31(0.19)
Married	0.21(0.11)	0.30(0.14)	0.17(0.12)	0.19(0.11)
Widowed	0.57(0.59)	0.96(0.60)	0.56(0.59)	0.49(0.59)
Non-white	0.03(0.15)	-0.01(0.18)	0.05(0.16)	0.08(0.15)
Has a health disability	-0.17(0.09)	-0.24(0.11)	-0.21(0.10)	-0.17(0.09)
Housing - Owner occupier	0.20(0.09)	0.23(0.11)	0.17(0.10)	0.22(0.09)
Education -				
Any educational qualification(i)	0.06(0.08)	-0.15(0.10)	0.02(0.08)	0.05(0.08)
Vocational training	0.23(0.08)	0.27(0.09)	0.21(0.08)	0.25(0.07)
Apprenticeship completed	0.15(0.09)	0.18(0.11)	0.15(0.10)	0.18(0.09)
Previous labour market experience -				
Trade union member in last full time job	-0.002(0.08)	-0.11(0.09)	0.05(0.08)	0.001(0.08)
Less than 12 months in last FT job	0.11(0.10)	0.003(0.12)	0.13(0.10)	0.11(0.10)
Registered unemployment in last 12 months	-0.29(0.09)	-0.27(0.11)	-0.27(0.09)	-0.26(0.09)
Voluntarily quit from last job	-0.25(0.08)	-0.17(0.09)	-0.27(0.09)	-0.25(0.08)
No full time job in last 12 months	-1.21(0.20)	-1.31(0.23)	-1.14(0.20)	-1.08(0.18)
Looked for work while in last job	0.06(0.08)	0.03(0.09)	0.07(0.08)	0.05(0.08)
Was disallowed from benefit receipts	0.11(0.08)	0.07(0.09)	0.15(0.08)	0.16(0.08)
Redundancy, holiday pay etc (ii)	-0.85(0.44)	-0.89(0.52)	-0.79(0.43)	-0.84(0.42)
Unemployment rate by Travel to work area(iii)	-0.01(0.01)	-0.02(0.01)	-0.01(0.01)	-0.01(0.01)
Employment income(iii) - log	0.93(0.18)	0.89(0.21)	0.88(0.19)	0.88(0.18)
Unemployment income(iii) - log				
qtr 1	-0.74(0.04)	-0.76(0.05)	-0.73(0.05)	-0.73(0.04)
qtr 2	-0.36(0.07)	-0.39(0.08)	-0.34(0.07)	-0.37(0.07)
qtr 3	-0.08(0.09)	-0.04(0.12)	-0.05(0.10)	-0.09(0.09)
qtr 4	-0.15(0.19)	-0.07(0.24)	-0.19(0.19)	-0.13(0.18)
Log likelihood	-4994.9	-3759.8	-4707.1	-5158.2
Proportion who exit into given state	0.511	0.368	0.476	0.535

Notes: See Table 2 notes.

TABLE 5 - Maximum Likelihood Estimates for Weekly Step Function Model.
Age Split.
(asymptotic standard errors)

Variable	Age < 45	Age ≥ 45	Age < 45	Age ≥ 45
	Single risk		Competing risks - FT job	
Age under 20	0.11 (0.12)		0.15 (0.15)	
25 - 34	-0.01 (0.10)		-0.12 (0.26)	
35 - 44	-0.12 (0.11)		-0.25 (0.13)	
45 - 54				
55 - 59		-0.28 (0.13)		-0.30 (0.18)
60 - 64		-0.42 (0.13)		-0.81 (0.20)
Married	0.01 (0.10)	0.69 (0.24)	0.17 (0.12)	0.65 (0.32)
Widowed	0.20 (1.01)	0.82 (0.56)		1.33 (0.52)
Non-white	0.11 (0.13)	0.11 (0.23)	0.11 (0.16)	-0.43 (0.45)
Has a health disability	-0.03 (0.09)	-0.19 (0.11)	-0.09 (0.11)	-0.31 (0.17)
Housing owner occupier	0.17 (0.09)	-0.37 (0.12)	0.22 (0.11)	-0.28 (0.17)
<u>Education</u>				
Any educational qualification(i)	0.10 (0.07)	-0.01 (0.14)	0.06 (0.09)	-0.17 (0.20)
Vocational training	0.15 (0.07)	0.06 (0.12)	0.20 (0.09)	0.32 (0.16)
Apprenticeship completed	0.10 (0.09)	-0.07 (0.13)	0.25 (0.11)	-0.14 (0.19)
<u>Previous labour market experience</u> -				
Trade union member in last full time job	-0.10 (0.07)	0.01 (0.12)	0.01 (0.09)	0.06 (0.17)
Less than 12 months in last FT job	0.08 (0.09)	0.35 (0.15)	-0.01 (0.11)	0.60 (0.20)
Registered unemployment in last 12 months	-0.27 (0.08)	-0.03 (0.14)	-0.27 (0.10)	-0.43 (0.19)
Voluntarily quit from last job	-0.07 (0.08)	-0.30 (0.13)	-0.15 (0.09)	-0.49 (0.18)
No full time job in last 12 months	-0.48 (0.15)	-0.19 (0.20)	-0.01 (0.19)	-1.59 (0.14)
Looked for work while in last job	-0.01 (0.07)	0.06 (0.13)	-0.01 (0.09)	0.09 (0.18)
Was disallowed from benefit receipts	0.02 (0.07)	0.29 (0.13)	0.03 (0.09)	0.36 (0.18)
Redundancy, holiday pay etc (ii)	0.31 (0.52)	-0.44 (0.25)	-1.60 (0.62)	-0.64 (0.41)
Unemployment rate by Travel to work area	-0.02 (0.01)	-0.01 (0.02)	-0.01 (0.02)	0.02 (0.04)
Employment income	0.85 (0.18)	0.54 (0.21)	1.13 (0.07)	0.51 (0.13)
Unemployment income -				
qtr 1	-0.70 (0.05)	-0.46 (0.08)	-0.84 (0.05)	-0.64 (0.09)
qtr 2	-0.37 (0.07)	-0.13 (0.09)	-0.43 (0.08)	0.22 (0.10)
qtr 3	-0.08 (0.09)	-0.07 (0.10)	0.10 (0.08)	0.11 (0.12)
qtr 4	-0.13 (0.16)	-0.25 (0.16)	-0.29 (0.11)	0.32 (0.12)
Log likelihood	-5570.4	-2386.5	-3732.5	-1195.9
Sample size	1080	491	1080	491
Proportion who exit into FT job			0.576	0.369

Notes: See Table 2 notes.

TABLE 6 - Maximum Likelihood Estimates for Weekly Step Function Model.
Manual / Non-manual Split.
(asymptotic standard errors)

Variable	Non-manual	Manual	Non-manual	Manual
	Single risk		Competing risks - FT job	
Age under 20	0.51 (0.34)	0.58 (0.13)	0.81 (0.48)	0.09 (0.17)
25 - 34	0.23 (0.26)	-0.04 (0.10)	0.15 (0.40)	-0.08 (0.13)
35 - 44	-0.001 (0.30)	-0.12 (0.11)	-0.03 (0.42)	-0.18 (0.14)
45 - 54	-0.70 (0.34)	-0.36 (0.13)	-0.79 (0.48)	-0.56 (0.17)
55 - 59	-0.91 (0.34)	-0.53 (0.15)	-1.54 (0.55)	-0.71 (0.20)
60 - 64	-0.74 (0.31)	-0.66 (0.16)	-1.28 (0.53)	-1.32 (0.26)
Married	0.36 (0.21)	-0.03 (0.10)	0.55 (0.31)	0.10 (0.13)
Widow	-0.62 (1.03)	0.83 (0.51)	-16.30 (0.71)	1.11 (0.60)
Non-white	0.47 (0.21)	-0.05 (0.13)	0.28 (0.30)	-0.09 (0.18)
Has a health disability	-0.04 (0.16)	-0.11 (0.08)	-0.09 (0.24)	-0.19 (0.10)
Housing owner occupier	0.24 (0.16)	0.31 (0.08)	0.20 (0.22)	0.29 (0.11)
<u>Education</u>				
Any educational qualification(i)	0.17 (0.15)	0.17 (0.08)	0.10 (0.20)	0.11 (0.10)
Vocational training	-0.02 (0.13)	0.16 (0.07)	-0.07 (0.18)	0.27 (0.09)
Apprenticeship completed	0.01 (0.18)	-0.05 (0.09)	-0.05 (0.26)	0.07 (0.11)
<u>Previous labour market experience</u> -				
Trade union member in last full time job	-0.27(0.17)	-0.11(0.07)	-0.25 (0.23)	-0.04 (0.09)
Less than 12 months in last FT job	0.36(0.18)	0.05(0.09)	0.54 (0.24)	-0.02 (0.11)
Registered unemployment in last 12 months	-0.06(0.16)	-0.24(0.08)	-0.36 (0.24)	-0.28 (0.10)
Voluntarily quit from last job	-0.01(0.15)	-0.19(0.07)	-0.14 (0.19)	-0.29 (0.09)
No full time job in last 12 months	-0.17(0.26)	-0.52(0.14)	-0.85 (0.42)	-1.50 (0.24)
Looked for work while in last job	0.21(0.15)	0.04(0.07)	0.06 (0.20)	0.09 (0.09)
Was disallowed from benefit receipts	-0.16(0.15)	0.13(0.07)	-0.04 (0.19)	0.14 (0.09)
Redundancy, holiday pay etc (ii)	-0.21(0.23)	-0.77(0.54)	-2.83 (1.31)	-0.44 (0.56)
Unemployment rate by Travel to work area	0.03(0.02)	-0.03(0.01)	0.05 (0.03)	-0.02 (0.01)
Employment income	0.32(0.29)	1.05(0.17)	0.33 (0.16)	1.30 (0.22)
Unemployment income -				
qtr 1	-0.64(0.07)	-0.67(0.05)	-0.73 (0.09)	-0.84 (0.05)
qtr 2	-0.28(0.11)	-0.32(0.06)	-0.23 (0.15)	-0.30 (0.11)
qtr 3	-0.05(0.14)	-0.09(0.08)	0.09 (0.19)	0.10 (0.14)
qtr 4	0.13(0.23)	-0.29(0.14)	0.42 (0.22)	-0.29 (0.22)
Log likelihood	-1623.5	-6322.0	-904.2	-4014.5
Sample size	328	1243	328	1243
Proportion who exit into FT job			0.460	0.525

Notes: See Table 2 notes.

FIG. 1

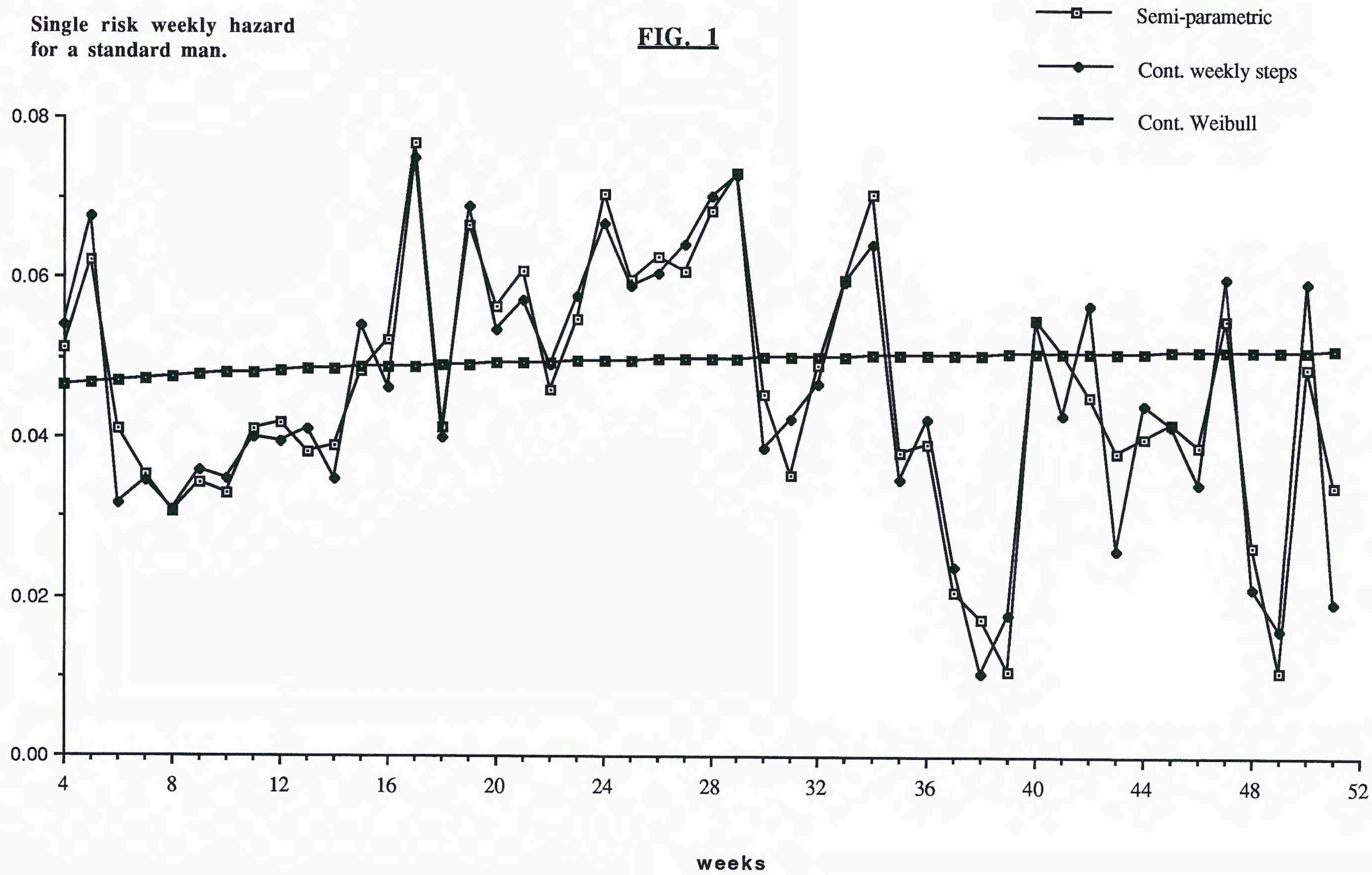
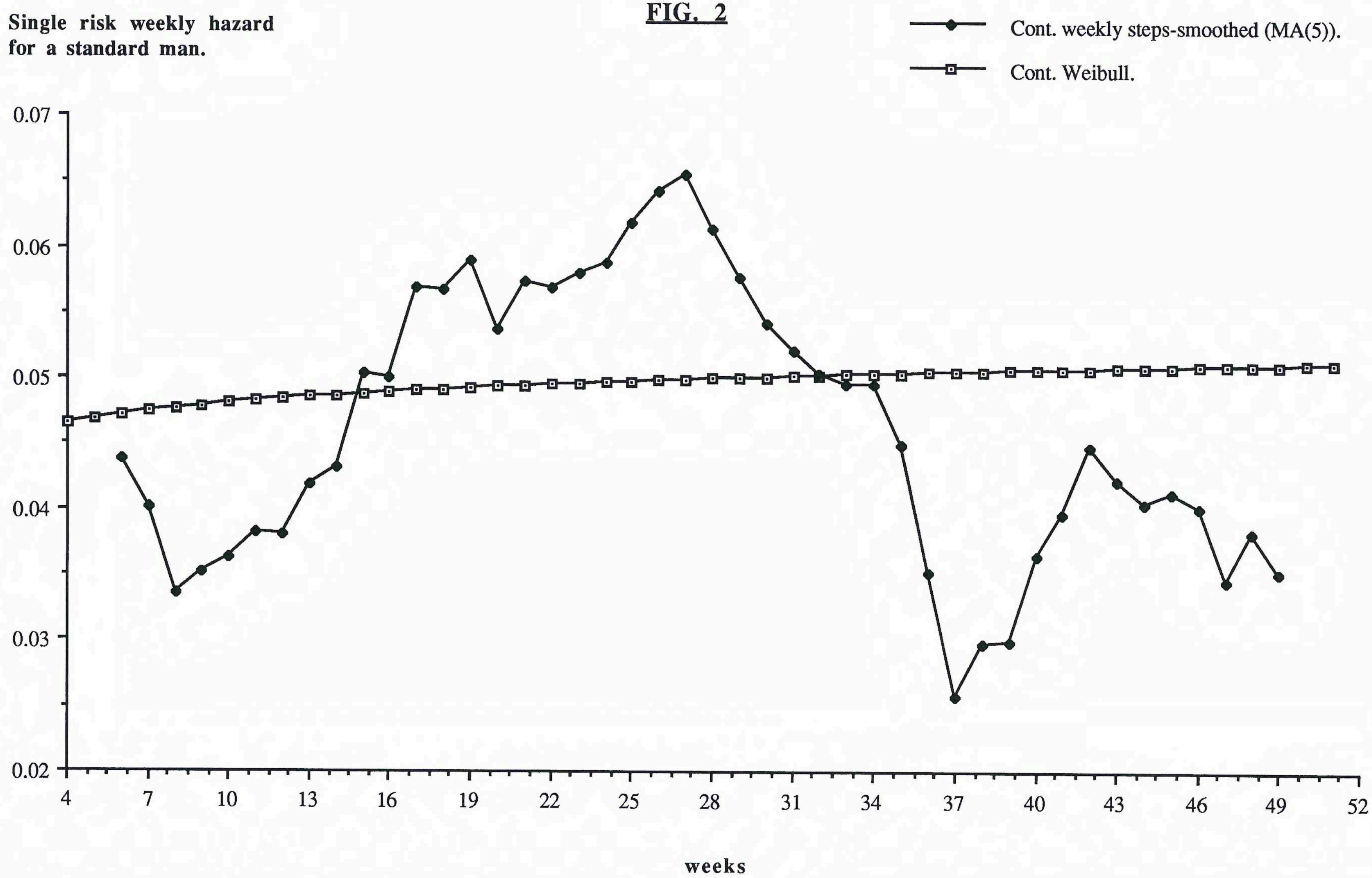

Single risk weekly hazard
for a standard man.
Semi-parametric
Cont. weekly steps
Cont. Weibull
0.08
0.06
0.04
0.02
0.00
4
8
12
16
20
24
28
32
36
40
44
48
52
weeks

FIG. 2


Single risk weekly hazard
for a standard man.
Cont. weekly steps-smoothed (MA(5)).
Cont. Weibull.
0.07
0.06
0.05
0.04
0.03
0.02
4
7
10
13
16
19
22
25
28
31
34
37
40
43
46
49
52
weeks

Single risk weekly hazard
for a standard man.

FIG. 3

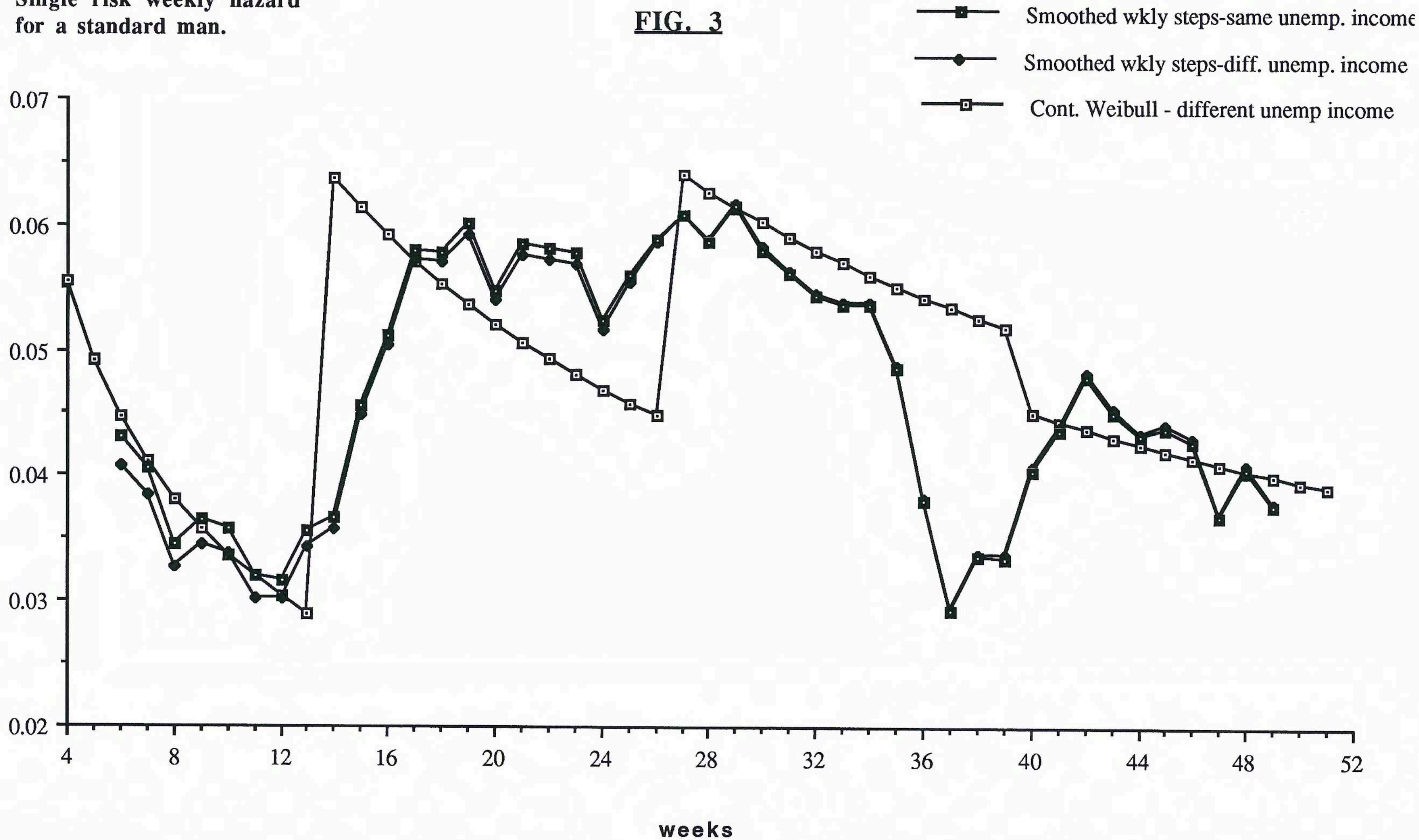


FIG. 4

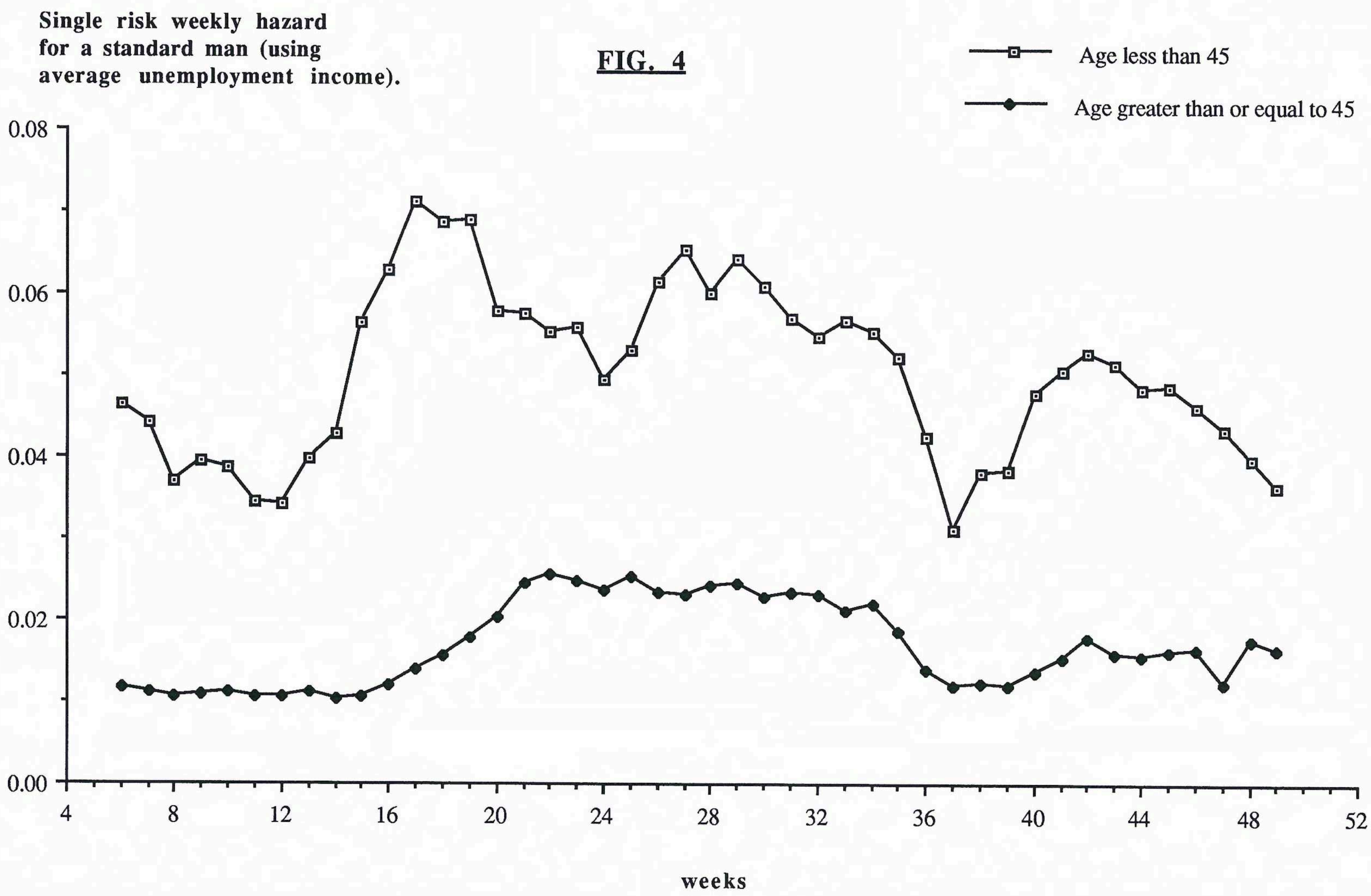
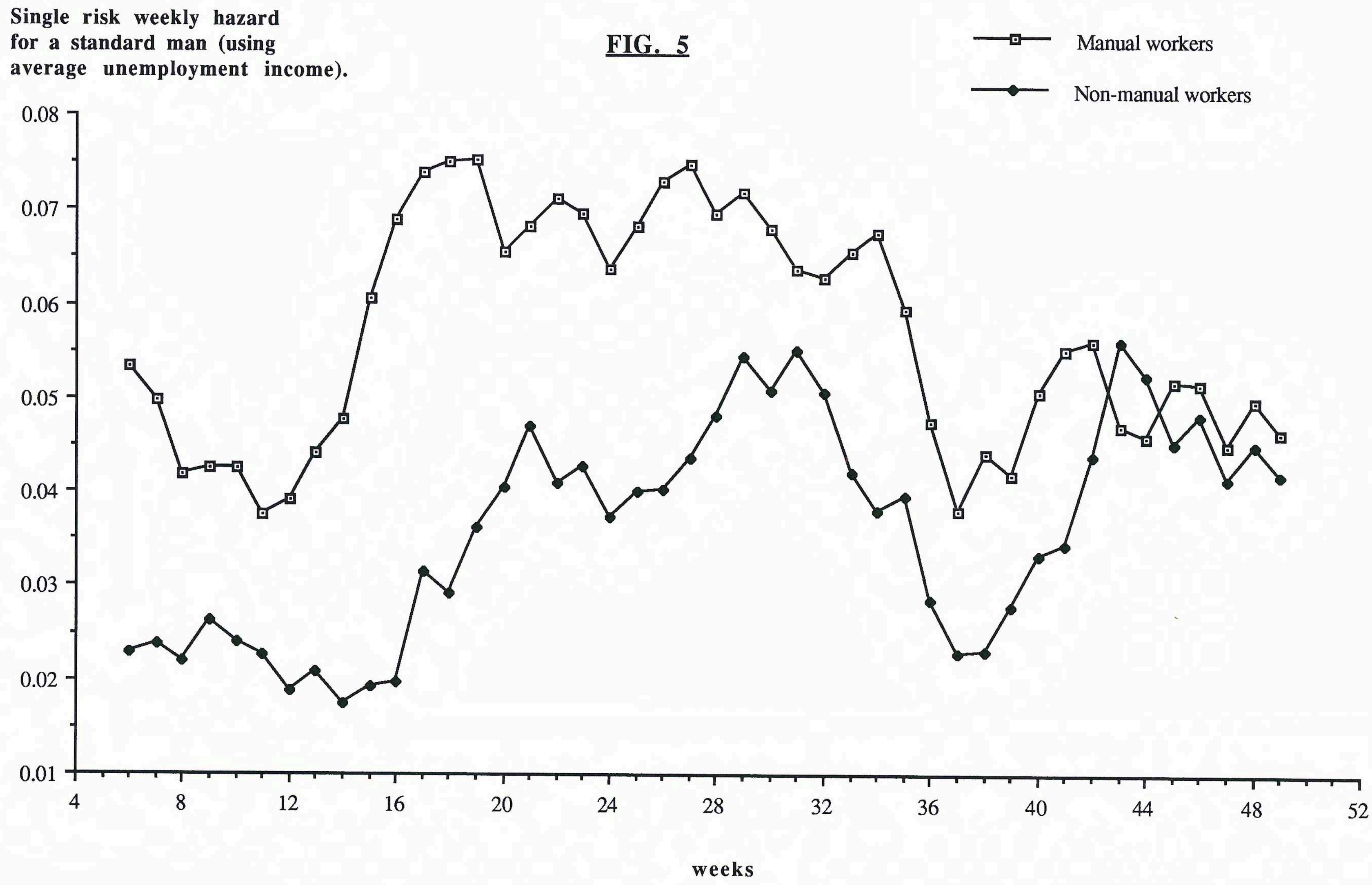

Single risk weekly hazard for a standard man (using average unemployment income).
Age less than 45
Age greater than or equal to 45
0.08
0.06
0.04
0.02
0.00
4
8
12
16
20
24
28
32
36
40
44
48
52
weeks

FIG. 5


Single risk weekly hazard for a standard man (using average unemployment income).
Manual workers
Non-manual workers
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
4
8
12
16
20
24
28
32
36
40
44
48
52
weeks