LOW PAY DYNAMICS AND TRANSITION PROBABILITIES

Mark B. Stewart and Joanna K. Swaffield

No.495

WARWICK ECONOMIC RESEARCH PAPERS

THE UNIVERSITY OF WARWICK

DEPARTMENT OF ECONOMICS

LOW PAY DYNAMICS AND TRANSITION PROBABILITIES

Mark B. Stewart and Joanna K. Swaffield
Department of Economics
University of Warwick
COVENTRY CV4 7AL
UK

No.495

July 1997

Low Pay Dynamics and Transition Probabilities*

Mark B. Stewart
University of Warwick

and

Joanna K. Swaffield
University of Warwick

July 1997

* We thank the ESRC for financial support (under grant R000236125). The BHPS data used in the paper were collected by the ESRC Research Centre on Micro-social Change at the University of Essex and made available through the ESRC Data Archive. Neither bear any responsibility for the analyses or interpretations presented here. We thank Wiji Arulampalam, Alison Booth and participants in the LoWER Conference at Université Montesquieu, Bordeaux, for helpful comments on an earlier draft of the paper.

Abstract

This paper investigates transitions into and out of low pay in Britain in the 1990s. It finds considerable persistence in low pay. In addition, the low paid are more likely to move into non-employment; those entering employment from a spell outside are more likely to be low paid; and those who had been low paid prior to the spell of non-employment are even more likely than other entrants to be low paid again when they subsequently move back into employment. There is thus evidence of a cycle of low pay and no pay.

Modelling transition probabilities into and out of low pay requires the 'initial conditions' problem to be addressed. Simple probability models of these transitions suffer from endogenous selection bias as a result of conditioning on the initial low pay state. This paper uses a bivariate model with endogenous selection to address this problem and parental variables to instrument the initial state.

The empirical evidence presented indicates that exogenous selection into the initial state is strongly rejected and that ignoring the endogenous selection of conditioning on the initial low pay state distorts the estimated coefficients. Typically the estimated coefficients (and their t-ratios) are much reduced (in absolute value) when allowance is made for endogenous selection. Ignoring the endogenous selection is found to result in the collective effect of observed current heterogeneity being overstated by a factor of about 2. However factors such as training, plant size, union coverage and gender generally retain their significant influence on the probability of remaining low paid, although with substantially reduced effects. There is evidence of considerable ceteris paribus dependence of the probability of being low paid on whether or not an individual was low paid in the previous year.

Key words: low pay, earnings mobility, transition probabilities, initial conditions problem.

JEL categories: J31, D31, C23, C25.

1. Introduction

The distribution of earnings in Britain has become increasingly unequal over the last two decades. In particular the relative position of those at the bottom end of the distribution has worsened considerably.[1] This increase in the number of people receiving "low pay" has in turn contributed to the widening of the distribution of total income and the increased incidence of poverty over this period.[2] The newly-elected Labour government is committed to introducing a national minimum wage and has appointed a low pay commission to advise on the level at which this should be set. Low pay has become an increasingly important policy issue.

Even when the distribution of earnings remains stable between two years, there is a great deal of turnover of individuals within the distribution. Some individuals move up (in terms of relative earnings) and others move down. Stability of the overall distribution does not imply stability for individuals. Changes in earnings inequality in Britain have largely been analysed by comparing cross-sectional pictures at different points in time. However these provide a series of snapshots of the overall distribution, rather than evidence on changes in the position of individuals. Such snapshots do not tell us about lifetime inequality or even inequality in the medium term. These depend on the extent to which individuals move up and down the distribution: on the extent of earnings mobility.[3]

This paper focuses on the bottom end of the earnings distribution and examines the persistence in low pay, i.e. the earnings mobility that causes transitions into and out of low pay. To know that a proportion p of individuals

---

[1] See Gregg and Machin (1994) and Gosling et al (1994) for evidence for the UK and Levy and Murnane (1992) for a survey of the US evidence.
[2] See Atkinson (1993) and Jenkins (1995) inter alia.
[3] The existing evidence on earnings mobility is surveyed in Atkinson et al. (1992).

is low paid (under some particular definition) tells only part of the story and is consistent with a range of different pictures when viewed in a dynamic context. If there is no mobility over the working life, then the proportion p are low paid throughout their working life and the remaining (1–p) never experience low pay. At the other extreme, if there is high mobility, it may be that each individual experiences low pay for a proportion p of their working life and is not low paid for the remaining (1–p) of the time, i.e. that everyone gets the same share of low pay in lifetime terms. The true situation of course lies somewhere between these two polar cases. Exactly where and the extent of the persistence in low pay has important welfare policy implications. It is important to know the extent to which low pay is "shared out" among individuals in a lifetime context and the extent to which it is concentrated onto a few.

Another way of viewing this issue is in terms of the degree of permanency in low pay. The evidence of increased inequality referred to above suggests that low pay has become more widespread. However this could have come about either because the incidence of permanent low pay has increased or because transitory fluctuations in earnings have increased (or a combination of the two).[4] It is therefore important to ask how permanent is the low pay state. This paper seeks to address this by modelling the ceteris paribus transitions into and out of low pay.

The above discussion of mobility within the earnings distribution has implicitly been about a world in which the set of individuals in the distribution, while moving around within the distribution, remain the same. However this is not

[4] Dickens (1996), using the New Earnings Survey, finds, in terms of the earnings distribution as a whole, that perhaps three-quarters of the variation in earnings is explained by its permanent component and attributes about a half of the rise in inequality over the period 1975-90 to the rise in this component and about half to increased transitory fluctuations.

the true situation. In addition to young workers entering the labour market and old workers retiring, many individuals experience transitions into and out of employment within their working lives. Since low paid workers are more likely to experience unemployment, a potentially misleading picture is given by restricting attention to those in employment when analysing transitions between low and higher pay. The difference made by examining transitions between earnings groups in conjunction with transitions into and out of the earnings distribution is examined in the paper.

A vitally important issue to address in the context of modelling transition probabilities concerns the initial conditions problem (Heckman, 1981a). Thinking in terms of transitions at a single point in time this can be viewed as a problem of endogenous sample selection. Conditioning on being low paid at t-1 to model the probability of a transition out of low pay at t, for example, will result in a selection bias in the estimates if the initial condition (being low paid at t-1) is not exogenous. Estimates of transition models under both the assumptions of endogenous and exogenous sample selection are presented to examine the extent of the bias that is induced in the estimates by assuming exogeneity.

The next section discusses data sources and how low pay should be defined. Section 3 examines the raw data on movements into and out of low pay, first simply within the earnings distribution and then also in conjunction with movements into and out of the earnings distribution. Section 4 then discusses the modelling of ceteris paribus transition probabilities into and out of low pay under various assumptions, most importantly considering the question of endogenous sample selection into the initial, conditioned upon, low paid state. The estimation results for these models are presented and discussed in section 5 and section 6 presents conclusions.

2. Data sources and the definition of low pay

Many different definitions of the low pay threshold have been suggested in the on-going public debate. These thresholds are usually based on a specified proportion of a measure of central tendency (mean or median) of the earnings distribution of a particular population. The mean or median, and hence the cut-off figure, is then usually calculated using the New Earnings Survey (NES), considered the most appropriate since it is the largest survey of earnings available in Britain and is conducted every year on a consistent basis.

However the NES is not an ideal source to use for the study of low pay, since for a number of reasons it undersamples those on low pay. First, it excludes most of those whose weekly pay falls below the NI and PAYE deduction thresholds. Second, those who are unemployed or out of the labour force when the sample is located but enter employment before the survey date are excluded. The low paid are likely to be over-represented in this excluded group. Third, those with one employer when the sample is located who have moved to another by the survey date and cannot be traced are also excluded. The low paid are probably disproportionately represented in this group also. Fourth, certain groups where low pay is common, such as domestic service workers, are excluded. Fifth, the NES also undersamples employees in small organisations, another group where low pay is more likely than in the population as a whole.[5] Finally the NES provides only limited information on individual characteristics and does not, for example, contain information on education levels attained or training undertaken.

---

[5] See Gregory and Elias (1994) for further discussion of these deficiencies and for an analysis of earnings transitions using the NES.

For these reasons the NES is not used for the analysis of low pay transitions in this paper. Rather the main vehicle for the analysis presented here is the British Household Panel Survey (BHPS). The BHPS is a nationally representative panel of individuals interviewed annually since 1991. The first five waves, 1991-95, are used in this paper. Since the NES is almost always used in the calculation of the low pay cut-offs used in the public debate, we follow that lead and use NES-based thresholds.

A comparison of the various thresholds that have been suggested in the debate and the implied figures for 1991-4 are provided by Stewart and Swaffield (1997b). Their examination suggests that it is useful to make use of more than one cut-off in any analysis of low pay. In this paper we use three thresholds found in the earlier paper to give a reasonable spread over the range usually considered: half the median, half the mean and two-thirds the median, all in terms of the overall distribution of gross hourly earnings (including overtime) for full-time men and women on adult rates. The lowest threshold (half median) is below the TUC's advocated initial minimum wage, but still defines 8% of men and 24% of women to be low paid on the basis of the 1991 wave of the BHPS. The highest threshold to be used in the analysis (two-thirds median) is below the TUC's stated long-term objective for a minimum wage (in 1991 terms), but defines 22% of men and 49% of women to be low paid on the basis of the 1991 wave of the BHPS. These cut-offs therefore seem reasonable highest and lowest thresholds for the analysis conducted in this paper.

The distinction between low pay definitions based on the mean rather than the median becomes more important as the two measures diverge. This is obviously an important consideration for the UK over the 1980s and 1990s as wage dispersion has dramatically increased and the mean and median points

have moved further apart. Figure 1 gives estimates of the percentages of workers low paid under these definitions in the NES itself among all full-time employees on adult rates, among men, among women and among manual men over the period 1985-96. It should however be kept in mind, as stated above, that the NES undersamples the low paid and hence, as will be illustrated below in terms of the BHPS, these figures understate the true percentages of people who are low paid. Never-the-less this comparison over time of the percentages of full-time employees falling below the low pay thresholds clearly shows the rise in the number of low paid. Men and women combined, men only and manual men all exhibited an increase in the incidence of low pay over the period under all three definitions. For women the proportions below the lower two thresholds show a rise over the period, but that below the top threshold considered shows a slight fall. Between 1985 and 1996 the percentage of male and female full-time employees on adult rates earning below the first threshold of half median hourly pay has more than doubled from 2.3% to 5.3%. The male manual figures show the highest rise of all groups with the percentage of workers below half the median quadrupling from 1.3% in 1985 to 5.5% in 1996. These figures clearly show the continuing rise of low pay in the British labour market from the mid 1980s to the second half of the 1990s.

The analysis of low pay transitions in this paper is based on the first five waves of the BHPS for 1991-5. As the BHPS interviews are conducted predominantly during September to November, with the median interview date for each wave being in October we calculate October low pay thresholds for each year by averaging those for the preceding and following April. These are given in Table 1.[6] The calculations for October 1993 for example give

[6] Throughout this paper, low pay in the BHPS is defined in terms of average hourly earnings, i.e. weekly earnings divided by total paid (including overtime) hours.

cut-offs of roughly £3.40, £4 and £4.50 an hour, all figures that have been extensively discussed in the public debate.[7]

3. Aggregate probabilities of movement into and out of low pay

It is not the same people who are in the low paid group each year (or even the same people in the earnings group each year). An informative way of looking at such movements is in terms of conditional probabilities. Table 2 presents the conditional probabilities of being low paid in year t given an individual's pay state in year t-1. For the moment attention is restricted to those who were employees in both periods. The transitions are pooled over the years 1992 to 1995. The probability of being low paid in year t is dramatically higher for those who were low paid in year t-1 than for those who were paid above the threshold. For women those who were low paid in year t-1 are roughly 10 times as likely to be low paid in year t as those who were not, and for men the ratio is even higher.[8]

These transition probabilities are instructive, but ignore the fact that transitions are made not just into and out of low pay, but also into and out of the employees-in-employment group. Table 3 presents year t status by that in year t-1 (pooling t over 1992 to 1995) using six status categories (low paid employee, higher paid employee, employee but with missing earnings information, self-employed, unemployed, and out of the labour force). Tabulations are given for each of the three low pay thresholds and separately

---

[7] Stewart and Swaffield (1997a) analyse the impact of individual and job characteristics on the ceteris paribus probability of low pay using probit models. As would be expected from the earnings function literature, the probability of being low paid declines with education and experience; being unionised, being employed in a large firm and having had recent training strongly reduce the probability of being low paid; and women are more likely to be low paid than men.

[8] See Stewart and Swaffield (1997a,b) for a more extensive investigation of movements into and out of low pay including patterns over a greater number of years and low pay probabilities conditional on low pay history in more than just the preceding year.

for men and women. Those not interviewed or with unknown employment status are assumed to be missing at random and excluded.

Looking first at the results for men and using the lowest threshold, almost a quarter of those low paid in year t-1 are excluded from the earnings distribution in year t. In some cases this is as a result of missing earnings information (with employment status known). Assuming that these too are missing at random, the implied year t conditional distributions can be calculated. Of those low paid in year t-1, 16.9% are self-employed, unemployed or out of the labour force in year t, 43.2% are still low paid in year t and the rest have moved up the distribution. Thus 60% do not move up the earnings distribution from low pay in year t when those who are not employees in employment are also included in the transition analysis. Of higher paid employees in year t-1, only 6.6% are self-employed, unemployed or out of the labour force in year t, only 2.2% have become low paid and over 90% are still above the low pay threshold.

For the second threshold the percentage of those low paid in year t-1 who are self-employed, unemployed or out of the labour force in year t falls to 15% and for the third threshold to 13%. For the second threshold 65% do not move up the earnings distribution and out of low pay, while for the third threshold the figure is 75%. For women, 75% of those low paid in year t-1 do not move up the earnings distribution over the first threshold in year t. For the second threshold it is 83% and for the third threshold it is 87%.

Table 2 gives the probability of not moving up above the threshold in year t from low pay, ignoring those no longer employees, as 52%, 59% and 71% for men in respect to each of the three thresholds. Table 3 implies corresponding figures of 60%, 65% and 75% from the inclusion of the non-

employees. Thus the exclusion of non-employees from the transition probabilities understates this probability by 8 percentage points in the case of the lowest threshold, 6 for the second threshold and 4 for the third threshold. In the case of women excluding those who become non-employees leads to underestimates of 5, 3 and 2 percentage points for the three thresholds respectively.

Those unemployed or out of the labour force in year t-1 who enter and are employees at t are more likely to be low paid than average. Table 3 indicates that of men unemployed in year t-1 who become employees in year t, 22.5% become low paid (using the first threshold definition), compared with 5.8% of those who were employees in t-1. Of those out of the labour force at t-1, who become employees at t, 32.9% become low paid. Thus the chance of being low paid at t is roughly 4 times as great for a man who was unemployed at t-1 as for one who was an employee at t-1 and nearly 6 times as great for one who was out of the labour force at t-1. For the second threshold it is roughly 4 times as great for someone unemployed and 5 times as great for someone out of the labour force. For the third threshold the chance is roughly 3 times as great for both the unemployed and those out of the labour force.

Of women unemployed at t-1 who become employees in year t, 48.2% become low paid (using the first threshold definition), compared with 20.3% of those who were employees at t-1. Of those out of the labour force at t-1, who become employees at t, 50.5% become low paid. Thus the chance of being low paid at t is roughly two and a half times as great for both groups as for a women who was an employee at t-1. For the second and third thresholds it is roughly twice as great for both groups.

Additionally entrants who had previously been low paid prior to unemployment or out of the labour force are even more likely than other entrants from unemployment or out of the labour force to be low paid on re-entering employment (see Stewart and Swaffield, 1997a). The low paid are therefore both more likely to move out of employment and more likely to be low paid when they move back into employment (even relative to other entrants, who themselves have a higher probability of being low paid than those already in employment). There is thus evidence of a cycle of low pay and no pay.

The investigation of the low pay transition probabilities above, conditioning upon past low pay experience, suggests considerable *state dependence* in these transition probabilities: that is to say, the probability of being low paid at t is considerably higher among those who were low paid at t-1 than among those who were higher paid at t-1. However the probabilities being considered above are aggregate probabilities and there is more than one possible explanation for this finding (Heckman, 1981c). It does not necessarily imply that this state dependence observed in aggregate is true for individuals.

It may be the result of *heterogeneity*, where certain individual characteristics increase the probability of an individual being low paid. This will create the appearance of state dependence in the aggregate transition probabilities if some of the relevant characteristics exhibit persistence over time (such as, for example, education), even if such an effect is absent in individual transition probabilities. A simple numerical illustration helps make the point. Suppose that there are two (equal sized) groups in the population, one with low pay probability 0.1 and the other with low pay probability 0.9, but that for both groups the probability of being low paid at t is independent of what happened

to them at t-1. The aggregate probabilities of being low paid at t will be 0.82 for those low paid at t-1 and 0.18 for those higher paid at t-1, exhibiting strong state dependence in the aggregate despite the lack of any state dependence at the individual level.

Alternatively, or in addition, there may be "true", or structural, state dependence for individuals: being low paid in one period may *in itself* increase the probability of being low paid in the next period, even relative to another individual with identical characteristics who was not low paid in the first period. Employers may view low paid employment with another firm as an indicator of an individual's low productivity and be discouraged from making a job offer. Employers may also treat holding a low paid job as a signal of a high turnover propensity. On the supply side, a spell of low paid employment may influence an individual's perception of their market value and discourage them from applying for better paid jobs. State dependence may also be the result in a dual labour market world of "good" jobs and "bad" jobs in which having a "good" job results in human capital accumulation and raises productivity, reducing the probability of being low paid in the future, while low paid jobs do not enhance human capital. Having a "good" job may also alter worker preferences and make them more likely to remain in that segment of the labour market.

In all these cases earnings correlates are altered by the experience of low pay. This contrasts with the *pure* heterogeneity case where individuals differ only in characteristics that affect their chances of being low paid, but that are not affected by the experience of low pay. State dependence in the aggregate probabilities that is due to heterogeneity can be influenced by changing individual characteristics, e.g. by providing training, but "true" state dependence may be harder to tackle. Distinguishing between structural state

dependence and omitted heterogeneity is difficult and requires additional information (e.g. in the form of suitable instruments). The next section models these transition probabilities, controls for observed heterogeneity and addresses the issue of omitted heterogeneity and hence the danger of spurious state dependence.

4. Modelling transition probabilities into and out of low pay

This section considers the modelling of transitions into and out of low pay and the factors that influence them. Such transition probabilities are the key issue from a welfare viewpoint. How easy is it to leave low pay and move up the distribution and who makes the transition? However transition probabilities such as this are not straightforward to model (Heckman, 1981b). A simple starting point is provided by standard binary probit models for the probability of being low paid in one year given low paid the previous year and given not low paid the previous year. However, it is important to be clear about the assumptions being made in the use of a model of this form.

The general model adopted for the transition probabilities under consideration is based on the following line of argument. Consider the movements between two successive years, t-1 and t, of a sample of individuals. Suppose that individual earnings in year t-1, prior to the potential transition, are generated by the following process

$$g_1(y_{it-1}^*) = x_{it-1}'\beta^* + \varepsilon_{i1} \qquad i = 1, \ldots, N \qquad (1)$$

where y_{it-1}^* is hourly earnings at the survey point in year t-1, x_{it-1} is a vector of earnings-determining characteristics and g_1 a suitable monotonic (but unspecified) transformation such that ε_{i1} is distributed N(0,1). Defining the

low pay cut-off as λ_{t-1} and an indicator variable $y_{it-1} = 1$ if individual i is low paid (i.e. has hourly earnings below the cut-off) and = 0 if not,

$$\begin{aligned} P[y_{it-1} = 1] &= P[y_{it-1}^* < \lambda_{t-1}] \\ &= P[g_1(y_{it-1}^*) < g_1(\lambda_{t-1})] \\ &= P[\varepsilon_{it-1} < g_1(\lambda_{t-1}) - x_{it-1}'\beta^*] \\ &= \Phi\{g_1(\lambda_{t-1}) - x_{it-1}'\beta^*\}, \end{aligned}$$

where Φ is the standard normal cumulative distribution function, giving a probit model for the probability of low pay. There is no need to specify the function g_1 unless we wish to retrieve an estimate of the intercept in β^*. If not, then the term $g_1(\lambda_{t-1})$ is subsumed into the intercept and the model can be estimated as

$$P[y_{it-1} = 1] = \Phi(x_{it-1}'\beta), \qquad (2)$$

where $\beta_j = -\beta_j^*$ for the slope coefficients and $g_1(\lambda_{t-1}) - \beta_0^*$ for the intercept.

Suppose next that the process determining the individual's earnings in year t depends on whether or not the individual was low paid in year t-1. Suppose that *if* $y_{it-1} = 1$, the process is given by

$$g_2(y_{it}^*) = z_{it}'\gamma^* + \varepsilon_{i2} \qquad i = 1, \ldots, N. \qquad (3)$$

For those with $y_{it-1} = 0$ a different γ^*-vector is allowed to apply, but the same error process is assumed. Note that although the above relationship is defined specifically for those with $y_{it-1} = 1$, it is assumed that the distribution of ε_{i2} is defined over all individuals. The distribution of $(\varepsilon_{i1}, \varepsilon_{i2})$ is assumed to be

bivariate standard normal with correlation ρ. The probability of individual i being low paid in both years is therefore given by

$$P[y_{it-1} = 1, y_{it} = 1] = \Phi_2(x_{it-1}'\beta, z_{it}'\gamma ; \rho), \tag{4}$$

where $\gamma_j = -\gamma_j^*$ for the slope coefficients and $g_2(\lambda_t) - \gamma_0^*$ for the intercept, λ_t being the threshold in year t, and where Φ_2 is the cumulative distribution function of the bivariate standard normal. The *conditional probability* of being low paid in year t given low paid in year t-1 is then given by

$$P[y_{it} = 1 \mid y_{it-1} = 1] = \Phi_2(x_{it-1}'\beta, z_{it}'\gamma ; \rho) / \Phi(x_{it-1}'\beta). \tag{5}$$

In the <u>special case</u> where ρ=0, this simplifies to

$$P[y_{it} = 1 \mid y_{it-1} = 1] = \Phi(z_{it}'\gamma). \tag{6}$$

In this case the conditional probability of remaining low paid can be modelled by a simple probit model, i.e. γ can be estimated using a probit for y_{it} over the sample with $y_{it-1} = 1$. A corresponding model can be constructed for those higher paid in year t-1. Estimates of simple models of this type for these two conditional probabilities are reported in the next section.

An obvious problem with these simple probit models is that they take the initial low pay state (that in year t-1) to be exogenous ($\rho = 0$).[9] This requires the observed persistence in low pay to be entirely due to observed explanatory variables. Correlation across time between the unobservables ($\rho \neq 0$) will generate a sample selection bias as a result of conditioning on

[9] This is the assumption implicitly made, for example, by Sloane and Theodossiou (1996) in their model.

being low paid (or on being higher paid) in year t-1. This is the initial conditions problem: see for example Heckman (1981a). It is difficult to deal with in a satisfactory way and as Heckman points out the full solution for his model is "computationally forbidding" (1981a, page 185).

The problem is addressed in this paper by restricting the autocorrelation in the disturbances (and hence unobservables) to be first order and approaching the problem, in the context of the model laid out above, as one of endogenous sample selection. This is a more difficult problem to deal with in the discrete dependent variable case than in the linear regression case. Addition to the model of the usual selectivity correction term based on the Mills ratio will not give consistent estimates in this case (O'Higgins, 1994). Instead it must be addressed directly in terms of the bivariate joint distribution of y_{t-1} and y_t. For those individuals who were low paid in year t-1 the terms in this joint distribution are given by equation (4) and

$$P[y_{it-1} = 1, y_{it} = 0] = \Phi_2(x_{it-1}'\beta, -z_{it}'\gamma ; -\rho). \tag{7}$$

If attention is restricted to the destinations of those low paid in year t-1, the model is a bivariate probit model with endogenous selection of the type used by Van de Ven and van Praag (1981) and described as case 3 in the Meng and Schmidt (1985) catalogue of bivariate models with partial observability. Information on y_t is only used for those with $y_{t-1} = 1$. The probit equation for y_{t-1} is taken to be completely observed, but that for y_t has an endogenously selected sample. The log-likelihood contribution for individual i is given by

$$\begin{aligned} \ln L_i = {} & y_{it-1}y_{it} \ln\Phi_2(x_{it-1}'\beta, z_{it}'\gamma ; \rho) + y_{it-1}(1-y_{it}) \ln\Phi_2(x_{it-1}'\beta, -z_{it}'\gamma ; -\rho) \\ & + (1-y_{it-1}) \ln\Phi(-x_{it-1}'\beta). \end{aligned} \tag{8}$$

(A corresponding model can also be constructed for those higher paid in year t-1.) Estimates of this more general form of model are presented in the next section, along with the Probit estimates of the model that results from assuming $\rho=0$.[10]

5. Results

The models are estimated on data pooled across waves 2 to 5, with the parameters β, γ and ρ taken to be constant over time. Results are presented first for the simpler model assuming independent disturbance terms ($\rho=0$): a simple probit for the conditional probability as given by equation (6). It is useful in the type of model being examined here to look at "marginal effects" of the z-variables on the conditional probability of being low paid. For the dummy variables in z it is instructive to look at these effects in the following way. Partition z into the dummy variable of interest, d, and the remaining variables, z*, and rewrite the model as

$$P[y_{it} = 1 \mid y_{i,t-1} = 1] = \Phi[z_{it}^{*\prime}\gamma_1 + \gamma_2 d_{it}]. \tag{9}$$

Then the effect on the probability of remaining low paid of the dummy variable d changing from 0 to 1 is given by

$$\begin{aligned} &P[y_{it} = 1 \mid y_{i,t-1} = 1;\ d_i=1] - P[y_{it} = 1 \mid y_{i,t-1} = 1;\ d_i=0] \\ &\qquad = \Phi[z_{it}^{*\prime}\gamma_1 + \gamma_2] - \Phi[z_{it}^{*\prime}\gamma_1]. \end{aligned} \tag{10}$$

This effect can be evaluated at different points. The estimated marginal effects presented here are evaluated at the means of the other explanatory variables. Marginal effects for continuous variables are usually estimated by

[10] This approach to handling the endogeneity of the initial state is similar to that of Bingley et al. (1995). The model here is simpler than theirs in that y is dichotomous and more general in that separate γ–vectors are allowed for those initially low and higher paid.

evaluating the partial derivative, which is equal to the corresponding γ-coefficient multiplied by an evaluation of the normal density. However for the two continuous variables in z we instead evaluate the marginal effects in a parallel way to that used for the dummies: for age completed full-time education we estimate the marginal effect as the difference between the evaluated probabilities at 17 and 16; for years of labour market experience we estimate the difference between 30 and 20 years of experience. As well as being equivalent to the method used for the dummies, it is also equivalent to the method used below for the more general bivariate endogenous selection model.

The estimated marginal effects on the conditional probability of being low paid at t given low paid at t-1 are presented in the first three columns of Table 4 for the three low pay thresholds. The maximum likelihood estimates of the γ-coefficients are given in square brackets beneath each marginal effect and the absolute asymptotic "t-ratio" in round brackets. The next three columns give the corresponding estimates conditional on being higher paid. In both cases the sample is restricted to individuals who are employees in employment in both years t-1 and t.

Section 3 demonstrated that the low paid are more likely to be out of employment in the next period than those higher up the earnings distribution. A simple examination of the sensitivity to this of the results presented in the first 6 columns of Table 4 is provided by looking at the probability of being low paid or not an employee (i.e. of not earning above the threshold) at t given low paid at t-1 and similarly conditional on being higher paid at t-1. The justification for looking at this probability is that for most of those in low paid employment, moving to self-employment, unemployment or out of the labour

force is not superior in terms of well-being to earning λ.[11] The estimated marginal effects for these probabilities are presented in the remaining 6 columns of Table 4.

Each year of education completed (prior to t-1) reduces the probability of remaining low paid by 2 to 3 percentage points and the probability of dropping into low pay by about one percentage point other things equal. Taking account of those no longer employees in the second year reduces the first of these effects slightly. Training in the 12 months prior to t-1 significantly reduces the probability of remaining low paid (by 5 to 10 percentage points) and the probability of dropping into low pay (by 2 to 4 percentage points). No very clear picture emerges for the impact of additional years of experience.

Low paid workers covered by a union at t-1 are less likely to remain low paid at t. The magnitude of the marginal effect is sensitive to the threshold used, ranging from about 7 percentage points to in excess of 20. Union workers are also less likely to drop into low pay. Those who work in establishments with at least 25 employees (at t-1) are less likely to remain low paid (by 7 to 10 percentage points). Women are more likely to remain low paid (by 15 to 20 percentage points) and more likely to fall into low pay (by 2 to 3 percentage points) than men, other things equal.

Ignoring transitions out of the earnings distribution results in some effects getting overstated and others understated. However the estimated effect when those who leave the earnings distribution are included as described above is typically not outside the 95% confidence interval for the effect when

[11] There is obviously a potential interpretation problem with this approach. Proper treatment of the non-employees would require the use of trivariate integrals. Sloane and Theodossiou's (1996) use of a multinomial logit model (as well as ignoring the initial endogenous selection problem) requires the 'independence of irrelevant alternatives' assumption to hold, which seems unlikely in the current context.

they are excluded. The differences are not dramatic. Although, as we saw in section 3, ignoring transitions out of the earnings distribution leads to overstatement of the aggregate conditional probability of moving up the earnings distribution and out of low pay, the impact on the estimated marginal effects in this model of the conditional probability is not very great.

In terms of the models laid out in the previous section, these estimates are under the assumption that $\rho = 0$. If this restriction does not hold, the estimates will be biased due to the initial conditions problem, i.e. there will be a sample selection bias as a result of selection on the basis of the initial low pay state. If ρ is non-zero the more general bivariate probit model with endogenous selection whose log-likelihood is given in equation (8) is required and identification restrictions are needed. The extra variables in x_{t-1} not in z_t can be viewed as instruments for the endogenous selection into the initial state.

The instruments used here for the endogenous selection into the initial state are parental variables indicating the socio-economic group of the respondent's parents when the respondent was 14. These variables were found to have a significant effect on the probability of being low paid (see Stewart and Swaffield, 1997b). The assumption being made here is that they do not however affect the probability of being low paid <u>given</u> the state in the previous period: they affect the level of the low pay status variable, but not the change. The instrument set used contains 18 dummy variables for the respondent's father's socio-economic group, plus two dummies for father deceased and father not working. Mother's socio-economic groups with small sample frequencies are amalgamated with other suitable similar groups and 14 socio-economic group dummies, plus ones for mother deceased and mother not working, included. The specification of the z-vector is as in

Table 4. The x-vector then contains the same variables plus the 36 parental variables of the instrument set just described.[12]

Table 5 reports the results from estimating the bivariate probit model with endogenous selection using the pooled BHPS sample. Again "marginal effects" are calculated from the estimated coefficients. However this is not quite as straightforward as in the probit case. A change in a variable common to both z and x will have effects on the conditional probability of remaining low paid, as given by equation (5), via both the arguments of the joint distribution in the numerator and via the conditioning distribution in the denominator. What is required is the effect of a change in an element of z holding constant the remaining elements of z and everything at t-1. The effect calculated is therefore that of the change in the particular dummy variable in z on the conditional probability at the means of the other z-variables and for someone who has x-characteristics such as to give them a predicted probability of being low paid at t-1 equal to the average predicted probability over the same sample as the z-variables are averaged over.

The univariate probit effects that result from imposing $\rho = 0$ are given for comparative purposes. Comparison of the effects from the two models for a given threshold indicates the impact of ignoring the endogenous selection.[13] The first 6 columns give estimates for models for the probability of being low paid at t given low paid at t-1, with the sample restricted to those in employment at both dates. The other 6 columns are for the probability of not moving up the earnings distribution and out of low pay, including in the sample those who leave the earnings distribution.

---

[12] In addition, as appropriate for the structure of the model, the x-vector contains a quadratic in experience, while the z-vector contains only a linear term.

[13] The samples used differ slightly from those in Table 4 due to exclusion here of individuals with missing information on the instruments.

For all three thresholds and both conditional probabilities, the restriction that $\rho = 0$ is strongly rejected. The estimate of ρ is negative in all cases. This is analogous to the negative correlation found between the change in earnings between years t-1 and t and the level of earnings at t-1. The estimate is more negative and the rejection of $\rho = 0$ stronger the lower the low pay threshold used.

Comparison of the two columns for a given threshold shows that the magnitudes of the marginal effects and the "t-ratios" on the estimated coefficients are sensitive to the imposition of the restriction $\rho = 0$. Typically both are much reduced in the bivariate probit model with endogenous selection, i.e. imposition of $\rho = 0$ inflates the estimates (the experience effects are an exception to this). For example, age completed full-time education has a strong negative and highly significant effect in the $\rho = 0$ model with a marginal effect of 2-3 percentage points. In the model with endogenous selection, its effect is in all cases less than a third of this (with sign reversal for threshold 1) and the estimated coefficient is insignificantly different from zero.

Training, plant size and union coverage all have strong negative effects for all three thresholds in the $\rho = 0$ model. In the model with endogenous selection all three are rendered insignificant for the first threshold. They retain their statistical significance for the third threshold, but the marginal effects are cut by about half. The gender effect is rendered insignificant for the first threshold also. It is significant for the other two thresholds, with marginal effects cut by half for the second threshold and slightly less than half for the third. Imposing $\rho = 0$ (i.e. ignoring the endogenous selection) distorts the estimated coefficients and leads to the estimated effects on the conditional

probability of remaining low paid being overstated. By comparison, there is not much impact on the marginal effects of statistically significant variables of excluding those who are not employees.

How much state dependence is there in the conditional probability of remaining low paid? The calculations required to answer this question in the context of the models estimated in this paper are laid out in Table 6. The raw aggregate probabilities of being low paid at t for those low paid at t-1 and those higher paid at t-1 are given as rows 1 and 2 in the table. As was seen in section 3 of the paper, the differences between them, given in row 3, are large. For both the univariate probit and bivariate endogenous selection models the "state dependence effect" is estimated in the following way. First the predicted conditional probability of being low paid at t given low paid at t-1, as given by equation (5) above, is calculated for each individual, for their given set of characteristics. These are then averaged over first those low paid at t-1 and then those higher paid at t-1. These averages are presented in Table 6 as rows 4 and 5 for the univariate probit model and rows 8 and 9 for the bivariate endogenous selection model. The difference between the two for a particular model is the contribution <u>not</u> due to state dependence and is given in row 6 for the univariate probit model and row 10 for the bivariate endogenous selection model.

The state dependence effect is then calculated as the difference between the average probability of being low paid at t given low paid at t-1 over the sample who were in fact higher paid at t-1 and the raw aggregate probability of being low paid at t over the same sample. The state dependence effect is given in row 7 for the univariate probit model and row 11 for the bivariate endogenous selection model. Since the average predicted probability of being low paid at t given low paid at t-1 over those who actually were low paid at t-1 is virtually

identical to the raw aggregate probability for this sample for both models and all 6 columns, the state dependence effect is also the gap between the differences in rows 6 and 10 and the difference in raw aggregate probabilities given in row 3.

The estimates in this table indicate that the contribution of structural state dependence in the estimated models is considerable. Over half the difference in aggregate probabilities is due to the fact of having been low paid at t-1, holding characteristics fixed.

For the simple probit model the difference given in row 6 of Table 6 gives the overall effect of differences in the z-variables. This is however not the interpretation of row 10 for the bivariate endogenous selection model. The marginal effects presented in Table 5 evaluate the effect of a change in a particular current characteristic, holding the factors that influence the probability of being low paid in the previous period fixed as well as other current characteristics. What is required for this model is a measure of the overall effect of differences solely in current characteristics on the difference in the aggregate probabilities of being low paid at t between those low paid and higher paid at t-1.

The conditional probability of being low paid at time t given low paid at time t-1 is given by equation (5). One method of evaluating the probability difference is to replace x_{it-1} in (5) by its mean over those with $y_{it-1} = 1$, evaluate β, γ and ρ at their ML estimates and calculate this predicted probability for each individual. The required overall measure is then defined to be the difference between the average predicted probability for those with $y_{it-1} = 1$ and for those with $y_{it-1} = 0$. It measures the contribution of differences in z-variables holding fixed the probability of being low paid at t-1. For the

probability of being low paid at t given low paid at t-1 this measure gives a difference of .01 for threshold 1 and .08 for thresholds 2 and 3. For the probability of being low paid or not an employee at t it gives less than .01 for threshold 1 and .07 for thresholds 2 and 3.[14] The contribution of differences in current characteristics alone is quite small, less than 10% of the difference in aggregate probabilities. Thus ignoring the endogenous selection results in the collective effect of observed current heterogeneity being overstated by a factor of about 2.

6. Conclusions

There is considerable persistence in low pay. The probability of being low paid in year t is dramatically higher for those who were low paid in year t-1 than for those who were paid above the threshold. For women those who were low paid in year t-1 are roughly 10 times as likely to be low paid in year t as those who were not, and for men the ratio is even higher.

In addition, those who are low paid are also more likely to make transitions into other non-employee states than those from higher up the earnings distribution. Hence restricting attention to those who are employees results in an overstatement of the probability of the low paid moving up the earnings

[14] Alternative methods of calculation are possible. One alternative is to calculate the predicted probability of being low paid at t-1 for each individual with $y_{it-1} = 1$, i.e. evaluate $\Phi(x_{it-1}'\beta)$ at the ML estimate of β. Define p_2 to be the average such probability over those with $y_{i1} = 1$ and $s_2 = \Phi^{-1}(p_2)$. Then evaluate the predicted conditional probability as $\Phi_2(s_2, z_{it}'\gamma ; \rho) / p_2$ (with γ and ρ evaluated at their ML estimates) for each individual. The alternative measure is then defined to be the difference between the average predicted conditional probabilities for those with $y_{it-1} = 1$ and for those with $y_{it-1} = 0$. A second alternative is to replace x_{it-1} by its average over those with $y_{it-1} = 1$ and then compare predicted probabilities with z_{it} replaced by its average over those with $y_{it-1} = 1$ and its average over those with $y_{it-1} = 0$. Each of these three methods also has a variant with x_{it-1} replaced by its average over those with $y_{it-1} = 0$. For a given threshold and model the 6 measures are all very similar to one another.

distribution. However it is not found to have much effect on the estimated effects of explanatory variables on this probability.

As well as the low paid being more likely to move into non-employment, those entering employment from a spell outside are more likely to be low paid, and those who had been low paid prior to the spell of non-employment are even more likely to be low paid again when they subsequently move back into work than other entrants. There is thus evidence of a cycle of low pay and no pay.

This dependence of the probability of being low paid on past low pay experience may result either from heterogeneity among individuals or from the impact of the experience of low pay itself. It is important to address the initial conditions problem when modelling transition probabilities. The empirical evidence in this paper indicates that exogenous selection into the initial low pay state ($\rho = 0$) is strongly rejected and that ignoring the endogenous selection of conditioning on the initial low pay state distorts the estimated coefficients. Typically the estimated marginal effects on the conditional probability of remaining low paid (and the asymptotic t-ratios on the Maximum Likelihood coefficient estimates) are much reduced when allowance is made for endogenous selection. Ignoring the endogenous selection is found to result in the collective effect of observed current heterogeneity being overstated by a factor of about 2.

However certain factors such as training, plant size, union coverage and gender retain their significant influence, although substantially reduced in magnitude, on the probability of remaining low paid (when the higher low pay thresholds are used). Finally, there is evidence of considerable ceteris paribus dependence of the probability of being low paid on whether or not an individual was low paid in the previous year.

References

Atkinson, A.B. (1993), "What is happening to the distribution of income in the UK?" STICERD Welfare State Programme DP WSP/87.

Atkinson, A.B., F. Bourguignon and C. Morrisson (1992), Empirical Studies of Earnings Mobility, Reading: Harwood.

Bingley, Paul, Niels Henning Bjorn and Niels Westergaard-Nielsen (1995), "Wage mobility in Denmark 1980-1990", CLS, Aarhus, Working Paper 95-10.

Dickens, Richard (1996), "The evolution of individual male earnings in Great Britain: 1975-94", Centre for Economic Performance, LSE, Discussion Paper No. 306, November.

Gosling, A., S. Machin and C. Meghir (1994), "What has happened to men's wages since the mid-1960s?" Fiscal Studies, 15, 63-87.

Gregg, Paul and Stephen Machin (1994), "Is the UK rise in inequality different?" in R. Barrell (ed.) The UK Labour Market, London: NIESR.

Gregory, Mary and Peter Elias (1994), "Earnings transitions of the low paid in Britain, 1976-91: A longitudinal study", International Journal of Manpower, 15, 170-188.

Heckman, James J. (1981a), "The incidental parameters problem and the problem of initial conditions in estimating a discrete time - discrete data stochastic process", in Charles F. Manski and Daniel McFadden (eds.), Structural Analysis of Discrete Data with Econometric Applications, Cambridge: MIT Press.

Heckman, James J. (1981b), "Statistical models for discrete panel data", in Charles F. Manski and Daniel McFadden (eds.), Structural Analysis of Discrete Data with Econometric Applications, Cambridge: MIT Press.

Heckman, James J. (1981c), "Heterogeneity and state dependence", in Sherwin Rosen (ed.), Studies in Labor Markets, Chicago: Chicago University Press.

Jarvis, Sarah and Stephen P. Jenkins (1995), "Do the poor stay poor? New evidence about income dynamics from the BHPS", ESRC Research Centre on Micro-social Change, Occasional paper 95-2.

Jenkins, Stephen (1995), "Accounting for inequality trends: Decomposition analysis for the UK 1971-86", Economica, 62, 29-63.

Levy, F. and R. Murnane (1992), "US earnings levels and earnings inequalities: A review of recent trends and proposed explanations", Journal of Economic Literature, 30, 1338-1381.

Meng, Chun-Lo and Peter Schmidt (1985), "On the cost of partial observability in the bivariate probit model", International Economic Review, 26, 71-85.

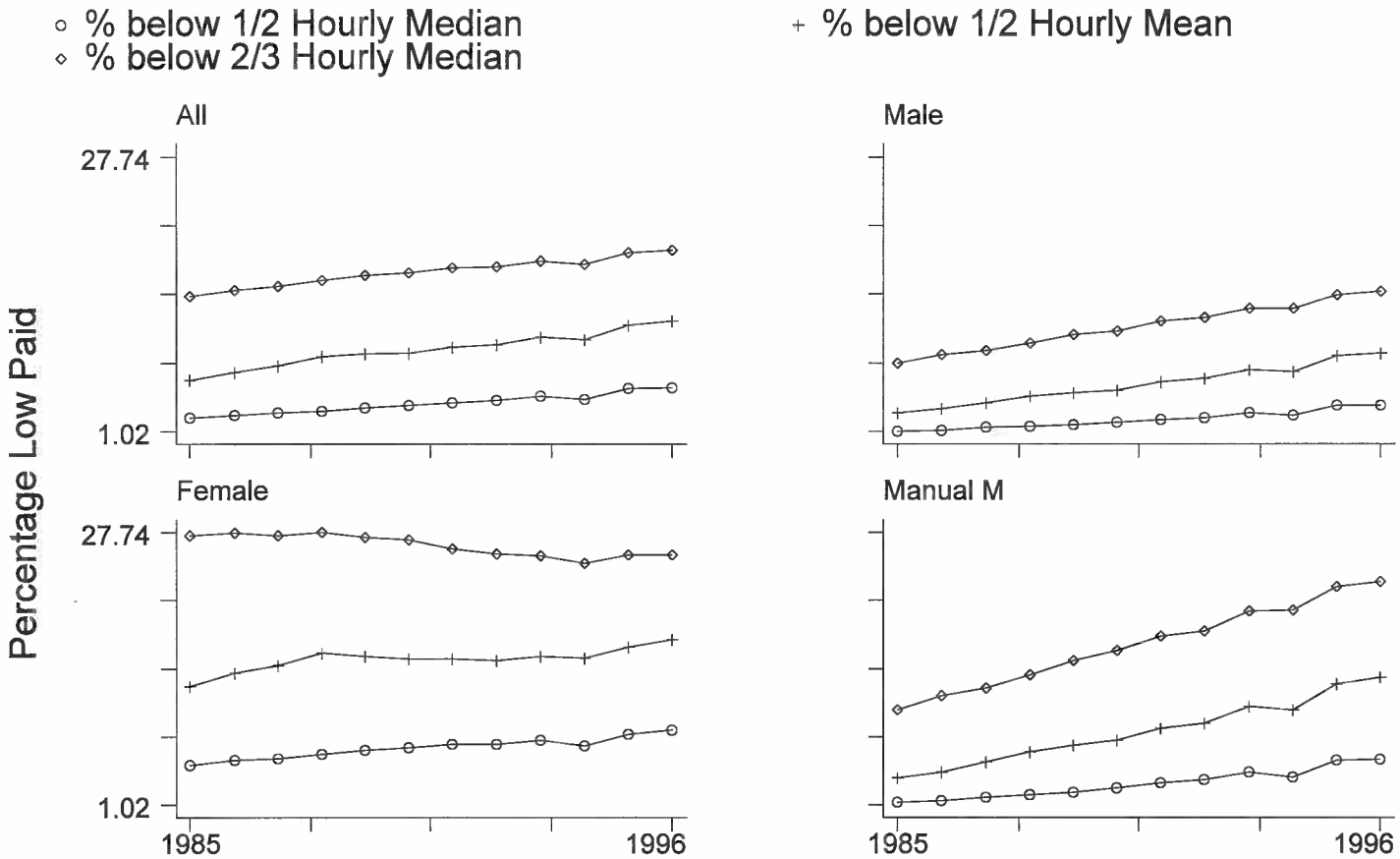
O'Higgins, N. (1994), "YTS, employment and sample selection bias", Oxford Economic Papers, 46, 605-628.

Sloane, P.J. and I. Theodossiou (1996), "Earnings mobility, family income and low pay", Economic Journal, 106, 657-666.

Stewart, Mark and Joanna Swaffield (1997a), "The dynamics of low pay in Britain", in Paul Gregg (ed), Jobs, Wages and Poverty: Patterns of Persistence and Mobility in the Flexible Labour Market, London: CEP.

Stewart, Mark B. and Joanna K. Swaffield (1997b), "Low pay dynamics and transition probabilities", mimeo, University of Warwick, January.

Van de Ven, P. and B. van Praag (1981), "The demand for deductibles in private health insurance: A probit model with sample selection", Journal of Econometrics, 17, 229-252.



New Earnings Survey: 1985-96: Full-time Employees on Adult Rates

Figure 1: Percentage Low Paid among various groups

Table 1

NES-based low pay thresholds for use with BHPS data

(October averages for each year)

	Low Pay Definition		£
	1/2 hourly median	1/2 hourly mean	2/3 hourly median
1991	3.12	3.63	4.16
1992	3.29	3.84	4.38
1993	3.39	3.97	4.52
1994	3.49	4.09	4.65
1995	3.61	4.26	4.82

Note: Each figure is the average of the corresponding figures for the previous and immediately following Aprils.

Table 2

Probability of being low paid conditional on pay state in previous period
(for those who are employees in both periods)

	Pay state @ t-1	Threshold 1	2	3
				%
Men:				
	Low Paid	52.0	59.0	71.0
	Higher Paid	2.4	4.9	6.7
Women:				
	Low Paid	69.6	79.8	84.6
	Higher Paid	6.7	7.8	8.5

Sample: t = 1992 to 1995
Sample size: 11,844

Table 3

Transition probabilities between labour market states, t-1 to t

Men: 1st Low Paid Threshold

		Destination (t) State Probabilities %					
Initial (t-1) State	Distribution t-1	1	2	3	4	5	6
1 Low Paid	4.3	38.7	35.8	8.6	3.7	7.5	5.7
2 Higher Paid	51.7	2.1	85.2	6.2	2.0	2.5	2.1
3 Employee (missing earnings)	9.6	2.7	32.7	53.5	3.0	4.7	3.4
4 Self-employed	15.2	0.6	4.8	2.4	86.4	2.9	2.9
5 Unemployed	7.5	5.9	20.3	5.9	8.3	43.5	16.1
6 Out of the labour force	11.8	2.6	5.3	2.1	2.5	8.9	78.5
All	100.0	3.8	51.1	9.7	15.5	6.8	12.6

Men: 2nd Low Paid Threshold

		Destination (t) State Probabilities %					
Initial (t-1) State	Distribution t-1	1	2	3	4	5	6
1 Low Paid	7.7	45.5	31.6	7.9	3.3	6.8	4.9
2 Higher Paid	48.2	4.3	83.4	6.1	2.0	2.2	1.9
3 Employee (missing earnings)	9.6	5.4	30.0	53.5	3.0	4.7	3.4
4 Self-employed	15.2	1.4	3.9	2.4	86.4	2.9	2.9
5 Unemployed	7.5	11.5	14.7	5.9	8.3	43.5	16.1
6 Out of the labour force	11.8	4.3	3.6	2.1	2.5	8.9	78.5
All	100.0	7.7	47.7	9.7	15.5	6.8	12.6

Men: 3rd Low Paid Threshold

		Destination (t) State Probabilities %					
Initial (t-1) State	Distribution t-1	1	2	3	4	5	6
1 Low Paid	12.3	56.4	23.1	7.5	3.1	5.9	4.0
2 Higher Paid	43.7	5.9	82.3	6.0	1.9	2.0	1.9
3 Employee (missing earnings)	9.6	8.3	27.1	53.5	3.0	4.7	3.4
4 Self-employed	15.2	1.7	3.7	2.4	86.4	2.9	2.9
5 Unemployed	7.5	14.1	12.1	5.9	8.3	43.5	16.1
6 Out of the labour force	11.8	5.2	2.8	2.1	2.5	8.9	78.5
All	100.0	12.2	43.2	9.7	15.5	6.8	12.6

Table 3 (continued)

Women: 1st Low Paid Threshold

		Destination (t) State Probabilities %					
Initial (t-1) State	Distribution t-1	1	2	3	4	5	6
1 Low Paid	13.5	54.5	23.8	6.0	1.8	3.6	10.5
2 Higher Paid	44.1	5.8	81.8	5.7	0.8	1.7	4.2
3 Employee (missing earnings)	6.5	11.5	40.5	35.6	2.2	2.4	7.8
4 Self-employed	5.1	2.9	7.4	3.7	73.3	2.7	10.1
5 Unemployed	4.8	17.2	18.5	4.9	2.7	26.3	30.5
6 Out of the labour force	26.0	5.3	5.2	2.1	1.8	6.4	79.3
All	100.0	13.0	44.6	6.6	5.0	4.4	26.4

Women: 2nd Low Paid Threshold

		Destination (t) State Probabilities %					
Initial (t-1) State	Distribution t-1	1	2	3	4	5	6
1 Low Paid	20.9	64.3	16.3	6.0	1.5	3.1	8.9
2 Higher Paid	36.7	6.9	81.3	5.7	0.8	1.5	3.8
3 Employee (missing earnings)	6.5	17.8	34.2	35.6	2.2	2.4	7.8
4 Self-employed	5.1	4.8	5.4	3.7	73.3	2.7	10.1
5 Unemployed	4.8	24.6	11.1	4.9	2.7	26.3	30.5
6 Out of the labour force	26.0	6.7	3.7	2.1	1.8	6.4	79.3
All	100.0	20.3	37.3	6.6	5.0	4.4	26.4

Women: 3rd Low Paid Threshold

		Destination (t) State Probabilities %					
Initial (t-1) State	Distribution t-1	1	2	3	4	5	6
1 Low Paid	26.5	68.8	12.5	6.1	1.3	3.0	8.3
2 Higher Paid	31.1	7.5	81.5	5.5	0.8	1.3	3.4
3 Employee (missing earnings)	6.5	24.0	28.0	35.6	2.2	2.4	7.8
4 Self-employed	5.1	5.6	4.6	3.7	73.3	2.7	10.1
5 Unemployed	4.8	27.8	7.9	4.9	2.7	26.3	30.5
6 Out of the labour force	26.0	7.6	2.9	2.1	1.8	6.4	79.3
All	100.0	25.7	31.8	6.6	5.0	4.4	26.4

Sample: t = 1992 to 1995
Sample size: 24,303

Table 4

Probit model estimated marginal effects on the conditional probability of being low paid in year t given status in year t-1

	Prob. of being low paid Sample restricted to those who are employees at t						Prob. of being low paid or not employee Sample unrestricted at t					
Sample:	Low paid in year t-1			High paid in year t-1			Low paid in year t-1			High paid in year t-1		
Threshold:	1	2	3	1	2	3	1	2	3	1	2	3
Age completed full-time education	-.027	-.027	-.019	-.009	-.014	-.017	-.016	-.021	-.016	-.008	-.011	-.012
	[-.074]	[-.088]	[-.073]	[-.100]	[-.111]	[-.109]	[-.048]	[-.075]	[-.066]	[-.040]	[-.051]	[-.054]
	(4.03)	(6.52)	(6.26)	(8.85)	(10.76)	(11.12)	(2.92)	(5.95)	(5.97)	(6.14)	(7.61)	(7.77)
Experience/10	.039	-.005	-.007	-.003	-.003	-.005	.027	-.007	-.010	.001	.005	.009
	[.110]	[-.016]	[-.027]	[-.054]	[-.035]	[-.045]	[.083]	[-.023]	[-.039]	[.007]	[.024]	[.042]
	(3.12)	(.59)	(1.11)	(2.21)	(1.53)	(1.90)	(2.57)	(.89)	(1.66)	(.40)	(1.38)	(2.26)
Training in last 12 months	-.055	-.077	-.105	-.021	-.031	-.042	-.073	-.082	-.101	-.042	-.048	-.056
	[-.148]	[-.235]	[-.367]	[-.328]	[-.331]	[-.369]	[-.209]	[-.272]	[-.384]	[-.249]	[-.260]	[-.289]
	(1.75)	(3.61)	(6.51)	(5.95)	(6.67)	(7.65)	(2.64)	(4.36)	(7.05)	(6.82)	(7.07)	(7.59)
Workplace with 25+ employees	-.099	-.106	-.073	-.015	-.022	-.023	-.086	-.099	-.068	-.037	-.039	-.040
	[-.269]	[-.340]	[-.282]	[-.211]	[-.212]	[-.181]	[-.253]	[-.346]	[-.290]	[-.202]	[-.196]	[-.190]
	(3.67)	(5.74)	(5.25)	(4.09)	(4.29)	(3.59)	(3.71)	(6.13)	(5.61)	(5.50)	(5.10)	(4.64)
Union recognised at workplace	-.209	-.102	-.066	-.016	-.019	-.026	-.181	-.096	-.066	-.042	-.043	-.044
	[-.551]	[-.315]	[-.246]	[-.234]	[-.192]	[-.216]	[-.506]	[-.324]	[-.267]	[-.233]	[-.219]	[-.216]
	(6.73)	(5.21)	(4.65)	(4.70)	(4.13)	(4.68)	(6.67)	(5.59)	(5.22)	(6.67)	(6.09)	(5.73)
Married	-.065	-.016	-.045	-.015	-.019	-.023	-.063	-.023	-.044	-.031	-.031	-.034
	[-.179]	[-.052]	[-.177]	[-.206]	[-.184]	[-.187]	[-.189]	[-.082]	[-.191]	[-.167]	[-.157]	[-.166]
	(2.19)	(.79)	(2.99)	(3.70)	(3.49)	(3.50)	(2.49)	(1.31)	(3.35)	(4.22)	(3.81)	(3.77)
Female	.182	.221	.148	.034	.026	.020	.141	.180	.126	.034	.027	.019
	[.479]	[.648]	[.518]	[.490]	[.261]	[.172]	[.396]	[.574]	[.485]	[.195]	[.140]	[.097]
	(5.67)	(10.30)	(9.83)	(9.76)	(5.78)	(3.80)	(5.16)	(9.72)	(9.59)	(5.80)	(4.02)	(2.62)
Constant	-	-	-	-	-	-	-	-	-	-	-	-
	[1.44]	[2.06]	[2.28]	[.361]	[.859]	[1.04]	[1.30]	[2.07]	[2.33]	[-.150]	[.117]	[.228]
	(4.31)	(8.18)	(10.20)	(1.64)	(4.17)	(5.13)	(4.31)	(8.73)	(10.93)	(1.11)	(.826)	(1.52)
Sample proportion	.647	.739	.801	.042	.060	.073	.706	.776	.827	.107	.120	.128
Sample size	1,531	2,576	3,563	9,828	8,783	7,796	1,834	3,000	4,097	10,543	9,377	8,280

Notes:

* In the cases of education and experience marginal effects were estimated as the difference between full-time education leaving ages of 16 & 17 years and 20 & 30 years of experience respectively

1. Estimated marginal effects reported in 1st row for each variable
2. ML coefficient estimates in square parentheses and absolute asymptotic t-ratios in round parentheses
3. Pooled BHPS data for t = 1992 to 1995

Table 5

Estimated marginal effects on the conditional probability of being low paid in year t given low paid in year t-1 using bivariate probit model with endogenous selection

Sample:	Prob (Low Paid in t | Low paid in t-1)						Prob (Low Paid or not employee in t | Low paid in t-1)					
Threshold:	1	1	2	2	3	3	1	1	2	2	3	3
Age Completed f-t education*	-.028	.007	-.027	-.006	-.019	-.006	-.016	.010	-.021	-.004	-.015	-.003
	[-.076]	[.016]	[-.086]	[-.019]	[-.072]	[-.024]	[-.047]	[.027]	[-.073]	[-.013]	[-.065]	[-.014]
	(3.98)	(.60)	(6.30)	(.87)	(6.09)	(1.22)	(2.81)	(1.22)	(5.71)	(.66)	(5.78)	(.77)
Experience/10*	.037	.061	-.004	.015	-.007	.004	.026	.047	-.005	.011	-.009	.003
	[.103]	[.156]	[-.013]	[.046]	[-.028]	[.016]	[.080]	[.134]	[-.018]	[.038]	[-.038]	[.013]
	(2.87)	(4.90)	(.46)	(1.55)	(1.12)	(.59)	(2.44)	(4.42)	(.67)	(1.35)	(1.60)	(.50)
Training in last 12 months	-.072	.001	-.078	-.024	-.103	-.066	-.087	-.017	-.084	-.033	-.100	-.060
	[-.191]	[.003]	[-.238]	[-.072]	[-.362]	[-.233]	[-.248]	[-.045]	[-.276]	[-.108]	[-.381]	[-.231]
	(2.21)	(.04)	(3.59)	(.95)	(6.33)	(3.31)	(3.07)	(.52)	(4.35)	(1.44)	(6.89)	(3.42)
Plant with 25+ employees	-.094	.0004	-.103	-.055	-.072	-.046	-.083	-.004	-.097	-.055	-.067	-.042
	[-.255]	[.001]	[-.329]	[-.165]	[-.276]	[-.172]	[-.243]	[-.010]	[-.337]	[-.183]	[.286]	[-.173]
	(3.42)	(.01)	(5.48)	(2.32)	(5.08)	(2.76)	(3.50)	(.12)	(5.90)	(2.67)	(5.46)	(2.95)
Union at the workplace	-.208	-.057	-.100	-.033	-.068	-.035	-.177	-.047	-.094	-.036	-.066	.033
	[-.549]	[-.134]	[-.310]	[-.098]	[-.251]	[-.130]	[-.495]	[-.124]	[-.316]	[-.119]	[-.269]	[-.133]
	(6.61)	(1.07)	(5.05)	(1.23)	(4.68)	(2.00)	(6.44)	(1.06)	(5.40)	(1.54)	(5.20)	(2.16)
Married	-.066	-.007	-.019	.014	-.049	-.029	-.065	-.009	-.027	.004	-.048	-.027
	[-.183]	[-.016]	[-.060]	[.042]	[-.193]	[-.109]	[-.195]	[-.025]	[-.095]	[.014]	[-.210]	[-.112]
	(2.19)	(.20)	(.90)	(.63)	(3.20)	(1.70)	(2.52)	(.310)	(1.49)	(.21)	(3.61)	(1.84)
Female	.186	.011	.230	.115	.153	.097	.142	-.002	.187	.090	.131	.075
	[.487]	[.027]	[.669]	[.325]	[.535]	[.340]	[.400]	[-.006]	[.591]	[.283]	[.502]	[.290]
	(5.61)	(.20)	(10.44)	(2.88)	(10.01)	(4.06)	(5.07)	(.053)	(9.84)	(2.75)	(9.78)	(3.79)
Constant	-	-	-	-	-	-	-	-	-	-	-	-
	[1.48]	[.61]	[2.01]	[1.24]	[2.26]	[1.60]	[1.29]	[.590]	[2.01]	[1.31]	[2.31]	[1.58]
	(4.26)	(1.63)	(7.78)	(3.80)	(9.93)	(5.08)	(4.16)	(1.78)	(8.31)	(4.27)	(10.63)	(5.39)
ρ	0	-.658	0	-.519	0	-.386	0	-.625	0	-.493	0	-.428
		(.126)		(.123)		(.120)		(.131)		(.123)		(.110)
Sample size	1,482	11,054	2,499	11,054	3,471	11,054	1,773	12,043	2,906	12,043	3,987	12,043

Notes:

* In the cases of education and experience marginal effects were estimated as the difference between full-time education leaving ages of 16 & 17 years and 20 & 30 years of experience respectively

1. Estimated marginal effects reported in 1st row for each variable
2. ML coefficient estimates in square parentheses and absolute asymptotic t-ratios in round parentheses
3. Pooled BHPS data for t = 1992 to 1995

Table 6

Dependence of probability of being low paid in year t on low pay status in year t-1

		P(LP in t | LP in t-1)			P(LP or not E in t | LP in t-1)		
	Threshold:	1	2	3	1	2	3
Row:							
	Raw aggregate probabilities of low paid in year t given:						
1.	Low paid at t-1	.648	.736	.801	.706	.773	.827
2.	Higher paid at t-1	.042	.061	.074	.107	.121	.128
3.	Difference	.606	.675	.727	.598	.652	.699
	Model predicted probabilities: Estimates of P(LP in year t | LP in year t-1)						
	Probit model:						
4.	Average over Low Paid at t-1 sample	.648	.737	.801	.706	.773	.827
5.	Average over Higher Paid at t-1 sample	.428	.539	.648	.520	.594	.683
6.	Difference	.220	.198	.154	.186	.179	.144
7.	State dependence effect	.386 (64%)	.477 (71%)	.574 (79%)	.412 (69%)	.473 (73%)	.555 (79%)
	Endogenous selection model:						
8.	Average over Low Paid at t-1 sample	.648	.737	.801	.706	.773	.827
9.	Average over Higher Paid at t-1 sample	.393	.513	.630	.484	.569	.663
10.	Difference	.255	.224	.171	.222	.204	.165
11.	State dependence effect	.351 (58%)	.452 (67%)	.556 (76%)	.376 (63%)	.448 (69%)	.534 (76%)

Notes:
1. Calculations based on estimated models given in Table 5.
2. LP denotes low paid and E employment