Transitions between unemployment and low pay[§]

Lorenzo Cappellari
(Università del Piemonte Orientale)

and

Stephen P. Jenkins
(University of Essex)

January 2004

Abstract

There is a great interest in Britain in the extent to which there exist a 'low pay/no pay cycle'. That is, to what extent are individuals who are currently low paid more likely to become unemployed than high paid individuals, and are those who are currently unemployed more likely to become low paid rather then high paid when they get a job? To address these and related questions, we model annual transitions between unemployment, low-paid employment and high-paid employment. We use a first order Markov model that also takes into account the endogeneity of initial conditions, selection into employment, and sample attrition. The application is based on data for men from the British Household Panel Survey covering survey years 1991–2000. Our results show that all three selectivity issues should be addressed when analysing men's labour market transitions. We find that low-paid men are more likely to become unemployed then high-paid men, and unemployed men have a greater chance of becoming low paid than do high-paid men. Transitions from unemployment to low pay are associated with having relatively few educational qualifications. There is also evidence that the experience of low pay or unemployment itself increases the chance of being trapped in those states (separately from the effects of individual heterogeneity).

Keywords: labour market transitions, unemployment, low pay
JEL code: C33, J31, J64

Correspondence
Cappellari: Dipartimento di Scienze Economiche e Metodi Quantitativi, Università del Piemonte Orientale, Via Perrone 18, 28100 Novara, Italy. Email: lorenzo.cappellari@eco.unipmn.it
Jenkins: Institute for Social and Economic Research, University of Essex, Wivenhoe Park, Colchester CO4 3SQ, UK. Email: stephenj@essex.ac.uk

[§] Research supported by a Nuffield Foundation New Career Development Fellowship and by ISER's core funding from the ESRC and the University of Essex. Cappellari acknowledges financial support from Regione Piemonte (grant no. 21302BAIPSE).

1. Introduction

There is a great interest in Britain in the 'low pay/no pay cycle' – the extent to which individuals who are low paid more likely to become unemployed than high paid individuals, and the extent to which those who are currently unemployed are more likely to become low paid rather then high paid when they get a job. In this paper we provide new evidence about the low pay/no pay cycle using a first order Markov model for multi-state labour market dynamics.

The emphasis of recent British labour market policy has been on getting unemployed people into a job. These jobs have often been low paid ones (albeit supplemented with in-work benefits such as the Working Families Tax Credit). If there is a strong 'low pay/no pay cycle', then most of these jobs do not last very long, and there is churning between the ranks of the unemployed and the low paid. Put another way, there is a form of labour market segmentation, with a divide between a primary sector (the high-paid) and a secondary sector comprising the individuals churning between unemployment and low-paid jobs with little chance of climbing up the pay ladder through time. We aim to shed light on these issues by modelling the annual rates of transition between being high-paid, low-paid, or being unemployed. A more specific question that we also address is whether the individuals who find themselves trapped in the secondary sector do so because they have poor educational qualifications and other disadvantageous characteristics, or because of the experience of unemployment or low pay itself. In other words, is the low pay/no pay cycle due to heterogeneity in characteristics (observed or unobserved), or due to state dependence? If heterogeneity effects dominate, then it suggests the need for targeting on specific groups of individuals, for example to improve their skills through training. If state dependence is a significant factor, then there is a pay-off from policies targeted generally towards reducing unemployment itself or the prevalence of low pay.

There has been much recent research for Britain about earnings mobility on the one hand, and unemployment dynamics on the other hand: see for example Stewart and Swaffield (1999) about the former, and Arulampalam et al. (2000) about the latter. The inter-relationships between the dynamics of low pay and unemployment have received much less attention, however. The only paper that we know of is by Stewart (2002), who modelled the probabilities of unemployment and low pay sequentially, using dynamic random effects probit regressions controlling for endogenous initial conditions. Using data from the British Household Panel Survey (BHPS) covering 1991–96, Stewart found evidence of the low pay/no pay phenomenon. The chance of becoming low paid was significantly more likely for unemployed individuals than for high-paid employees and, among employed individuals, the chances of entering unemployment were larger for individuals who were low-paid rather than high-paid. There was also evidence that low pay acted as a conduit to repeat unemployment: the unemployed who found a low-paid job were more likely to fall back into unemployment than those who had found a high-paid job.

In this paper we provide new evidence about 'low pay/no pay cycles' in Britain. We model annual labour market transitions using BHPS data, as Stewart (2002) did. We extend his work in several directions however. We model movements into and out of work (low-paid and high-paid jobs) jointly rather than sequentially. Stewart took account of a potential correlation between the unobserved individual factors affecting the probability of a transition into unemployment and those affecting whether an individual was unemployed in the first place. Not only do we allow for this endogeneity of initial conditions but, in addition, we also allow for correlations between the unobserved individual factors affecting the probability of having a job, whether an employed individual has a low-paid job rather than a high paid job, and whether an individual was a respondent at two consecutive BHPS interviews. In sum, our first-order Markov model of labour market transitions controls for endogenous initial conditions, selection into employment, and panel attrition. We account for the presence of repeated observations on the same individual in the pooled transitions by using a robust variance estimator. Our BHPS data cover a longer period than Stewart's, 1991–2000.

We find evidence of all three sources of endogeneity (initial conditions, selection, attrition) when estimating rates of transition between low pay, high pay, and unemployment. (Put another way, estimates of transition probabilities based on models that ignore these phenomena yield biased estimates.) The endogeneity of selection into employment when estimating low pay transitions suggests that part of the low pay/no pay cycle is due to unobserved heterogeneity. We find that transitions from unemployment to low pay are associated with having few educational qualifications. There is also evidence that, controlling for observed and unobserved individual heterogeneity, past experience of being low-paid or unemployment market states increases the chances of being found in those states currently.

2. Data and descriptive patterns of transitions between unemployment and low pay

We use interview waves 1–10, survey years 1991–2000, of the British Household Panel Survey (Taylor, 2001). Data from consecutive waves, call them year t–1 and year t, are used to estimate annual transition rates, using a sample that pools all transitions. We analyse the experience of men who were aged 16–64 years in year *t*–1 who were either unemployed or employees, and not full-time students. We restricted attention to men in order to avoid addressing issues of endogenous female labour supply. Following Arulampalam et al. (2000) and Stewart (2002), we do not model the endogeneity of being economically active or of self-employment. We defined a man to be unemployed if he was not working and had been looking for a job during the four weeks prior to the interview. The low pay threshold was defined as 60 percent of median hourly earnings, in August 2000 prices.

Table 1 reports the raw transition rates for our sample and provides a description of the extent of the 'low pay/no pay cycle' in aggregate.[1] The table shows, for example, that the chances of being low paid in one year were four times greater for those who were unemployed rather than high-paid the previous year. On the other hand, the probability of being unemployed in one year was three times more likely among those who were low-paid rather than high-paid previous year. Of those who left unemployment, 37 percent (= 17.8/(17.8+29.35)) got a low paid job, which is almost three times the cross-sectional low pay probability (13 percent in our sample). Overall, the evidence suggests that there is substantial churning between unemployment and low pay.

<Table 1 near here>

There also appears to be persistence in the experience of low pay and unemployment. Among those unemployed in year *t*–1, the probability of unemployment in year *t* was 53 percent, compared to 6.5 percent of those who were low-paid and less than 2 percent for those high-paid. Similarly, the probability of low pay in year *t* was 52 percent for those who were low-paid at year *t*–1, but 18 percent for those who were unemployed, and only 4 percent for those who were high-paid. Together the evidence of churning and of persistence indicate the strong association between a man's labour market state this year and his state in the previous year. The extent to which such 'aggregate state dependence' is due to (observed or unobserved) heterogeneity or to 'genuine state dependence' (labour market scarring) is an issue we addressed below.

Table 1 also shows the transition rates obtained when 'attrition from the sample' was included as a fourth destination state at year *t*: these are the estimates shown in parentheses. Sample dropout rates were highest among those who were unemployed at year *t*–1 (40

[1] Stewart (2002) pooled data for men and women, and reported higher low pay transition rates and lower unemployment transition rates than those show in Table 1 below. When we pooled data for men and women, we found transition rates to be very close to the ones reported by Stewart.

percent), smaller for those were low-paid (22 percent), and lower still among those who were high-paid (13 percent). This pattern suggests that attrition probabilities depend on labour market state, and hence econometric analysis of transitions between states needs to take account of potential correlations between the unobserved factors affecting attrition and transition probabilities (i.e. endogenous attrition).

3. A model of transitions between unemployment and low pay

In order to estimate an econometric model of transitions between unemployment and low pay, several issues need to be addressed. First, the dynamic nature of the model means that unobserved factors affecting transitions between states may be correlated with those determining the origin state – the 'initial conditions problem' (Heckman, 1981*a*). Second, earnings are observed only for individuals who have a job, and it is well known from the labour economics literature that parameter estimates of earnings equations for the population as a whole derived from a sample restricted to workers may be subject to 'selection biases' (Heckman, 1974; Keane et al, 1988). This endogenous selection issue is also potentially relevant in our application: employed men may have low pay propensities that are systematically higher than the propensities for unemployed men. Third, as Table 1 suggested, sample attrition might not be random. Finally, in order to distinguish between heterogeneity and state dependence as explanations for the persistence in labour market states that is observed, one needs to allow for some intertemporal correlation in the unobserved factors in the relevant processes (Heckman, 1981*b*). We address all four issues by developing a multivariate probit model with endogenous selection and endogenous switching.

Consider a group of men indexed by i observed in unemployment, low paid employment, or higher paid employment in year t–1. Transitions between the three states for individual i can be observed only if he is also observed in year t; let the sample retention propensity between the two waves, r^*_{it}, be a linear function of observable attributes at t–1 plus an error term distributed as standard normal (summarising unobserved attributes):

$$r^*_{it} = \psi' x_{it-1} + \xi_{it}, \qquad \xi_{it} \sim N(0,1). \tag{1}$$

Whenever r_{it}^* is greater than some threshold, that can be set to 0 without loss of generality, individual i is observed in both panel waves; let $R_{it} = I(r^*_{it} > 0)$ be a dichotomous indicator for that event, where the indicator function $I(\ )$ equals one if its argument holds, and zero otherwise.

Assume that employment chances in year t–1 can be written in terms of an unobserved latent employment propensity, e^*_{it-1}, a linear function of observable characteristics plus an error term distributed as standard normal (again summarising unobserved attributes):

$$e^*_{it-1} = \beta' z_{it-1} + \varepsilon_{it-1}, \qquad \varepsilon_{it-1} \sim N(0,1). \qquad (2)$$

Let $E_{it-1} = I(e^*_{it-1} > 0)$ be a dummy variable indicating whether i is employed in year t–1.

If individual i is employed at t–1, earnings can be observed, and assume that they can be specified as:

$$f(w_{it-1}) = \gamma' m_{it-1} + u_{it-1}, \qquad u_{it-1} \sim N(0,1). \qquad (3)$$

where $f(\ )$ is a suitable monotonic transformation of earnings such that the error term in (3) has a standard normal distribution. Let τ_{t-1} be low pay threshold for year t–1. An individual is low-paid whenever $w_{it-1} < \tau_{t-1}$, i.e. when $f(w_{it-1}) < f(\tau_{t-1})$. By subtracting both sides of equation (3) from $f(\tau_{t-1})$, this expression may be rewritten as:

$$l^*_{it-1} = \delta' m_{it-1} + v_{it-1} \qquad v_{it-1} \sim N(0,1) \qquad (3')$$

where $l^*_{it-1} \equiv f(\tau_{t-1}) - f(w_{it-1})$. The intercept term in parameter vector δ is the difference between $f(\tau_{t-1})$ and the intercept term in vector γ. The other parameters in δ are the same as the corresponding ones in γ, but have the opposite sign, and $v_{it-1} \equiv - u_{it-1}$. If the latent variable l^*_{it-1} is positive, individual i is low paid. Let the low pay binary indicator $L_{it-1} = I(l^*_{it-1} > 0)$ characterise that event.[2]

If individuals do not drop out of the sample, their status in year t can be observed in addition to the state at t–1. In order to characterise probabilities of transition between unemployment and low pay, we condition year t states on t–1 states. Clearly, such an exercise could not be performed by including E_{it-1} and L_{it-1} among the regressors of year t equations, since low pay status at t–1 is only observed for men who were employed at that time. Because of this, we proceed by allowing there to be two different specifications for the year t equations depending on the value of E_{it-1} (i.e. there is endogenous switching), and we include L_{it-1} among the explanatory variables for the case when $E_{it-1} = 1$. For example, we specify year t employment propensities as:

$$e^*_{it} = E_{it-1}(\lambda_1' h_{1it-1} + \theta_e L_{it-1}) + (1 - E_{it-1})\lambda_2' h_{2it-1} + \omega_{it} \qquad \omega_{it} \sim N(0,1). \tag{4}$$

Besides the inclusion of L_{it-1} among the regressors for those who were employed in t–1, the effects of other explanatory variables are also allowed to differ depending on past employment: in particular, the vector of observables h_{1it-1} will contain all the variables present in $h_{2it-}1$ plus some job attributes. We measure regressors at date t–1 in order to avoid simultaneity between changes in employment propensities and changes in regressors. We characterise year t employment status by means of a dummy variable, $E_{it} = I(e^*_{it} > 0)$. Note that equation (4) is conditional on equations (1), (2), (3´).

The final processes to be specified are those characterising low pay at date t – observed only if $R_{it} = 1$ and $E_{it} = 1$. Moreover, the equations need to include conditioning on what on whether employed, high-paid or low paid at t–1. Arguments similar to the ones we made about the specification of the latent employment propensity e^*_{it} also point to the need to allow for endogenous switching in this case as well. We specify the process determining low pay at t directly in terms of a low pay propensity, l^*_{it}, which can be derived from a equation for earnings at t in a fashion similar to the one used to relate l^*_{it-1} to earnings at t–1:

$$l^*_{it} = E_{it-1}(\varphi_1' k_{1it-1} + \theta_l L_{it-1}) + (1 - E_{it-1})\varphi_2' k_{2it-1} + \eta_{it} \qquad \eta_{it} \sim N(0,1). \tag{5}$$

and remarks about differences in regressors according to lagged employment (the vectors k_{1it-1} and k_{2it-1}) similar to those raised when commenting equation (4) also apply now. Let $L_{it} = I(l^*_{it} > 0)$ be the binary indicator summarising observed low pay status at t.

We allow the unobservable factors in the five equations to be jointly distributed as five-variate normal with zero means, unit variances, and unrestricted correlations:

$$(\xi_{it}, \varepsilon_{it-1}, v_{it-1}, \omega_{it}, \eta_{it}) \sim N_5(0,\Sigma) \tag{6}$$

[2] One advantage of working with the dichotomous low pay indicator rather than with the continuous earnings variable in the multivariate normal context of this paper is the avoidance of a normality assumption on earnings or log-earnings; rather, normality is assumed only up to any monotonic transformation of the earnings variable.

Unobserved heterogeneity is parameterised by the correlation coefficients forming the off-diagonal elements of Σ.[3] Estimation of the cross-equation correlations allows for the endogeneity of panel attrition, of lagged states and selection into employment, and tests of the null hypothesis of exogeneity of the various processes can be performed by testing the statistical significance of the elements of Σ (see below).

In sum, our econometric model is a five-variate probit regression model with an endogenous dummy variable (lagged low pay), endogenous switching (in year *t* equations), and endogenous selection (of year *t* equations with respect to attrition, and of pay equations with respect to employment). The likelihood function therefore involves normal integrals of various dimensions, the largest being five. The computational problem posed by the evaluation of these integrals is tackled by simulation, in particular by employing the so-called GHK simulator.

The model is estimated pooling annual transitions from BHPS interview waves 1–10, with t = 1992, …, 2000. There are repeated observations on the same individual for each man who was a respondent at least two interviews. These repeated observations mean that the i.i.d. assumption is violated. To account for this, we used a Pseudo Simulated Maximum Likelihood (PSML) estimator, as follows. The complex survey statistics literature has developed methods for adjusting the estimates of the parameter covariance matrix to account for sample clustering, using formulae that allow for arbitrary correlations between observations within the same sample cluster, an individual in our case. See *inter alia* Huber (1967) and Binder (1983) and, for an independent derivation in the econometrics literature, White (1982). The sample log-likelihood is a 'pseudo-likelihood' in this case (Gourieroux and Monfort, 1996), from which can be derived a 'robust' variance estimator of the parameter estimates using Taylor-series linearisation. Our estimator is a PSML estimator because the pseudo-likelihood was evaluated using the GHK simulator.

Exclusion restrictions are required in order to identify the model. Our instrument for attrition is a binary variable summarising whether the year t–1 interview was assessed as being problematic by the interviewer. Stewart (2002) suggested instrumenting employment equations using variables summarising the characteristics of an individual's first-ever employment spell. In addition, recent papers have reported that wages are less sensitive to unemployment in the UK than they are elsewhere (see Barth et al., 2002, and Montuega et al., 2003). This suggests that measures of labour market tightness as the unemployment vacancy ratio in the relevant travel-to-work area could also be used as instruments in employment equations. We found that, while these variables worked well as instruments for identifying employment at t–1, measures of the characteristics of the first employment spell performed better in equations for employment at t. (The measures were binary indicators of whether the first spell was in full-time work, and whether the information was missing.) Finally, as instruments for initial conditions, we used a series of binary indicators summarising parental socio-economic status measured when the respondents were aged 14 (primarily occupation variables, plus variables to indicate no parent or missing information).

Because our model controls for observed and unobserved heterogeneity, it allows assessment of the extent to which the observed persistence in labour market states is due to the experience of adverse states in itself, rather than to differences between the groups of individuals who do and do not experience those states. As a benchmark for assessing 'genuine state dependence', parameter estimates can be used to compute the equivalent of the raw overall differences in transition rates shown in Table 1. In particular, we generate predicted transition rates for each sample member and then take their averages over the relevant subsamples.

The absence of genuine state dependence can be investigated by testing whether there is a difference in the parameters associated with the different states at t–1, i.e. whether the past has any influence on the probabilities of current states after controlling for observed and unobserved heterogeneity. For the effects of lagged low pay, this amounts at testing whether θ_e and θ_l are statistically different from zero (see equations 4 and 5). For lagged employment, according to which the whole set of coefficients (not only the intercept term) switches, we test the equality of the coefficients estimates for the two employment states at t–1, i.e. H_{01}: $\lambda^{-}_{1} = \lambda_2$ and H_{02}: $\varphi^{-}_{1} = \varphi_2$, where a '–' denotes vectors deprived of coefficients that have no counterpats in the equations for the unemployed of t-1.

Measures of the degree of genuine state dependence need to quantify the shift in the probabilities of year t states due to shifts in the relevant coefficients across year t–1 states, while abstracting from heterogeneity. To assess the impact of lagged low pay, one can compute the marginal effects associated with L_{t-1}. This is not possible for lagged employment (given the 'switching' nature of the model). An alternative measure of genuine state dependence for the case in which the whole vector of relevant coefficients switches was

[3] Arulampalam and Booth (2000) identified the serial correlation induced by unobserved heterogeneity on a two

proposed by Cappellari and Jenkins (2002) for the case of poverty transitions. Assume that individual i was in state $S \in \{L, E\}$ in year t–1 and denote the estimated transition probability by $\Pr(S_{it} | S_{it-1} = 1; \alpha_1)$. Given personal characteristics, this probability is a function of the relevant vector of coefficients α_1. Estimation of the model allows computation of a counterfactual transition probability, the probability that individual i would have experienced had he started the transition not in state S: $\Pr(S_{it} | S_{it-1} = 0; \alpha_2)$. For example, when $S_{it} = E_{it}$ and $S_{it-1} = E_{it-1}$, $\alpha_1 = (\lambda_1, \theta_e)$ and $\alpha_2 = \lambda_2$.[4] The shift in the probabilities of year t states due to differences in coefficients across year t–1 states is then $\Pr(S_{it} | S_{it-1} = 1; \alpha_1) - \Pr(S_{it} | S_{it-1} = 0; \alpha_2)$. This difference in probabilities measures state dependence at the individual level and therefore abstracts from heterogeneity, and sample means of these differences offer a measure of the degree of genuine state dependence.

4. Results

Instrument validity, correlations between unobserved factors, and tests for endogenous selection

Table 2 reports the tests of the validity of the instruments. As there was no obvious identifying restriction that could have been used to perform over-identification tests, we used the non-linearity of the five-variate probit as the identifying restriction, and tested the validity of the instruments discussed in the previous section. Overall, the data supported the proposed identification strategy. Instruments were generally statistically significant in the relevant selection equations, and non statistically significant in the relevant outcome equation.

<Table 2 near here>

The estimated correlation structure of the unobserved factors is shown in Table 3, together with results of tests for the ignorability of the retention, initial conditions and employment processes. These are based on the elements of the correlation matrix. Unobserved factors in the retention equation were positively associated with those in the lagged employment equation and negatively associated with the ones in the current low pay equation. This echoes the pattern in Table 1 noted earlier, i.e. that men dropping out of the sample were concentrated among the unemployed and the low paid. The correlation between unobserved factors affecting initial employment and conditional current employment was

---

waves panel using a bivariate probit model.

[4] When $S_{it} = L_{it}$ and $S_{it-1} = E_{it-1}$, $\alpha_1 = (\varphi_1, \theta_l)$ and $\alpha_2 = \varphi_2$.

negative and statistically significant. Since this correlation refers to those who were already employed – since the year t equation switches depending on the states at t–1 – the negative sign can be interpreted as an example of Galtonian regression towards the mean in employment propensities. (See Stewart and Swaffield, 1999, and Cappellari, 2002, for analogous findings in the context of low pay transitions models.)

The correlation between unobserved factors in the lagged employment and lagged low pay equations was positive and precisely estimated, indicating that earnings potential was higher for men who were not employed compared to men who were, other things being equal. This fact might reflect higher reservation wages for unemployed men compared to employed men, or higher hiring probabilities in low-wage industries or workplaces compared to high-wage ones. Alternatively, it might reflect a higher chance of losing jobs during recessions among high-wage workers than among low-wage ones, as Keane et al. (1988) found for the USA. A similar interpretation can be given to the positive correlation estimated between unobserved factors determining lagged employment and current low pay. On the other hand, the correlations between unobserved factors in the current employment and low pay equations were not precisely estimated. Finally, the correlation between unobserved factors in the two low pay equations was positive, although statistically significant only at the 20 percent level. (Taken at face value, it appears that, after controlling for differences in observed characteristics and in lagged low pay states, there remains some unobserved heterogeneity in low pay.)

Overall, the data give support to the proposed estimation strategy. According to the tests reported at the bottom of the table, none of the three endogenous selection processes considered should be ignored in the estimation of low pay/unemployment transitions: testing that all the correlation coefficient that "load" a given selection process into the model are jointly equal to zero lead to reject the null hypothesis at conventional confidence levels.

<Table 3 near here>

Employment transition probabilities: parameter estimates

In Table 4 we provide estimates of the coefficients in the equations for the probability of employment. In the 'full model', probabilities differ depending on employment status (and low pay) at t–1; hence the two columns of estimates. The table also reports the 'marginal effects' associated with each variable, evaluated at the sample means of explanatory variables. For comparative purposes, the table also includes the estimates from 'univariate models'.

These result from the estimation of the employment probability equations without controlling for endogenous attrition, selection into employment, or initial conditions.

Looking first at the full model estimates, we find that the probability of unemployment is about one percentage point higher for a man who was low-paid in t–1 rather than high-paid, other things being equal. As this marginal effect is calculated holding observed and unobserved personal attributes fixed, it is an indication of the extent of genuine state dependence in employment with respect to low pay. Taking the probability of unemployment for men who were high-paid at t–1 as a benchmark (1.95 percent, see Table 1), our estimates imply that, by itself, low pay raises unemployment probabilities by about a half. The corresponding marginal effect in the univariate model is twice the size of that in the full model (two percent), suggesting that not accounting for unobserved heterogeneity, in this case, would lead to an overstatement of the impact of lagged low pay on the probability of employment by nearly 100 percent. Also the relevant coefficient in the univariate model is precisely estimated (with a p-value less than 0.05, compared to the one in the full model, for which the p-value is 0.147.)

<Table 4 near here>

Being married was associated with higher employment probabilities if one was already employed, and with a lower probability for the previously-unemployed. In the first case the effect may reflect the presence of family responsibilities which favour employment stability; in the second case, it might reflect the presence of the partner's incomes which lengthen job search duration, other things being equal. Employment probabilities had an inverse-U relationship with age, but life-cycle variation was limited: the probability was 0.5 percent higher for a man aged 45 rather 26 years (these are the third and first quartiles of the sample age distribution).

Having better educational qualifications had a positive impact on employment probabilities, especially for those who were previously unemployed. For example the probability of getting a job was about 25 percent higher for an unemployed man with a university degree compared to an unemployed man with no educational qualifications. It is noteworthy that these effects would have been estimated to be even larger – by approximately 5 percent – if (wrongly) endogeneity issues had been ignored. (See the univariate model estimates.) Since men with unobserved characteristics that are not favourable to employment are over-represented among the unemployed, the effect of characteristics that are associated with higher employment probabilities is overestimated if unobserved heterogeneity is ignored.

The presence of health problems, on the other hand, seems to be associated with higher probabilities of becoming unemployed.

Low pay transition probabilities: parameter estimates

Estimates of the models of the probabilities of low pay are reported in Table 5. The first two columns of numbers again show the full model, with coefficients varying with lagged employment status. The 'univariate model' estimates are those resulting from models that did not control for endogeneity.

The marginal effect associated with having been low-paid at t–1 indicates that the probability of being low-paid would be about 25 percentage points higher for a man who was low-paid at year t–1 rather than high-paid. Given that the average low-pay probability in year t among men who were high-paid at t–1 is 4 percent, the large marginal effect indicates that the chances of being low-paid are closely associated with the experience of low pay in the past. This association may can be interpreted as causal, in the sense that both observed and unobserved heterogeneity have been taken into account. Had unobserved heterogeneity been overlooked (univariate models), the resulting marginal effect would have been 33 percent (and the associated t-ratio would have changed from 6.2 to 28.3). These results suggest that probability of being low-paid is influenced by sizeable genuine state dependence effects.

<Table 5 near here>

Being married was associated with lower low pay probabilities for formerly-employed men, whereas among formerly-unemployed men, the effect was positive but imprecisely estimated. Low pay probabilities had a U-shaped relationship with age. A man aged 45 rather than 26 had a slightly lower probability of low pay if they were employed at t–1, but the effect was much larger (20 percent) if they were unemployed at t–1. The corresponding effect in the model that did not control for endogenous selection was only two percent. Since coefficients associated with age are rather stable across columns, part of the change must be attributable to changes in the other coefficients, which enter the computation of the baseline probabilities.

Having better educational qualifications was associated with lower chances of being low-paid, and the two points already made about employment probabilities also apply in this case. First, the marginal effects associated with having educational qualifications are larger for men who were unemployed rather than employed at t–1. Second, for the previously-unemployed, controlling for endogeneity reduces the estimated impact of having educational qualifications. There were also statistically significant associations between low pay probabilities and region, firm size, and occupation. Probabilities were lower for men living in London and the South East, for men who worked in large firms, and for those who worked in a skilled occupation.

Variations in the parameter estimates associated with the two alternative states at t–1 are consistent with existence of genuine state dependence effects. The hypothesis of an absence of a genuine state dependence effect from having been low paid in the past is overwhelmingly rejected in the equation for low pay in year t, whereas rejection is more marginal in the equation for year t employment (p = 0.15): see the estimates associated with lagged low pay dummies in Tables 4 and 5. Tests of equality of coefficients across the two employment states at t–1 (see Section 3) overwhelmingly reject the null hypothesis of no differences (results, not reported, are available upon request).

Predicted transition rates and state dependence

Table 6 reports transition rates computed from the model estimates, and these are the basis of our calculations of aggregate state dependence effects. The predicted rates correspond well with the raw transition rates reported in Table 1.[5] Measures of aggregate state dependence were calculated as differences in transition rates for men with different initial labour market states. The genuine state dependence effects presented in the table are the marginal effects associated with lagged low pay dummies, or the alternative measure presented in Section 3. The results indicate that genuine state dependence is a non-trivial share of aggregate state dependence. In particular, when looking at unemployment probabilities, these effects account for almost all of the observed state dependence, indicating that human capital depreciation or negative signalling may be important in those cases.

Of particular interest are the effects computed comparing unemployment and pay states at year t–1, since they can be informative about the low pay/no pay cycles. For example differences in low pay probability at year t between men who were low-paid and unemployed at t–1 were largely due to state dependence, whereas heterogeneity drives the differential in the low pay probability between men who were unemployed rather than higher paid. This evidence is consistent with the arguments about the two-sector labour market adduced in the Introduction, as there appears to be little heterogeneity effects distinguishing the chances of

[5] Predictions were derived for each man, and then averaged over the relevant subsamples. For example, predicted low pay persistence is the predicted probability of low pay at t conditional on low pay at t-1 and retention, averaged over those who were lo0w paid at t-1 did not drop out of the sample during the transition.

those who were unemployed rather than low paid. This suggests a common set of policies for this relatively homogenous group.

Results are different when year t unemployment probabilities are considered. Now genuine state dependence appears to be the driving force also for the difference in probabilities between men who were previously-unemployed rather than high paid. This suggests that unemployment has scarring effects, irrespective of the comparison group.

<Table 6 near here>

5. Concluding remarks

There is substantial persistence in the chances of being unemployed and low-paid. More than one half of the men who were in either of these two states was in the same states a year earlier. Unemployment and low pay are also labour market states that are closely linked. Becoming unemployed in one year was more likely for men with a low-paid job in the previous year and, among unemployed men who got a job, the chances of that job being a low-paid one were about three times the unconditional low pay probability.

To gain greater understanding of these patterns, this paper has modelled transitions between unemployment and low pay versus high pay using data for men from the British Household Panel Survey, which particular attention given to controlling for the endogeneity of associated processes, in initial conditions, selection into employment, and in attrition from the panel. Our results confirmed the application of this: none of the three processes was found to be exogenous in the estimation of the transitions of principal interest.

The interrelationship between the chances of being unemployed and the chances of being low paid remained strong, even after controlling for the three endogeneity issues and for observed characteristics. Men who had been low-paid had higher probabilities of unemployment than high-paid men, and men who had been unemployed had higher chances of being low paid rather than high-paid if they get a job. The first finding suggests that low-paid jobs are characterised by greater turnover than high-paid jobs. The second finding suggests that the experience of unemployment leads to lower quality jobs. (This would be consistent with the idea that an individual's human capital depreciates the longer he is unemployed or, alternatively, employers use unemployment duration as a signal of poor quality workers.) In general, there appear to be genuine state dependence effects helping to determine men's chances of being low-paid or unemployed. Hence policies targeted on unemployed men may reduce the chances of being low-paid once they get a job, and measures designed to raise the earnings potential of the low-paid may also reduce their chances of becoming unemployed in future.

References

Arulampalam, W., Booth, A.L., and Taylor, M.P. (2000), 'Unemployment persistence', *Oxford Economic Papers*, 52, 24–50.

Arulampalam W. and Booth, A.L. (2000), 'Union status of young men in Britain: a decade of change', *Journal of Applied Econometrics*, 15, 289–310.

Barth, E., Bratsberg, B., Naylor R. A., and Raaum O. (2002), 'Why and how wage curves differ: Evidence by union status for the United States, Great Britain and Norway', unpublished manuscript, Department of Economics, University of Warwick, http://www2.warwick.ac.uk/fac/soc/economics/staff/faculty/naylor/wp/

Binder, D.A. (1983), 'On the variances of aymptotically normal estimators from complex surveys', *International Statistical Review*, 51, 279–92.

Cappellari, L. (2002), 'Do the 'working poor' stay poor? An analysis of low pay transitions in Italy', *Oxford Bulletin of Economics and Statistics*, 64, 87–110.

Cappellari, L. and Jenkins, S.P. (2002), 'Modelling low income transitions', Working Paper 2003-08, Institute for Social and Economic Research, University of Essex, Colchester. http://www.iser.essex.ac.uk/pubs/workpaps/pdf/2002-08.pdf

Gourieroux C. and Monfort A. (1996), Simulation Based Econometric Methods, Oxford: Oxford University Press.

Heckman, J.J. (1974), 'Shadow prices, market wages, and labor supply', *Econometrica*, 42, 679–694.

Heckman, J.J. (1981a), 'The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process', in Manski, C.F. and McFadden, D. (eds), *Structural Analysis of Discrete Data with Econometric Applications*, MIT Press, Cambridge MA.

Heckman, J.J. (1981b), 'Statistical models for discrete panel data', in Manski, C.F. and McFadden, D. (eds), *Structural Analysis of Discrete Data with Econometric Applications*, MIT Press, Cambridge MA.

Huber, P.J. (1967), 'The behaviour of maximum likelihood estimators under non-standard conditions', in *Proceedings of the Fifth Berkeley Symposium in Mathematical Statistics and Probability*, University of California Press, Berkeley CA.

Keane, M., Moffitt, R., and Runkle, D. (1988), 'Real wages over the business cycle: estimating the impact of heterogeneity with micro-data', *The Journal of Political Economy*, 96, 1232–1266.

Montuenga, V., Garcýa, I., and Fernandez, M. (2003), 'Wage flexibility: evidence from five EU countries based on the wage curve', *Economics Letters*, 78, 169–174.

Stewart, M.B. (2002), 'The inter-related dynamics of unemployment and low pay', revised version of EALE Conference paper, Economics Department, University of Warwick. http://www2.warwick.ac.uk/fac/soc/economics/staff/faculty/stewart/wp/

Stewart, M.B. and Swaffield, J.K. (1999), 'Low pay dynamics and transition probabilities', *Economica*, 66, 23–42.

Taylor, M.F. (ed.) (2001). *British Household Panel Survey User Manual. Introduction, Technical Reports and Appendices*, ISER, University of Essex, Colchester. http://www.iser.essex.ac.uk/bhps/doc/index.html

White, H. (1982), 'Maximum likelihood estimation of misspecified models', *Econometrica*, 50, 1–25.

Table 1: Transition rates among unemployment, low pay, high pay
(row percentages)

	Year t state			
Year t–1 *state*	Unemployed	Low pay	High pay	Dropped out of sample
Unemployed	52.85	17.80	29.35	
	(31.91)	(10.74)	(17.72)	(39.63)
Low pay	6.51	51.87	41.61	
	(5.11)	(40.67)	(32.62)	(21.60)
High pay	1.95	4.14	93.91	
	(1.69)	(3.60)	(81.53)	(13.18)

Pooled transitions from British Household Panel Survey, waves 1–10. Number in parentheses are estimates including sample dropout as a fourth destination state. Sample size = 18,372 (22,081). Adult men aged 16–64, excluding full-time students and self-employed. The low pay threshold is 60% of median contemporary hourly earnings.

Table 2.
Tests of the validity of the instruments

	χ^2	(d.f.)	p-value
Sample retention			
Significance in retention equation	7.60	(1)	0.005
Significance in low pay year *t*	0.49	(2)	0.782
Significance in employment year *t*	3.13	(2)	0.209
Initial conditions			
Significance in low pay year *t*–1	21.29	(10)	0.019
Significance in employment year *t*–1	27.24	(10)	0.002
Significance in low pay year *t*	22.28	(20)	0.325
Significance in employment year *t*	19.38	(20)	0.497
Employment			
Significance in employment year *t*–1	4.01	(1)	0.045
Significance in low pay year *t*–1	0.02	(10	0.900
Significance in employment year *t*	16.16	(4)	0.003
Significance in low pay year *t*	5.79	(4)	0.216

Table 3
Estimated correlation structure of unobservables,
and tests of the ignorability of selection processes

Correlation in unobservables		Estimate	|t|
Retention and employment at *t*–1	(ρ_1)	0.349	(19.70)
Retention and employment at *t*	(ρ_2)	0.086	(0.23)
Retention and low pay at *t*–1	(ρ_3)	0.003	(0.10)
Retention and low pay at *t*	(ρ_4)	–0.314	(1.86)
Employment at *t*–1 and employment at *t*	(ρ_5)	–0.270	(2.24)
Employment at *t*–1 and low pay at *t*–1	(ρ_6)	0.372	(2.99)
Employment at *t*–1 and low pay *t*	(ρ_7)	0.363	(2.58)
Employment at *t* and low pay at *t*–1	(ρ_8)	–0.090	(1.25)
Employment *t* and low pay at *t*	(ρ_9)	–0.269	(1.07)
Low pay *t*–1 and low pay at *t*	(ρ_{10})	0.163	(1.57)

Test	χ^2	p-value
Ignorability of retention	391.06	0.0000
H_0: $\rho_1 = \rho_2 = \rho_3 = \rho_4 = 0$		
Ignorability of lagged employment	447.09	0.0000
H_0: $\rho_1 = \rho_5 = \rho_6 = \rho_7 = 0$		
Ignorability of lagged low pay	14.05	0.0071
H_0: $\rho_3 = \rho_6 = \rho_8 = \rho_{10} = 0$		
Ignorability of employment/low pay unobserved heterogeneity	9.98	0.0408
H_0: $\rho 6 = \rho 7 = \rho 8 = \rho 9 = 0$		

Table 4. Estimates of the employment transition probabilities.

	(1) Full model						(2) Univariate models					
	$P(E_t=1\|E_{t-1}=1)$			$P(E_t=1\|E_{t-1}=0)$			$P(E_t=1\|E_{t-1}=1)$			$P(E_t=1\|E_{t-1}=0)$		
	m.e.	coeff.	|t|	m.e.	coeff.	|t|	m.e.	coeff.	|t|	m.e.	coeff.	|t|
Married	0.013	0.238	(3.68)	-0.063	-0.193	(1.68)	0.013	0.245	(4.52)	-0.058	-0.146	(1.32)
Age	0.005	0.057	(2.49)	-0.069	-0.012	(0.38)	0.006	0.048	(3.53)	-0.024	-0.003	(0.13)
Age squared		-0.001	(2.68)		0.00005	(0.12)		-0.001	(3.92)		-0.00003	(0.09)
Education												
Other qualification	0.004	0.085	(0.86)	0.076	0.220	(1.67)	0.004	0.083	(0.89)	0.110	0.276	(2.01)
O-level	0.004	0.087	(1.06)	0.141	0.402	(3.03)	0.005	0.098	(1.24)	0.209	0.533	(4.04)
A-level	0.004	0.078	(0.93)	0.245	0.666	(4.53)	0.004	0.092	(1.11)	0.312	0.825	(5.74)
Other higher degree	0.007	0.149	(1.79)	0.187	0.517	(3.78)	0.007	0.158	(2.03)	0.259	0.671	(5.00)
First degree or higher	0.010	0.240	(2.47)	0.242	0.654	(3.77)	0.010	0.237	(2.47)	0.308	0.822	(4.65)
Number of reported health problems												
1	-0.003	-0.056	(1.10)	-0.011	-0.032	(0.39)	-0.003	-0.058	(1.15)	-0.021	-0.054	(0.64)
2	-0.003	-0.058	(0.74)	-0.072	-0.229	(1.67)	-0.004	-0.072	(0.96)	-0.104	-0.267	(1.88)
3	-0.017	-0.262	(2.14)	-0.065	-0.209	(0.92)	-0.017	-0.260	(2.18)	-0.105	-0.268	(1.16)
4+	-0.009	-0.151	(0.64)	0.161	0.439	(1.19)	-0.009	-0.150	(0.67)	0.152	0.386	(1.04)
Lived in South East	0.003	0.054	(1.00)	0.012	0.035	(0.35)	0.002	0.051	(0.91)	0.020	0.050	(0.46)
Lived in London	0.0003	0.006	(0.08)	-0.031	-0.097	(0.71)	0.000	0.000	(0.00)	-0.043	-0.108	(0.72)
Firm size > 100	0.003	0.057	(0.51)				0.002	0.044	(0.39)			
Skilled occupation	0.005	0.118	(0.95)				0.005	0.119	(0.95)			
First labour market spell												
Full time employment	0.007	0.140	(2.23)	0.042	0.126	(1.18)	0.008	0.152	(2.35)	0.074	0.185	(1.62)
Missing information	-0.003	-0.054	(0.72)	0.125	0.365	(3.06)	-0.003	-0.054	(0.72)	0.155	0.391	(3.07)
Low paid at t–1	-0.011	-0.194	(1.45)				-0.020	-0.316	(5.04)			
Constant		0.371	(0.62)		-0.760	-(1.16)		0.539	(2.10)		-0.544	(1.32)
Log Likelihood			–28035					–1873			–824	
Model p-value [df]		0.0000			[192]		0.0000		[27]	0.0000		[24]
Number of observations			21935					17074			1298	

Note: The GHK simulator for column (1) used 150 random draws. Marginal effects were computed at the means of explanatory variables. For dummy variables, they show the change in the relevant probability when the variable changes from 0 to 1. For age, the effect is the change in probability when age changes from 26 to 45 (the sample 25th and 75th percentiles). Robust asymptotic t-ratios refer to estimated coefficients. The reference individual was not married, had no educational qualifications, did not report any health problems, lived outside the South East or London areas, and worked in a small firm in an unskilled occupation. His first labour market spell was not full time employment, and he was high-paid at t–1. Regressions include controls for survey year.

Table 5. Estimates of low pay transition probabilities.

	(1) Full model						(2) Univariate models					
	$\Pr(L_t=1 \mid E_{t-1}=1)$			$\Pr(L_t=1 \mid E_{t-1}=0)$			$\Pr(L_t=1 \mid E_{t-1}=1)$			$\Pr(L_t=1 \mid E_{t-1}=0)$		
	m.e.	coeff.	|t|	m.e.	coeff.	|t|	m.e.	coeff.	|t|	m.e.	coeff.	|t|
Married	–0.024	-0.182	(3.50)	0.058	0.184	(1.14)	-0.018	-0.162	(3.39)	0.059	0.156	(0.87)
Age	-0.007	-0.142	(9.81)	-0.203	-0.168	(4.84)	-0.008	-0.123	(12.15)	-0.020	-0.200	(6.56)
Age squared		0.002	(9.62)		0.002	(4.57)		0.001	(11.24)		0.002	(5.58)
Education												
Other qualification	-0.023	-0.203	(2.88)	-0.105	-0.304	(1.42)	-0.018	-0.191	(2.80)	-0.125	-0.361	(1.54)
O-level	-0.028	-0.251	(4.12)	-0.062	-0.188	(0.98)	-0.025	-0.260	(4.49)	-0.098	-0.270	(1.40)
A-level	-0.041	-0.406	(5.97)	-0.120	-0.349	(1.60)	-0.036	-0.420	(6.59)	-0.163	-0.476	(2.26)
Other higher degree	-0.052	-0.482	(7.19)	-0.073	-0.218	(1.06)	-0.043	-0.477	(7.62)	-0.124	-0.351	(1.74)
First degree or higher	-0.061	-0.692	(8.09)	-0.253	-0.695	(2.68)	-0.051	-0.699	(8.75)	-0.271	-0.895	(3.35)
Number of reported health problems												
1	0.010	0.080	(2.12)	0.088	0.284	(2.52)	0.009	0.079	(2.06)	0.132	0.349	(2.84)
2	0.021	0.149	(2.47)	0.097	0.334	(1.58)	0.018	0.154	(2.56)	0.168	0.432	(1.86)
3	0.063	0.384	(4.41)	-0.042	-0.125	(0.27)	0.052	0.368	(4.20)	-0.061	-0.169	(0.33)
4+	0.079	0.454	(2.69)	0.073	0.245	(0.53)	0.062	0.418	(2.53)	0.130	0.336	(0.66)
Lived in South East	-0.017	-0.142	(3.18)	-0.087	-0.257	(1.84)	-0.015	-0.143	(3.26)	-0.117	-0.328	(2.06)
Lived in London	-0.028	-0.262	(3.68)	-0.063	-0.186	(1.11)	-0.024	-0.260	(3.87)	-0.084	-0.234	(1.27)
Firm size > 100	-0.042	-0.436	(4.14)				-0.034	-0.426	(4.07)			
Skilled occupation	-0.037	-0.362	(3.26)				-0.031	-0.370	(3.24)			
Low paid at t–1	0.254	1.139	(6.21)				0.327	1.443	(28.31)			
Constant		2.124	(6.17)		3.406	(6.50)		1.599	(7.57)		3.004	(5.74)
Log Likelihood			–28035					–3591			–338	
Model p-value [df]		0.0000			[192]		0.0000		[25]	0.0000		[22]
Number of observations		21935						16644			612	

Notes as for Table 4.

Table 6: Predicted transition rates and state dependence effects

	Predicted transition rates	
$\Pr(L_t = 1 \mid L_{t-1} = 1)$	51.19	
$\Pr(L_t = 1 \mid H_{t-1} = 1)$	4.82	
$\Pr(L_t = 1 \mid U_{t-1} = 1)$	16.12	
$\Pr(U_t = 1 \mid L_{t-1} = 1)$	3.71	
$\Pr(U_t = 1 \mid H_{t-1} = 1)$	1.79	
$\Pr(U_t = 1 \mid U_{t-1} = 1)$	57.72	
	State dependence	
	Aggregate	Genuine
$\Pr(L_t = 1 \mid L_{t-1} = 1) - \Pr(L_t = 1 \mid H_{t-1} = 1)$	46.36	25.40
$\Pr(L_t = 1 \mid L_{t-1} = 1) - \Pr(L_t = 1 \mid U_{t-1} = 1)$	35.07	29.09
$\Pr(L_t = 1 \mid U_{t-1} = 1) - \Pr(L_t = 1 \mid H_{t-1} = 1)$	11.29	3.76
$\Pr(U_t = 1 \mid U_{t-1} = 1) - \Pr(U_t = 1 \mid L_{t-1} = 1)$	54.01	48.86
$\Pr(U_t = 1 \mid U_{t-1} = 1) - \Pr(U_t = 1 \mid H_{t-1} = 1)$	55.93	52.92
$\Pr(U_t = 1 \mid L_{t-1} = 1) - \Pr(U_t = 1 \mid H_{t-1} = 1)$	1.91	1.11