UNION STATUS OF YOUNG MEN IN BRITAIN: A DECADE OF CHANGE*

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Abstract

Previous empirical studies of individual union status in Britain have been cross-sectional. In contrast, we use longitudinal data from the National Child Development Study, to estimate the determinants of male trade union membership over the period 1981-1991. As suggested by union theories, we find that it is important to control for unobserved individual heterogeneity, and our preferred model allows for correlation of individual heterogeneity with observable variables. Our estimates reveal that the observed decline in very large workplaces, and the contraction of the public sector, explain about one third of the predicted decline in union membership over the period.
I. INTRODUCTION

There has been a dramatic decline in aggregate trade union density in Britain over the period since the Thatcher government came to power in 1979. Aggregate union density stood at 57.4 percent in 1979, falling to just 43.5 percent by 1990.\(^1\) The purpose of this paper is to estimate the determinants of union membership, and changes in union membership, using the only available British panel data survey containing information on individual union membership for the crucial decade 1981-1991 - the National Child Development Study (NCDS).

While a number of other studies have examined changes in union membership and union recognition over this period, they have typically used cross-sectional establishment level data from the Workplace Industrial Relations Surveys (see for example Disney et al (1996), Gregg and Naylor (1993), and Andrews and Naylor (1994)). These cross-sectional surveys do not tell us if individuals observed to belong to a union at any point in time are lifetime members (in which case union membership is highly persistent), or if instead everyone has the same chance of belonging to a union at any particular point in time (in which case membership is a random process). Of course, the reality is likely to lie somewhere in between, but observations on the same individuals over time are required to distinguish this. Delineating between the two effects is vital not only to provide information about the determinants of unions membership, but also to improve our understanding about the longer-term implications of trends in union status amongst young people. Our paper is the first British study of changes in individual membership across time for a single cohort of individuals, and for a panel of the same individuals over time.\(^2\)

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1 Aggregate union density is defined here as union membership expressed as a proportion of civilian employment. The aggregate figures are from Bird et al (1992).

2 Disney et al (1998) present charts showing that the main changes observed in union membership over the past 20 years in Britain are dominated by cohort effects rather than age effects. Their data are the Family and Working Lives Survey, a cross-section of individuals aged between 16 and 69 in 1994/95, with retrospective information on union status.
The NCDS shows that nearly 62 percent of young men in employment in both 1981 and 1991 were in a trade union in 1981. But by 1991, this figure had dropped to just under 50 percent. Only 43 percent of young men in employment in 1981 and 1991 were union members at both dates. Moreover, the flow of young men out of union membership was almost twice as great as the flow into union membership. What has caused this decline in union membership? Are changes in workplace attributes responsible? To what extent do changes in observable individual circumstances affect membership? Does unobservable individual heterogeneity play a role in affecting dynamic patterns of union membership? Since the NCDS represents a cohort of individuals followed over time, we are able to provide some answers to these questions. In particular, we chart changing patterns of union membership before and after a decade of considerable labour market change.

Earlier studies using British individual-level cross-sectional data find that observable individual characteristics typically have an insignificant impact on the probability of union membership, but that firm attributes are significant determinants (Booth (1986), Wright (1995)). However, economic theories of union membership suggest a number of factors likely to persuade individuals to join a union in the absence of coercion - for example, political beliefs, family background, commitment to unions, and solidarity. These factors are typically unobservable to the econometrician. Because earlier studies have been based on cross-sectional surveys, they have been unable to control for individual-specific unobservable effects that may otherwise bias the estimates of the impact of observable characteristics.

However, in this paper we use panel data estimation techniques to control for unobservable individual-specific effects. We also allow the effects of the covariates to be time dependent, and we
test for possible correlation between included time-varying covariates and unobservable fixed individual characteristics. If such correlation is not allowed for, the estimated coefficients may otherwise be picking up some of the impact of the unobservable individual-specific effect. Indeed, we find that workplace attributes, and whether the individual is a white-collar worker, are all correlated with unobservable individual effects. Our results suggest that models which do not control for this produce biased estimates, in particular of the effects of workplace attributes.

The remainder of this paper is set out as follows. The next section outlines the theoretical framework, followed by a description of the data. The econometric specification is set out in Section IV. Section V presents estimates of the determinants of union status in 1981 and 1991, and Section VI reports predicted union status probabilities based on these estimates. The final section concludes.

II. THEORETICAL BACKGROUND

Why do individuals join a trade union? There has been a considerable amount of theoretical work explaining why individuals might want to join a union. In the absence of coercion (through closed shop arrangements), individuals will join a union where the net expected gains from so doing are positive. But if membership is voluntary, if the union-set wage is a public good applying to all workers in the sector irrespective of union status, and if there are positive costs to membership, why do workers join the union instead of taking a free ride?

Union wage premia are a benefit to all workers covered by a union collective agreement, and there is evidence for Britain that union wage mark-ups vary substantially with the degree of

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3 Green and Soper (1993) use the fifth sweep of the NCDS to estimate a cross-section model of union membership. They focus on the impact of attitudinal variables on union membership in 1991, rather than on changes in membership over time.

product market competition and monopoly union power (Stewart (1994)). But in terms of explaining individual union membership, there is a problem with suggesting that the individual joins a union to receive high union wages. This is because individuals can obtain, in the absence of coercion, the wage benefits of unionisation without paying the costs, since the union-negotiated wage rates apply to all workers covered by a union-negotiated collective agreement irrespective of their individual union status.\(^5\) However, union-provided benefits that are available only to union members may induce individuals to join the union and thereby overcome the free rider problem. Such excludable benefits include reputation from complying with the group norm of union membership (Booth (1985) and Naylor (1989)), and any incentive private goods supplied by unions to their members (Booth and Chatterji (1995)).

The costs of union membership are also likely to vary across individuals, and may include psychic costs or harassment from employers (Farber (1983) and Naylor and Rauum (1993)), as well as the monetary costs of union subscriptions.

The cost-benefit calculus sketched out above suggests that individuals will unionise in order to take advantage of incentive excludable goods provided by unions to their members, and in situations where management is supportive of trade unions. Incentive private goods might include protection from unfair dismissal, grievance procedures, protection against discrimination due to ethnicity, pensions advice and the implementation of well-defined dismissal arrangements in periods of adverse demand. Individuals will also unionise if they are coerced, for example through closed shop arrangements, or if there is strong social pressure to join at the workplace level. Less direct

\(^5\) The extent of free riding on union membership is very much greater in Britain than in the US. Hirsch and Macpherson (1993) show that in 1991 only about 2 percent of workers in the US take a free ride on union membership (union contract coverage is 18 percent and union membership 16 percent of civilian employment). In contrast, in Britain in 1991 about 13 percent of male and 17 percent of female civilian employees are free riders (Booth, 1995:5). (The British Household Panel Survey conducted in 1991 show coverage is 57 percent and membership is 44 percent for males; For females coverage is 57 percent and membership is 40 percent).
coercion may arise through parental influence or employer encouragement (perhaps via co-operation in check-off arrangements for the payment of union subscriptions). 6

A number of factors affecting the costs and benefits of joining a union are inherently hard, if not impossible, to measure. For example, social pressure or individual commitment is typically unobservable to the econometrician. Because of this, our membership models do not represent a test of various union theories. Rather, they are reduced form models aiming to describe the data, to estimate the importance of observable and unobservable individual characteristics, and to chart changes in union membership patterns across the decade. While we cannot, owing to the nature of the data, consider changes in union membership that are cohort effects, we can for example consider the following. Individuals may be characterised by a level of commitment or a set of beliefs about unions, making them more or less likely to be union members all their lives regardless of where they are working. It is the possibility of controlling for such unobserved individual heterogeneity that makes the NCDS longitudinal data set particularly attractive for estimation of union membership models.

III. THE DATA

The data come from the National Child Development Study (NCDS), a longitudinal study of all children born in Britain in the week of 3-9 March 1958. Data were collected on each individual at birth, and at five follow-ups at ages 7, 11, 16, 23 and 33. All immigrants arriving in Britain in the

6 The availability or ‘supply’ of union services is also relevant to the individual union membership decision. Workers may not benefit from joining a union if there is no recognised union at the workplace. While there was little union de-recognition over the 1980s, there is evidence of a decline in union recognition in new establishments (Smith and Morton, (1993)). Consequently, union density may decline simply because the availability of union services has been reduced. We are unable to test this directly with the data set used in this paper - the National Child Development Study (NCDS) - since it is an individual-level data set; moreover it does not report union coverage in 1991. However, we attempt to deal with this problem by including, in the union membership model, variables that are strongly correlated with union recognition (see Disney, Gosling and Machin (1995, 1996)). The estimated impact on union membership of variables that may be correlated with union recognition - such as sector and firm size - might therefore be interpreted as a combination of ‘supply’ and demand side effects.
period 1958-74 and born in the week 3-9 March were added to the survey sample. The union status of our sample members is given in Table 1. The sample of 1363 men comprises observations with complete information and who were in employment in both 1981 and 1991.\(^7\) We find that 62 percent of young men in employment in both 1981 and 1991 were union members in 1981, as compared with just 50 percent in 1991, a decline of 12 percentage points.\(^8\) The comparable Labour Force Survey 1991 figure for union density is 40 percent for male employees in the age group 25-34 years (see Beatson and Butcher (1993)).\(^9\) An advantage of the NCDS data is that union status question was asked in both 1981 and 1991, and therefore our data are unlikely to suffer from problems of recall that may be present in retrospective surveys.\(^10\)

The data in Table 1 also reveal some interesting flows. Some 31 percent of unionists in 1981 were no longer members by 1991, and just under 18 percent of men who were non-members in 1981 had chosen to join a union by 1991. These figures emphasise the threat to British trade unions, since the flow out of unions was nearly twice as great as the flow in.

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\(^7\) We do not analyse women, since their labour market participation decision would then need to be modelled.

\(^8\) There were 5641 men surveyed in 1991. Of these, 83.4\% (4703 men) were also surveyed in 1981. Of these, 4663 had valid information on employment status, and 2952 were in employment (excluding self-employment) in both 1981 and 1991. In 1981, 3085 men were in employment and gave valid information about their union status (1301 non-members and 1784 members). In 1991, 4112 men were in employment and gave valid information about their union status (2351 non-members and 1761 members). We do not show in Table 1 how many changes of union membership also involve job changes, because there were large number of missing cases for the number of jobs in the data, and use of this variable would have reduced our sample size further.

\(^9\) The Labour Force Survey (LFS) only began asking about union status in 1989, and so we cannot make a comparison of the NCDS and LFS for 1981. See Beatson and Butcher (1993) for a discussion of differences between the LFS and the aggregate density figures obtained from the Certification Officer returns. The General Household Survey (GHS) asked about union status in 1983 only, and the Family Expenditure Survey asks about union status only through the indirect measure of check-off of union dues, which gives a misleading measure of union membership.

\(^10\) There is an interesting strand of US literature, looking at the effects of unions on wages, that has been concerned with possible measurement errors in the ‘union’ variable (see Freeman (1984), Card (1996)). In the UK context, there is a considerable difference between union coverage and membership. We believe that, to the extent that measurement errors are due to individuals mis-reporting, measurement error will be negligible in the case of membership status, unlike in the case of ‘coverage’ variable. Individuals are likely to know whether or not they are in a union, although they may be less certain about whether or not their wages are covered by union collective bargaining agreements. For this reason we do not believe that measurement error is a problem in our data.
IV. THE ECONOMETRIC MODEL

Individual union membership is a binary variable, taking the value of unity if the individual is a union member and zero otherwise. This variable is observed at two time periods, 1981 when the individual was 23 years old, and 1991 when the individual was 33. We specify the model for individual i in time period t as

\[ y_{it}^* = x_{it}' \beta_t + v_{it}, \quad i=1,2,...,n \quad \text{and} \quad t=1,2 \]  

(1)

and

\[ y_{it} = 1 \quad \text{if} \quad y_{it}^* > 0 \quad \text{and} \quad = 0 \quad \text{else}, \]

where \( y^* \) denotes the unobservable individual propensity to join a union, y is observed membership status, \( x \) is a vector of observable time-varying and time-invariant strictly exogenous characteristics which influence \( y^* \), \( \beta \) is the vector of coefficients associated with \( x \), and \( v \) is the unobservable error term.\(^{11}\) Thus it is assumed that the membership status for an individual is observed when the individual’s propensity to join a union crosses a threshold (zero in this case). This specification, referred to as Model 1 below, assumes that all the inter-individual heterogeneity can be captured by the observed variables. However, unobserved, and possibly unobservable, variables may also influence the individual’s propensity to join a union. Assuming the heterogeneity across individuals is time-invariant, we decompose the error term \( v_{it} \) in (1) as

\[ v_{it} = \alpha_i + u_{it} \]  

(2)

where the \( \alpha_i \) denotes the individual specific unobservable effect and the \( u_{it} \) is a random error.

We now consider the nature of \( \alpha_i \), which may be treated as fixed or random. If it is treated as fixed, we cannot obtain consistent estimates of \( \alpha_i \) since the number of \( \alpha_i \) increases with the

\(^{11}\) For a survey of these models, see Hsiao (1986) and Maddala (1987).
sample size. This is the familiar incidental parameter problem addressed by Neyman and Scott (1948). In the case of fixed effects, an assumption of a logistic distribution for \( u_i \) produces a computationally simple maximum likelihood estimator. This is the conditional maximum likelihood estimator, where the conditioning is carried out with respect to the minimal sufficient statistics in order to eliminate the unobservable \( \alpha_i \) (Andersen (1970), Chamberlain (1980)). But unfortunately the effects of time-invariant covariates cannot be estimated, as they get eliminated with the fixed effects when the conditioning is carried out. On the other hand, estimation of a fixed effects probit model does not produce consistent parameter estimates of either the \( \beta \) or the \( \alpha_i \).

In the case of random effects, the multivariate logistic distribution has the disadvantage that it has a very restrictive structure for the correlations (Maddala (1987)). We therefore chose to use random effects probit models, estimated under the common assumption that \( u_i \sim \text{IN}(0, \sigma^2_u) \) and the \( u_i \) are independent of the \( x_{it} \). To marginalise the likelihood, we assume that \( \alpha_i \sim \text{IN}(0, \sigma^2_{\alpha}) \) and is independent of the \( u_i \) and the \( x_{it} \). This implies that the correlation between two successive error terms for the same individual is a constant, given by

\[
\rho = \text{corr}(v_{it2}, v_{it1}) = \frac{\sigma^2_{\alpha}}{\sigma^2_{\alpha} + \sigma^2_u}.
\]

This formulation is referred to as the specification of ‘equicorrelation’ in the literature, since the correlation between the \( v_{it} \) s over time are the same. As shown in Heckman (1981), the parameters of this model are easily estimated by noting that the distribution of \( y_{it}^* \) conditional on \( \alpha_i \) is independent normal. We have

\[
\text{Prob}(y_{it} = 1 \mid x_{it}, \alpha_i) = \text{Prob}(\frac{u_{it}}{\sigma_u} > -\frac{x_{it}' \beta_i - \alpha_i}{\sigma_{\beta}}) = \Phi(\frac{x_{it}' \hat{\beta}_i}{\sqrt{\frac{\sigma^2_{\alpha}}{1 - \rho^2}}} + \frac{\rho}{\sqrt{1 - \rho^2}} \hat{\alpha}_i)
\]

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12 See Narendranathan and Elias (1993) for an application of the conditional and marginal likelihood estimation in the case of a logit model specification.
where $\tilde{\beta}_i = \beta_i / \sigma_\alpha$, $\rho$ given by (3), and $\tilde{\alpha}_i = \alpha_i / \sigma_\alpha$. We then marginalise the conditional likelihood for $y_{it}$ given $\alpha_i$ with respect to the $\alpha_i$. Hence the likelihood function for the sample, which we term Model 2, is given by

$$\prod_i \left\{ \int \int \left[ 1 - \Phi(\mathbf{x}_{it} ' \tilde{\beta}_i + \sqrt{\frac{\rho}{1-\rho}} \tilde{\alpha}_i) \right]^{\gamma_i} \left[ \Phi(\mathbf{x}_{it} ' \tilde{\beta}_i + \sqrt{\frac{\rho}{1-\rho}} \tilde{\alpha}_i) \right]^\gamma \phi(\tilde{\alpha}_i) d\tilde{\alpha}_i \right\}$$

(5)

where $\phi$ and $\Phi$ are the density and the distribution function of the standard normal variate. The random effects model is most commonly estimated with the restriction that the effects of covariates are constant over time. Given the 10 year time interval between the two observations for each individual, we relax the assumption of time-invariant effects. Of course, this is a testable assumption and the result of this test in our general model is given in Table 2, row 6.

There are three points to note about the above specification. First, the above random effects probit model is convenient if one is interested in imposing a positive correlation structure for the error term over time for the same individual. Although this model is easier to estimate than one with an unrestricted error covariance structure, if this assumption is violated the maximum likelihood procedure will result in inconsistent parameter estimates.

Second, consistent parameter estimates of the $\beta$ coefficients could be obtained by ignoring the correlation structure and estimating the model as univariate cross-sectional probits - Model 1- (Maddala (1987) or, as a pooled model which includes all the appropriate interaction terms to capture the time varying effects of the covariates. But the standard errors in the pooled model will be wrongly calculated. An estimate of the covariance matrix may be obtained as $H^{-1} G H^{-1}$ where, $H$ is the hessian and the $G$ the outer product of the score matrix. This is the quasi-maximum likelihood estimator covariance matrix (White (1982), Guilkey and Murphy (1993), Gourieroux and Monfort

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\(^{15}\) IN refers to Independent Normal distribution.
Third, we only have two time period observations per individual in our data set. Thus if we want to allow for a general variance-covariance structure for \( v_i \) in (1), we can estimate a bivariate probit model which will allow for heteroskedasticity over time as well as unrestricted correlation between \( v_{i1} \) and \( v_{i2} \). The log-likelihood for the sample under the assumption of a bivariate probit model (and the normalisation that \( \sigma_{v1}^2 = \sigma_{v2}^2 = 1 \)) is:  

\[
L = \prod_i F\left(\left(2y_{i1} - 1\right)x_{i1}'\beta_1 + \left(2y_{i2} - 1\right)x_{i2}'\beta_2 \right, \left(2y_{i1} - 1\right)/\left(2y_{i2} - 1\right)\rho\right)
\]

(6)

where \( F \) is the standard bivariate normal distribution function and \( \rho \) is the correlation between \( v_{i1} \) and \( v_{i2} \) which is unrestricted. Since \( T=2 \) in our case, if the parameter \( \rho \) is positive and the errors \( v_i \) are homoskedastic over time, the above likelihood function, in a different form, will be the same as the likelihood function for the random effects probit model given by (5). Thus a comparison between the bivariate probit model results with those of the random effects probit model results will shed some light on the validity of the assumption of the presence of time invariant unobservable heterogeneity in the model. But note that the coefficients are not directly comparable, owing to the different normalisation used in estimation of this model using standard software. The random effects probit model coefficients have to be multiplied by \( \sqrt{1-\rho} \) (see Arulampalam (1998) for a discussion).

The models considered so far assume that \( \alpha_i \) is independent of the observable \( x_{it} \) for all \( i \) and \( t \). If this assumption is violated, maximum likelihood estimates will be inconsistent; the estimated \( \beta \) coefficients will pick up some of the effects of the unobservable \( \alpha \). As an example, suppose that the individual-specific component \( \alpha \) represents individual commitment to worker solidarity, making
the individual both more likely to join a union and more likely to work in a larger establishment. Any model that does not allow for the correlation between establishment size and \( \alpha_i \) will suffer from omitted variable bias. In this example, the estimates of the impact of plant size on union status will be biased. To avoid this problem, we relax the assumption that \( \alpha_i \) is independent of the observable time-varying characteristics in \( x_{it} \). Following Chamberlain (1980, 1984), we model the dependence between \( \alpha \) and \( x \) by assuming that the regression function of \( \alpha_i \) is linear in all the time-varying covariates. We write this as our Model 3, where \( \alpha_i \) in (2) is specified as follows:

\[
\alpha_i = \alpha_0 + a_{1i}'x_{i1} + a_{2i}'x_{i2} + e_i
\]

(7)

where we also assume that \( e \sim \text{IN}(0, \sigma^2_e) \) and is independent of the \( x_{it} \) and the \( u_{it} \). \( \alpha_0 \) is the intercept, and \( x_{i1} \) and \( x_{i2} \) refer to the vector of observations for individual \( i \) in time period 1 and 2 respectively. Thus equation (1) becomes

\[
y_{it}^* = x_{it}'b_t + a_{1i}'x_{i1} + a_{2i}'x_{i2} + e_i + u_{it}, \quad i=1,2,...,n \text{ and } t=1,2
\]

(8)

where we have absorbed the intercept \( \alpha_0 \) into the \( b \). Note that the coefficients in \( a_1 \) and \( a_2 \) corresponding to the time-invariant variables in equations (7) and (8) are set equal to zero.\(^{15}\) This is equivalent to the random effects probit model (or the bivariate probit model in the case of unrestricted correlation between \( v_{i1} \) and \( v_{i2} \)) with additional regressors \( x_{i1} \) and \( x_{i2} \).

To summarise, we estimated a number of models: (i) univariate pooled cross-sectional probits given as Model 1; (ii) a random effects probit model allowing the effects of the covariates to differ in the two time periods - Model 2 and equation (5); and (iii) a random effects probit model

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\(^{14}\) In the model which imposes the restriction that the coefficients in the two periods are equal, one only needs one of the variance normalisations and hence one can test the assumption of homoskedasticity over time. The result of this test is presented in Table 2 note (iii).

\(^{15}\) Since the \( \alpha_i \)'s are time invariant, if we were to specify equation (8) to include the time-invariant characteristics, the effects of these variables would get absorbed in the \( b \)'s.
which allows for dependence between the time-varying covariates in \( x_{it} \) and the unobservable individual specific term \( \alpha_i \), given as Model 3 and equation (8).

We also estimated expanded versions of Models 2 and 3 that include an additional variable indicating whether or not the individual worked in 1981 in a workplace which bargained with a union over pay - ‘wage covered by a union in 1981’. These expanded versions termed Models 4 and 5 respectively represent a means of capturing any additional correlation between the observables and the unobserved heterogeneity. The Model 5 specification was also estimated as a bivariate probit model for comparisons and tests of various restrictions.

V. THE ESTIMATES

All models were estimated using Limdep version 7.0 (Greene (1995). Limdep uses two different algorithms for the estimation of the bivariate and the random effects probit models. As a result, the maximised values of the log-likelihood functions were not numerically identical, although they were nearly the same (as will be seen from row [1] of Table 2). As we saw earlier, under the assumptions of a positive correlation between the two time period errors and homoskedasticity over time, the bivariate probit model and the random effect probit model are equivalent. Comparing the bivariate probit and random effects probit estimates, we found that, after correcting for the normalisation, the coefficient estimates were equal to 2 to 3 decimal places. We also found the estimated correlation

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16 This information is not available for 1991.
17 We did not estimate Model 1 with the inclusion of the 1981 coverage variable for the following reasons. First, the 1981 coverage variable was included in the other models to capture some ‘unobservable/ unmeasurable’ characteristics that make an individual work in the covered sector, and not to model the membership decision conditional on coverage. Second, if we had included the 1981 coverage variable in Model 1, the estimated results from this model will not be directly comparable to the other model results. This is because assuming the membership decision conditional on coverage to be of the probit form does not imply that the unconditional membership decision models are of the probit form, and vice versa. The model results presented in this paper refer to unconditional membership decisions.
18 As we saw earlier, the random effects model with a full set of interaction dummies to allow the effects of all the covariates to be different in the two time periods is equivalent to the bivariate probit Model. This is also equivalent to the first step in the two step minimum distance estimator proposed by Chamberlain (1984) where all the effects of the covariates are allowed to change over time.
We thus conclude that the random effects probit model is an adequate model.

V.1 The Testing Procedure

We now consider the testing procedures used to discriminate between the various models.\textsuperscript{19} In Table 2 we report the Likelihood Ratio (LR) statistic values for testing hypotheses regarding the significance of various variables, and tests of various restrictions in the equations. The tests are conducted on the basis of using Model 5 as our maintained model.

We now allow for correlation between the time-varying covariates and the unobservable heterogeneity term - the random effects model (see (7) and (8)). This produces 16 extra variables - the leads and lags of some of the time-varying covariates. A likelihood ratio statistic of 45.50 with 16 degrees of freedom (Row 2, Table 2) is obtained for the test of $H_0$: no correlation between the time-varying explanatory variables and the $\alpha$. The LR statistic value for the same test but with the addition of the coverage variable was 466.30 with 18 degrees of freedom (Row 4, Table 2). This null hypothesis is easily rejected at all conventional levels of significance. Row 3 of Table 2 gives the LR statistic value for testing if the effects of the coverage variables are zero. This null hypothesis is also rejected at all conventional levels of significance.

In addition to the above tests, we also tested to see whether all the coefficients, including and excluding the intercepts were equal in the two time periods. These were also rejected (rows 5 and 6, Table 2). Based on these tests, our preferred specification is Model 5 - the random effects probit model allowing for correlation between the time-varying regressors and the $\alpha$, and also including the 1981 coverage variable to capture possible additional correlation.

\textsuperscript{19} As with any empirical analyses, initial specification search was carried out prior to arriving at the specifications presented in this paper. Although these types of sequential estimation and testing will be
Normality is an important assumption in our specification. We thus provide in the bottom rows of Table 3 (which also contains the model estimates) test for normality in all models estimated. This test is the conditional moment test, which is based on the third and fourth order generalised errors (Chesher and Irish (1987)). The alternative model considered here is the Pearsonian family of distributions which nests the normal distribution. As we can see all models estimated do not reject the null of normality of errors.

We also report the Zavoina-McKelvey pseudo-$R^2$ measure for our models (Greene (1995), p.421). Our preferred model, Model 5, has the largest value for this statistic.

V.2 The Estimates

Table 3 presents the model estimates. We categorise variables that are potential determinants of the individual decision to unionise into five groups: time-invariant individual and family background variables; time-varying individual characteristics; time-varying attributes of the workplace employing the individual; the regional unemployment rate; and (in Models 4 and 5) coverage by union in 1981. If it were the case that the attributes of an individual’s employer perfectly defined firms with union recognition, then the inclusion of employer attributes provides an answer to the question as to who is more likely to join a union of those working in union-recognised establishments, while exclusion of employer attributes gives a measure of which individuals are more likely to join a union. This should be borne in mind by the reader when interpreting the estimates.

As noted earlier, under the assumption that the covariates are uncorrelated with the $\alpha$, any estimation which ignores the correlation between $v_{i1}$ and $v_{i2}$ produces consistent parameter

\footnote{This may not always be the case. For example, all public sector may be union-recognised for pay bargaining, but it is also possible in the absence of closed shops that individuals will only join in the larger public sector establishments where there may be shop steward or social pressure to do so. So the inclusion of employer-}
estimates, although the standard errors are biased. We therefore present, in Column [1] of Table 3, the univariate probit estimates (Model 1). The random effects probit models, without and with allowance for correlation between the included time-varying covariates and unobservable omitted heterogeneity, are presented in Columns [2] and [3] (Models 2 and 3) respectively. Columns [4] and [5] report the results of Models 2 and 3 respectively, augmented by the inclusion of the coverage variable, ‘Wage covered by union in 1981’.

We first look at the estimates of Model 3 (preferred to Model 2 on the basis of tests reported in Table 2), and then comment later in this section on how these results change with the inclusion of the extra variable for 1981 union recognition. The explanatory variables were chosen in the light of the theoretical background outlined in Section I. The time-varying variables used in Models 3 and 5 were the leads and lags of all the workplace attributes (excluding the industry dummies) and the variable ‘Professional/ Managerial/Administration’ (reflecting high occupational status). As noted above, these are included to capture correlation between the explanatory variables in the model and the unobserved individual-specific error term.

The time-invariant individual characteristics which were found to have a significant influence on the probability of union membership are ‘Father-non-manual’, ‘Father left school under 16’, and ‘Apprenticeship completed’. These variables might be interpreted as representing ‘social custom’ influences on union membership. It is interesting that young men whose fathers left school under the age of 16 were significantly more likely to be union members in 1981, but not in 1991, ceteris paribus. This variable is likely to proxy a working class background. The finding of a differential impact in 1981 to 1991 suggests either diminishing paternal influence as the respondent ages, or perhaps the growing dissatisfaction of the working class with the trade union movement. We also

size variables may pick up not only a direct union recognition effect, but also an individual effect of responsiveness to local social pressure.
find a differential impact for ‘Father-non manual’, a variable taking the value unity if the young man’s father was in a non-manual occupation at the time of his son’s birth. This variable is found to have a significant negative impact in 1991 but not in 1981, relative to individuals with fathers in unskilled manual occupations.

The ‘Apprenticeship completed’ variable is a dummy which takes a value of unity if the individual had completed a trade apprenticeship before 1981, typically after a 3-5 year indenture period begun at age 16 (in 1974). The form of apprenticeship covered by this variable involved training for skilled manual workers. At that time, entry into an apprenticeship usually also involved entry into union membership. The fact that this variable has a significant positive impact on union status in 1981 may reflect closed shop arrangements for skilled manual workers at that time, when to practise a trade workers had to carry a union card. The impact of this is reduced in 1991.

Next, we consider the impact of time-varying individual characteristics. ‘Full-time experience’ has a significant positive impact on union membership: men with more exposure to work (and possibly with a greater commitment to the labour market) are more likely to be union members in both 1981 and 1991. The other time-varying variables which are found to have a significant influence are ‘Married with children’ and ‘Voted in the last general election’. Men with family responsibilities were more likely to be union members in 1981, but this has no significant impact by 1991. The variable ‘Voted in the last general election’ is a proxy for individual commitment. In Britain where voting in a general election is not compulsory, it has often been suggested that voters may feel unable to affect the outcome and therefore not bother voting.

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21 Booth and Satchell (1994) discuss this form of British apprenticeship; over the period 1974-1981, the predominant form of training for NCDS young men leaving school at age 16 was the apprenticeship. The effect of the variable indicating white collar status changes from being negative in models which do not allow for correlation between x and α, to being positive when this correlation is captured using this variable. Our conjecture is that this may be due to unobservable variables reflecting new conservatism of the lower middle class workers observed during the Thatcher decade.
Individuals who do bother to vote may be characterised by a level of individual commitment that may also make them more likely to join a union.\textsuperscript{23}

The effects of workplace attributes are as expected. The base for workplace size is plants with fewer than 25 employees in the private sector. The larger the workplace in both private and public sectors, the more likely is a man to join a union ceteris paribus. This may reflect group pressure to join from workmates, or pressure from shop stewards who are more likely to be present in larger plants. Or it may be that workers in larger workplaces require more protection from managerial whim. An additional explanation, and one that we are unable to test with NCDS data, is that plant size proxies union recognition. There may be no union presence in very small plants, and so workers may not have the opportunity to join. Indeed, other studies have shown that recognition is positively correlated with plant size (Disney, Gosling and Machin (1996)).

The magnitude of the workforce size effects is found to be substantially larger in the public sector than in the private sector. This may be because closed shop arrangements (implicit through peer pressure or explicit) are less prevalent in the private sector, or because there is less union recognition in private sector firms. The privatisation programme of the Conservative government may have indirectly contributed to the decline in male union membership over the decade. While 61 percent of our sample worked in the private sector in 1981, this had increased to 69 percent by 1991. Since private sector workers are less likely to unionise, then this trend of shrinking public sector employment may explain part of the observed decline in union density in Britain. It is interesting that the 1-digit industry dummy variables included in all the models had an insignificant impact on union membership, with the exception of the “Utilities” and the

\textsuperscript{23} The NCDS also indicates the political party for which the individual voted (conditional on voting) in the last general election. This information was not included, since it is likely to be endogenous; people who join the unions are also more likely to vote labour. It is interesting that ‘voted in the last general election’ is insignificant in Models 4 and 5, in which union coverage is included as an additional regressor.
“Transport/Communication” industries in 1981 and the “Distribution, Hotels, Catering and Repairs” in 1991 (significant at the 10 percent level). The utilities and transport industries are the industries affected by the government’s privatisation programme.24

Finally, the regional unemployment rate was found to have a significant impact on the male unionisation probability in both 1981 and 1991. The average regional unemployment rate declined from 11.24% in 1981 to 8% in 1991, and yet the size of the estimated impact of unemployment on union membership increased over the period. This finding suggests that our cohort may have become more concerned about job insecurity as they aged a decade.

We also note from Table 3 that about 61 percent (estimate of $\rho$) of the unexplained variation in this model is attributed to the unobservable individual specific term.

Model 3 assumed that the unobservable individual specific component is correlated with the included variables, whereas Model 2 did not make this assumption. A comparison of the estimates of Models 2 and 3 (see Columns [2] and [3] in Table 3) reveals the importance of allowing for such potential correlation when modelling union membership. Although most of the estimated effects are qualitatively the same across these models, there are some important quantitative differences. First, relative to private sector workplaces with less than 25 employees, the effects of public sector workplace attributes in 1981 are estimated to be generally smaller in Model 3 compared to Model 2. Second, within the private sector, the differential workplace size effects are more pronounced in Model 2. We thus conclude that models that do not make allowance for correlation between the

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24 Utilities accounted for 5.8 percent of the sample in 1981, and 4.3 percent in 1991. Metal manufactures and Other manufactures (traditionally strongly unionised) fell from, respectively, 14.1 percent and 9.1 percent in 1981, to 11 percent and 8.4 percent by 1991. The services industries (traditionally less strongly unionised) grew over the period. Other industries remained fairly stable.
observed time-varying covariates and the unobservable individual-specific component produce biased estimates.\footnote{Note, the factors that have to be used in the scaling of the coefficients for Models 2 and 3 for purposes of comparison are 0.650 and 0.625 respectively.}

Columns [4] and [5] of Table 3 report the results of estimation of Models 2 and 3 with an extra regressor - whether or not the individual’s wages in 1981 were covered by union bargaining. There is a considerable improvement in the log-likelihood for each model; for example, Model 3 has a log-likelihood of -1218.87, but the same model with the inclusion of the 1981 union coverage variable produces a log-likelihood of -1029.09 (see Column [5]). Estimated rho, while still significantly positive, has diminished in magnitude from 0.606 to 0.518, implying that now only about 52 percent of the total error variation is attributed to the unobservable individual heterogeneity.\footnote{It is not strictly valid to compare the estimated $\rho$ from Model 2 with that of Model 4, or Model 3 with that of Model 5. The estimated $\rho$ can be interpreted as the proportion of the total error variance attributable to unobserved individual heterogeneity under the mained assumptions. Since, the ‘81 coverage’ variable is significant in Models 4 and 5, Models 2 and 3 would be considered as misspecified.}

The 1981 union coverage variable has a significantly positive impact on union membership for both 1981 and 1991; however, the 1981 effect is over twice as large as the 1991 effect. Inspection of the estimates reported in Columns [4] and [5] reveals that the effects of significant time-varying time-invariant individual characteristics are reduced in magnitude when 1981 union coverage is included. For Model 5, the \textit{time-invariant} variable ‘Father non-manual’ is only significant at 10\% level (1991 union membership). Of the \textit{time-varying} individual characteristics, ‘Married with kids’ and ‘Full-time experience’ still have a significantly positive effect on 1981 union membership, while 1991 union membership is affected only by ‘Full-time experience’ and ‘Voted in the last general election’. The regional unemployment rate is now found to have a significant effect on the 1981 union membership decision only at the 10\% level.

\section*{VI. INTERPRETATION OF THE ESTIMATES}
How do we interpret the various estimates in the models with unobservable individual specific components? In standard cross-sectional univariate probits, it is customary to provide expected changes in the union membership probability when particular characteristics are changed one at a time - the marginal effects. Given the panel nature of our data, we have to distinguish between a permanent and a temporary change. But as discussed in Chamberlain (1984), any such calculation must take into account the correlation between the included variables and $\alpha_i$. The following is based closely on Chamberlain (1984).

Consider the mean effect of changing $x_i$ from $\bar{x}$ to $\tilde{x}$ on the probability that a randomly chosen individual will belong to the union. This is given by,

\[
\int \left[ \text{prob}(y_i = 1 | x_i = \bar{x}, \alpha) - \text{prob}(y_i = 1 | x_i = \tilde{x}, \alpha) \right] \mu(d\alpha)
\]

which is equal to

\[
\int \left[ \text{prob}(y_i = 1 | x_i = \bar{x}, A) - \text{prob}(y_i = 1 | x_i = \tilde{x}, A) \right] \mu(dA)
\]

where $\mu(d\alpha)$ is the population probability measure for $\alpha$, $\alpha_i = A_i + e_i$ (see equation (7)) and $\mu(dA)$ is the population probability measure for $A$. But, the distribution of $y_i$ conditional on $x_{i1}, x_{i2}$ but marginal on $\alpha$ has a probit form given by,

\[
\text{prob}(y_i=1|x_{i1},x_{i2}) = \Phi \left( \frac{x_i\beta_t + a_1 x_{i1} + a_2 x_{i2}}{\sqrt{\sigma_u^2 + \sigma_c^2}} \right)
\]

A consistent estimate of (10) is given by,

\[
\frac{1}{N} \sum_{i=1}^{N} \left\{ \Phi \left( \frac{x_i\beta_t + a_1 x_{i1} + a_2 x_{i2}}{\sqrt{\sigma_u^2 + \sigma_c^2}} \right) - \Phi \left( \frac{\tilde{x}_i\beta_t + a_1 x_{i1} + a_2 x_{i2}}{\sqrt{\sigma_u^2 + \sigma_c^2}} \right) \right\}
\]
where the parameters in this equation are replaced by their estimates. It is important to note that the above calculations are conditional on the estimated value of $\alpha$ (see equation (7)).

In Table 4 we present estimates of the expected change in the union membership probability, when we change some of the characteristics of a randomly drawn individual. These are calculated as the average of the predicted probabilities before and after the change. In the case of Models 3 and 5, these calculations are also performed keeping the estimated expected value of $\alpha$ fixed (see (12)).

We also provide standard errors for the predicted probabilities calculated as the square root of

$$
\hat{\theta} \left[ cov(\hat{\theta}) \right] \hat{\theta} + \frac{1}{n^2} \sum \left( \hat{P}(\hat{\theta}) - \hat{P}(\hat{\theta}) \right)^2.
$$

where $\hat{\theta}$ are the maximum likelihood estimates with the corresponding estimated covariance matrix $cov(\hat{\theta})$, $\hat{P}(\hat{\theta}) = \frac{1}{n} \sum \hat{P}(\hat{\theta})$. See Arulampalam and Pudney (1999) for details of the derivation of this expression.

Ceteris paribus, holding an apprenticeship in 1981 increases the union membership probability by 7.8 percentage points (0.6845-0.6067 in %) in 1981 and 5.5 percentage points in 1991, as estimated from Model 1. Model 2 predicts the same probability to be 8.1 percentage points. For Model 4, the effect of holding an apprenticeship is around 4 percentage points in 1981 and 3 percentage points in 1991.

Moving across Row 1 in Table 4, we see that, from Model 3, the predicted effect of holding an apprenticeship in 1981 on the union membership probability is 6.9 percentage points (0.6795-0.6109 in %). This is slightly smaller than the predicted apprenticeship impact of Models 1 and 2.

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27 Since the variable ‘wage covered in 1981’ is used only to capture possible correlation between the observables and the unobservable heterogeneity, it is not legitimate to look at the effect of a change in this
Models 4 and 5 - including the coverage variable - predict these probabilities to be smaller still, since they predict the effect of holding an apprenticeship to be around 4 percentage points in 1981 and 3 percentage points in 1991. In general, we find that predictions based on changes to personal characteristics produce very similar predicted probabilities in Models 4 and 5, where the coverage variable is included.

The calculations presented in other rows in Table 4 follow the same procedure. Since Model 5 is our preferred specification, we briefly highlight some of the main results given in the last column of Table 4. The third row in Table 4 shows the estimated union membership probability for a randomly chosen man employed in a private sector workplace of less than 25 employees in both 1981 and 1991 (the base category). From Model 5, his predicted probability of being in a union in 1981 is 51 percent, but this falls to 32 percent by 1991. Next consider changes in the predicted probabilities of union membership when an individual moves from the smallest size private sector workplace in 1981 to the smallest size public sector workplace in 1991 (Row 3 versus Row 5). Model 5 predicts this change to be about 22 percentage points.

The seventh row in Table 4 looks at predicted union membership probabilities when the workplace industry, sector and size distribution in 1991 is restricted to be the same as in 1981. From Model 5, the predicted probabilities of union status are 63 percent in 1981 and 52 percent by 1991. In other words, had the distribution of workplace attributes been kept at 1981 levels, the predicted decline in union density over the period would have been approximately 11 percentage points (0.629 - 0.520 in %). Actual density fell over the period by 12 percentage points (see Table 1). Comparing this to Model 4 which only includes the coverage variable to pick up possible correlation between the regressors and the unobserved heterogeneity, we find that Model 4 also

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variable on the union membership decision in this framework.
predicts this decline to be also around 11 percentage points. Model 3 results are also similar. This implies that the coverage variable is acting as a good proxy for some of the correlations which are picked up by workplace attributes, and suggests that the inclusion of employer attributes provides an answer to the question as to who is more likely to join a union of those working in union-recognised establishments.

In summary, random effects models which do not allow for correlation between the observable time-varying covariates and unobservable individual effects (Models 2 and 4) produce biased estimates of the effects of workplace attributes on the probability of union membership. These results reinforce our previous conclusions regarding the importance of allowing for correlations between observables and unobservable individual characteristics in these models. Of course this can only be satisfactorily carried out with longitudinal information.

Table 5 presents the predicted transition matrix for a randomly chosen individual, for all five models. It is striking that, without exception, the predictions from Model 5 are closest to the actual transitions (reported in Table 1 and repeated in Table 5).

VII. CONCLUSION

Economic theories of union membership suggest a number of factors likely to persuade individuals to join a union in the absence of coercion, factors which are typically unobservable to the econometrician. Past studies on the determinants of trade union membership have been based on cross-sectional surveys, and have therefore been unable to control for these unobservable effects. In this paper we have used panel data from the National Child Development Study to examine the determinants of trade union membership over the period 1981 to 1991, for young men who were employees in 1981 and 1991 (at the ages of 23 and 33 respectively).
What do our results suggest caused the observed decline in union density over the period 1981 to 1991 in our cohort? We find that the decline in very large workplaces, the reduction in the size of the public sector between 1981 and 1991, and industrial compositional changes between 1981 and 1991, are likely to have contributed to the observed fall in union status from 62 percent in 1981 to 50 percent in 1991. Changes in workplace size and privatisation explain about one third of the predicted decline. Industry has an insignificant effect with the exception of utilities and communication industries in 1981, and service industries in 1991.

We find that it is important to control for unobserved individual heterogeneity and to allow this to be correlated with the observables in the model. Perhaps the principal gain from using panel data to estimate the unionisation probability is that it allows us to exploit a number of binary panel data techniques to control for unobserved individual heterogeneity. This is particularly important because theory suggests that unobservable individual heterogeneity will affect the union membership decision. Moreover, we have allowed this heterogeneity to be correlated with time-varying observable covariates. We find that models that do not control for unobservable heterogeneity, and its correlation with observables, produce biased coefficient estimates of the impact of workplace attributes.

While our results are the first to use longitudinal data for Britain, a number of caveats remain. First, our study indicates that unobserved heterogeneity is important in modelling union status and that failure to control for this leads to biased estimates. While this finding is consistent with social custom union theories, it is also consistent with missing data on employer attributes (such as the presence of an implicit closed shop at the workplace). Second, our data set is for a cohort. Thus it does not allow us to distinguish calendar time effects from life-cycle effects. While this represents a weakness, our approach nonetheless represents a substantial advance on earlier cross-sectional
models which cannot control for unobserved heterogeneity nor distinguish age effects from cohort effects. Moreover, these surveys typically do not have information about parental background and voting patterns, variables which we find are significant determinants of union status. It is hoped that in the future union membership might be modelled using linked employer-employee surveys.
REFERENCES


### Table 1: Male Union Membership Density 1981 and 1991 (%)

<table>
<thead>
<tr>
<th>Year t (1981)</th>
<th>Year t+1 (1991)</th>
<th>Union Member</th>
<th>Non-Member</th>
<th>Row Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Union Member</td>
<td></td>
<td>42.92</td>
<td>18.93</td>
<td>61.85</td>
</tr>
<tr>
<td>percent of total</td>
<td></td>
<td>69.39</td>
<td>30.61</td>
<td></td>
</tr>
<tr>
<td>percent of row</td>
<td></td>
<td>6.68</td>
<td>31.47</td>
<td>38.15</td>
</tr>
<tr>
<td>Non-member</td>
<td></td>
<td>17.51</td>
<td>82.49</td>
<td></td>
</tr>
<tr>
<td>percent of total</td>
<td></td>
<td>6.68</td>
<td>31.47</td>
<td></td>
</tr>
<tr>
<td>percent of row</td>
<td></td>
<td>17.51</td>
<td>82.49</td>
<td></td>
</tr>
<tr>
<td>Column Totals</td>
<td></td>
<td>49.60</td>
<td>50.40</td>
<td>100.00</td>
</tr>
</tbody>
</table>

**Source:** NCDS Data

**Notes:**

i. The data in Table 1 were elicited from responses to a question "Are you currently a member of a trade union or staff association?".

ii. The sample is the 1363 young men who were in employment in both 1981 and 1991.

iii. We follow the common practice for micro-data and calculate the density figures as the number of men who are union members divided by the number in employment, expressed as percentage.
### Table 2: Specification Tests - Likelihood Ratio Tests

<table>
<thead>
<tr>
<th>Maintained Model (ln likelihood)</th>
<th>Restricted Model (ln likelihood)</th>
<th>Restrictions tested</th>
<th>Test statistic - asy. ( \chi^2 ) (degrees of freedom) [p-value]</th>
</tr>
</thead>
<tbody>
<tr>
<td>[1] Bivariate Probit specification of Model 5 Effects of covariates unrestricted across time ( ^6 ) (-1029.12)</td>
<td>[2] Model 5 Random effects probit model with correlation and with coverage (-1029.09)</td>
<td>Homoskedasticity over time and ( \rho &gt; 0 )</td>
<td>0.06</td>
</tr>
<tr>
<td>[2] Model 5 Random effects probit model with correlation and with coverage (-1029.09)</td>
<td>Model 4 Random effects probit model without correlation but with coverage (-1051.84)</td>
<td>Explanatory variables independent of unobserved heterogeneity ( \alpha ) (conditional on coverage). i.e. coefficients on the additional variables = 0</td>
<td>45.50 (16)</td>
</tr>
<tr>
<td>[3] Model 5 Random effects probit model with correlation and with coverage (-1029.09)</td>
<td>Model 3 Random effects probit model with correlation but without coverage (-1218.87)</td>
<td>Effects of coverage = 0 when allowance for correlation is made</td>
<td>379.56 (2)</td>
</tr>
<tr>
<td>[4] Model 5 Random effects probit model with correlation and with coverage (-1029.09)</td>
<td>Model 2 Random effects probit model without correlation and without coverage (-1262.24)</td>
<td>Explanatory variables independent of unobserved heterogeneity ( \alpha ). i.e. coefficients on the additional variables = 0 (unconditional on coverage)</td>
<td>466.30 (18)</td>
</tr>
<tr>
<td>[5] Model 5 Random effects probit model with correlation and with coverage (-1029.09)</td>
<td>Restricted Model 5 All coefficients equal over time except the intercepts (-1154.20)</td>
<td>All coefficients equal over time</td>
<td>250.22 (36)</td>
</tr>
<tr>
<td>[6] Model 5 Random effects probit model with correlation and with coverage (-1029.09)</td>
<td>Restricted Model 5 All coefficients equal over time (-1172.52)</td>
<td>All coefficients equal over time</td>
<td>286.86 (37)</td>
</tr>
</tbody>
</table>

Notes: (i) The row numbers are given in square brackets. With and without correlation here means with and without allowance for correlation between the \( x \)s and the \( \alpha \).
(ii) The estimated \( \rho = 0.518 \) with a t-value for \( H_0: \rho = 0 \) of 9.122.
(iii) A comparison of row [5] restricted model log-likelihood value of -1154.20 with that of the row [6] restricted model log-likelihood value of -1172.52 provides a test of whether the variances are equal in the two time periods in the model which assumes that all the effects of the covariates are the same. Equality of the variances is easily rejected in this particular model.
### Table 3: Determinants of Union Status - 1981 to 1991  [Coefficient (absolute t-ratio)]

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Cross-section Probit</td>
<td>Random Effects Probit</td>
<td>Random Effects Probit</td>
<td>Random Effects Probit</td>
<td>Random Effects Probit</td>
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<tr>
<td></td>
<td>(81 coverage excluded)</td>
<td>(81 coverage excluded)</td>
<td>(81 coverage excluded)</td>
<td>(81 coverage included)</td>
<td>(81 coverage included)</td>
</tr>
<tr>
<td><strong>Time invariant Individual Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Father - non manual</td>
<td>-0.139 (0.95) -0.351 (2.56)**</td>
<td>-0.246 (1.09) -0.551 (2.58)**</td>
<td>-0.193 (0.80) -0.469 (2.04)**</td>
<td>0.020 (0.08) -0.434 (2.09)**</td>
<td>0.029 (0.10) -0.394 (1.82)**</td>
</tr>
<tr>
<td>Father - skilled manual</td>
<td>0.022 (0.17) -0.083 (0.72)</td>
<td>0.021 (0.11) -0.139 (0.78)</td>
<td>0.037 (0.18) -0.100 (0.53)</td>
<td>0.125 (0.57) -0.110 (0.64)</td>
<td>0.136 (0.60) -0.086 (0.48)</td>
</tr>
<tr>
<td>Father left school under 16</td>
<td>0.254 (2.37)** -0.006 (0.06)</td>
<td>0.402 (2.37)** 0.034 (0.21)</td>
<td>0.337 (1.82)** -0.012 (0.07)</td>
<td>0.182 (0.95) -0.085 (0.55)</td>
<td>0.120 (0.58) -0.117 (0.72)</td>
</tr>
<tr>
<td>Apprenticeship completed by ’81</td>
<td>0.300 (2.93)** 0.185 (1.98)</td>
<td>0.460 (2.62)** 0.284 (2.00)</td>
<td>0.430 (2.30)** 0.257 (1.69)</td>
<td>0.328 (1.73)** 0.166 (1.21)</td>
<td>0.307 (1.53) 0.154 (1.08)</td>
</tr>
<tr>
<td><strong>Time varying individual characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married with kids</td>
<td>0.467 (3.11)** -0.071 (0.65)</td>
<td>0.601 (2.81)** -0.084 (0.45)</td>
<td>0.553 (2.34)** -0.085 (0.48)</td>
<td>0.798 (3.11)** -0.097 (0.59)</td>
<td>0.775 (2.79)** -0.098 (0.58)</td>
</tr>
<tr>
<td>Married and no kids</td>
<td>0.019 (0.21) -0.165 (1.33)</td>
<td>-0.008 (0.06) -0.240 (1.27)</td>
<td>-0.003 (0.02) -0.265 (1.33)</td>
<td>-0.107 (0.66) -0.247 (1.35)</td>
<td>-0.096 (0.55) -0.254 (1.36)</td>
</tr>
<tr>
<td>Prof/Manag/Admin worker</td>
<td>-0.379 (3.97)** -0.574 (6.88)**</td>
<td>-0.480 (3.11)** -0.726 (5.62)**</td>
<td>0.104 (0.48) -0.124 (0.66)</td>
<td>-0.249 (1.42) -0.655 (5.21)**</td>
<td>0.282 (1.18) 0.009 (0.04)</td>
</tr>
<tr>
<td>Voted in the last general election</td>
<td>0.273 (2.90)** 0.214 (2.04)**</td>
<td>0.402 (2.78)** 0.306 (2.04)**</td>
<td>0.389 (2.53)** 0.294 (1.84)</td>
<td>0.271 (1.55) 0.262 (1.80)</td>
<td>0.278 (1.50) 0.267 (1.77)</td>
</tr>
<tr>
<td>Full-time experience - months/100</td>
<td>0.396 (2.25)** 0.245 (2.30)**</td>
<td>0.632 (2.19)** 0.426 (2.69)**</td>
<td>0.598 (1.88) 0.358 (2.11)</td>
<td>0.967 (2.93) 0.372 (2.46)</td>
<td>0.922 (2.63) 0.339 (2.15)**</td>
</tr>
<tr>
<td>Regional unemp. rate - %</td>
<td>0.080 (4.81)** 0.073 (2.15)**</td>
<td>0.109 (4.31)** 0.128 (2.43)**</td>
<td>0.103 (3.79)** 0.124 (2.21)</td>
<td>0.060 (2.11)** 0.082 (1.62)</td>
<td>0.055 (1.79) 0.080 (1.50)</td>
</tr>
<tr>
<td><strong>Workplace Attributes</strong></td>
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<tr>
<td>Private Sector AND</td>
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</tr>
<tr>
<td>25-99 employees</td>
<td>0.560 (4.10)** 0.341 (2.39)**</td>
<td>0.728 (3.58)** 0.508 (4.25)**</td>
<td>0.493 (1.71)** 0.349 (1.27)</td>
<td>0.570 (2.49)** 0.486 (2.37)**</td>
<td>0.489 (1.61) 0.267 (0.88)</td>
</tr>
<tr>
<td>100-499 employees</td>
<td>0.908 (6.76)** 0.691 (5.33)</td>
<td>1.286 (6.17) 0.945 (4.49)</td>
<td>1.015 (3.77)** 0.373 (1.34)</td>
<td>0.907 (3.83)** 0.790 (3.84)**</td>
<td>0.920 (3.12)** 0.343 (1.10)</td>
</tr>
<tr>
<td>500+ employees</td>
<td>1.326 (9.29)** 1.118 (7.99)</td>
<td>1.697 (7.21) 1.604 (6.69)</td>
<td>0.923 (2.95) 0.932 (2.83)</td>
<td>0.890 (3.30) 1.348 (5.74)</td>
<td>0.571 (1.69) 0.940 (2.67)**</td>
</tr>
<tr>
<td>Public Sector AND</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>less than 25 employees</td>
<td>1.794 (8.52)** 1.506 (6.95)</td>
<td>2.307 (6.96)** 2.268 (6.14)</td>
<td>1.418 (3.78)** 1.985 (3.89)</td>
<td>1.605 (3.67) 2.029 (5.63)</td>
<td>1.244 (2.61) 2.012 (3.72)**</td>
</tr>
<tr>
<td>25-99 employees</td>
<td>2.097 (9.29)** 1.715 (8.74)</td>
<td>2.836 (10.2) 2.395 (8.48)</td>
<td>1.954 (5.57) 1.554 (4.28)</td>
<td>1.858 (6.27)** 2.115 (7.45)</td>
<td>1.555 (4.07)** 1.569 (4.09)**</td>
</tr>
<tr>
<td>100-499 employees</td>
<td>1.866 (9.90)** 1.501 (8.09)</td>
<td>2.495 (8.29) 2.144 (7.52)</td>
<td>1.486 (4.06) 1.324 (3.43)</td>
<td>1.708 (4.99) 1.779 (6.36)</td>
<td>1.221 (2.93)** 1.380 (3.16)</td>
</tr>
<tr>
<td>500+ employees</td>
<td>1.737 (9.85)** 1.661 (9.84)</td>
<td>2.413 (8.76) 2.508 (8.52)</td>
<td>1.732 (4.96) 1.988 (5.27)</td>
<td>1.507 (4.57)** 2.090 (7.18)</td>
<td>1.469 (3.41)** 2.253 (5.44)**</td>
</tr>
<tr>
<td>Wage covered by union in 81</td>
<td>2.905 (12.0)** 1.380 (8.52)</td>
<td>2.966 (11.5)** 1.252 (7.38)**</td>
<td>2.905 (12.0)** 1.380 (8.52)</td>
<td>2.966 (11.5)** 1.252 (7.38)**</td>
<td>2.905 (12.0)** 1.380 (8.52)</td>
</tr>
<tr>
<td>Industry dummies (one digit) with time varying effects</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Estimated rho*</td>
<td>ZM Goodness of Fit measure**</td>
<td>Test for Normality* [p-value]</td>
<td>Model log likelihood</td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------------</td>
<td>------------------------------</td>
<td>-------------------------------</td>
<td>---------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.595</td>
<td>0.559</td>
<td>0.573 (7.25)**</td>
<td>0.606 (13.92)**</td>
<td>0.501 (5.43)**</td>
</tr>
<tr>
<td>ZM Goodness of Fit measure</td>
<td>0.595</td>
<td>0.559</td>
<td>0.608</td>
<td>0.576</td>
<td>0.704</td>
</tr>
<tr>
<td>Test for Normality* [p-value]</td>
<td>0.934 [0.63]</td>
<td>3.641 [0.16]</td>
<td>0.934 [0.63]</td>
<td>3.641 [0.16]</td>
<td>1.611 [0.45]</td>
</tr>
<tr>
<td>Model log likelihood</td>
<td>-623.50</td>
<td>-701.29</td>
<td>-1262.24</td>
<td>-1218.87</td>
<td>-1051.85</td>
</tr>
</tbody>
</table>
Notes:

(*) The interpretation of the estimated rho is given in equation (3) in the text.

(#) This is the Zavoina & MaKelvey Goodness of Fit measure for the univariate probit Model (see Greene (1995, p.421)). The models were estimated as univariate probits which give consistent parameter estimates.

(+) This is the conditional moment test for Normality which uses the third and fourth order generalised residuals (Chesher and Irish (1987)). The probit model is nested within the Pearsonian family of distributions (see Maddala (1995), Lehner (1995)).


(2) The factors that have to be used in the scaling of the coefficients for Models 2, 3, 4 and 5 for purposes of comparison are 0.650, 0.625, 0.701 and 0.688.

(3) **, * coefficient significant at 5%, 10% significance levels respectively, for a two sided test.

(4) Column (3) also includes the leads and lags of Prof/Manag/Admin worker, and all the variables relating to the workplace attributes. These are included to capture the correlations between the explanatory variables in the model and the unobserved individual specific error term.
### Table 4: Estimated probability (std. error) of union membership due to changes in some characteristics

<table>
<thead>
<tr>
<th>The Nature of Change</th>
<th>Univariate cross-sectional Probits</th>
<th>Random Effects Probit (no corr between the regressors and the error)</th>
<th>Random Effects Probit (with corr between the regressors and the error)</th>
<th>Random Effects Probit (no corr between the regressors and the error)</th>
<th>Random Effects Probit (with corr between the regressors and the error)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[81 coverage excluded]</td>
<td>[81 coverage excluded]</td>
<td>[81 coverage excluded]</td>
<td>[81 coverage included]</td>
<td>[81 coverage included]</td>
</tr>
<tr>
<td>1. No apprenticeship in ‘81</td>
<td>0.6067</td>
<td>0.4827</td>
<td>0.6118</td>
<td>0.4777</td>
<td>0.6109</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.015)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>2. Only has 9 years of ft job exp during 81-91</td>
<td>0.6265</td>
<td>0.4985</td>
<td>0.6233</td>
<td>0.4943</td>
<td>0.6238</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>3. Worked in the Private sector with lt 25 employees in 1981 and in 1991</td>
<td>0.7101</td>
<td>0.5863</td>
<td>0.6920</td>
<td>0.5762</td>
<td>0.6296</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.035)</td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>4. Worked in the Private sector with 500+ employees in 1981 and in 1991</td>
<td>0.8272</td>
<td>0.7106</td>
<td>0.7975</td>
<td>0.7178</td>
<td>0.7167</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.057)</td>
<td>(0.044)</td>
<td>(0.061)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>5. Worked in the Public sector with lt 25 employees in 1981 and in 1991</td>
<td>0.8149</td>
<td>0.7548</td>
<td>0.8131</td>
<td>0.7623</td>
<td>0.7658</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.037)</td>
<td>(0.031)</td>
<td>(0.037)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>6. Worked in the Public sector with 500+ employees in 1981 and in 1991</td>
<td>0.6265</td>
<td>0.5217</td>
<td>0.6232</td>
<td>0.5186</td>
<td>0.6283</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>7. Industry, Sector and Size distribution same as in 1981</td>
<td>0.6034</td>
<td>0.4980</td>
<td>0.6101</td>
<td>0.4935</td>
<td>0.6172</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>8. Industry, Sector and Size distribution same as in 1991</td>
<td>0.5659</td>
<td>0.4980</td>
<td>0.5671</td>
<td>0.4935</td>
<td>0.5733</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.014)</td>
<td>(0.021)</td>
<td>(0.014)</td>
<td>(0.021)</td>
</tr>
</tbody>
</table>

Notes: (i) The estimated probability is \( E(P_a) \) and is calculated as \( \frac{1}{N} \sum_{i=1}^{N} (\hat{P}_{it}) \) - see Chamberlain (1984) for further details.

(ii) See text and Arulampalam and Pudney (1999) for further details of the derivation of the standard errors.
Table 5: Male Union Membership Density 1981 and 1991 (%)

<table>
<thead>
<tr>
<th>Year t (1981)</th>
<th>Union Member</th>
<th>Year t+1 (1991)</th>
<th>Non-Member</th>
<th>Row Totals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
<td>Model 4</td>
</tr>
<tr>
<td>Union Member</td>
<td>35.72</td>
<td>35.41</td>
<td>37.68</td>
<td>39.77</td>
</tr>
<tr>
<td>percent of total</td>
<td>57.01</td>
<td>55.99</td>
<td>59.97</td>
<td>63.10</td>
</tr>
<tr>
<td>Non-member</td>
<td>14.08</td>
<td>13.94</td>
<td>11.92</td>
<td>9.92</td>
</tr>
<tr>
<td>percent of total</td>
<td>37.70</td>
<td>37.71</td>
<td>31.99</td>
<td>26.83</td>
</tr>
<tr>
<td>Column Totals</td>
<td>49.80</td>
<td>49.35</td>
<td>49.60</td>
<td>49.69</td>
</tr>
</tbody>
</table>

Notes: (i) For each individual, the cell probabilities were calculated and then averaged over all the individuals, to arrive at the above predicted aggregate transition probabilities.