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# ABSTRACT

## Low Paid Employment in Britain: Estimating State-Dependence and Stepping Stone Effects*

Using 18 waves of the British Household Panel Study, this paper examines state dependence and stepping stone effects of low pay. A distinguishing feature is that five types of transition- not in the labour force (NILF), unemployment, self-employment, low pay and higher pay are modelled separately. The results show that both state dependence and stepping stone effects of low pay are present. However, there is no evidence to support a low-pay no-pay cycle. The introduction of the national minimum wage does not appear to have affected state-dependence and stepping stone effects of low pay.

JEL Classification: J24, J31, I21

Keywords: low pay, unemployment, state dependence, dynamic models

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* Data from the British Household Panel Study have been provided by the UK Data Archive.

## 1. Introduction

There is a sizable body of literature examining low paid employment with a focus on state-dependence of low pay – that is, whether and to what extent current low paid employment increases the probability of remaining in low pay in the future (see for instance, Sloane and Theodossiou, 1996; Stewart and Swaffield 1999; Cappellari 2002, 2007; Cappellari and Jenkins 2008; Clarke and Kanellopoulos 2013; and Fok et al. 2015). The interest in state-dependence of low pay arises from a concern that with increasing earnings inequality, if there is state-dependence of low pay (i.e. low pay is persistent), life-time earnings inequality will increase as well. Indeed, state-dependence of low pay has been found in a number of studies (among them, Stewart and Swaffield 1999; Cappellari 2002; Clarke and Kanellopoulos 2013; and Fok et al. 2015) even after individual heterogeneity is controlled for.

However, there is another form of state-dependence of low pay to which earlier studies have paid little attention – that is the effect of current low pay on influencing the probability of moving to higher pay in the future. We will refer to this form of state-dependence of low pay as a stepping stone effect of low pay. To be consistent with the earlier literature, we will continue to use the term state-dependence to refer to the first type of state-dependence of low pay (i.e. its persistence). Answers to the question whether and to what extent low paid employment has a stepping stone effect are particularly relevant to policy makers. From a welfare policy perspective, if low pay employment acts as a stepping stone to higher pay, welfare reforms that promote employment, even it is low paid, such as the work-first approach to welfare recipients, have a good chance of improving the financial well-being of welfare recipients over time and are therefore justified. This study extends the literature by estimating a dynamic multinomial logit model to examine both state-dependence and stepping stone effects of low pay.

It appears that there are only two studies that take a similar modelling approach to the analysis contained in this paper, namely Uhlendorff (2006) and Fok et al. (2015). Using the German Socio-Economic Panel Study (SOEP) waves 1998 to 2003, Uhlendorff (2006) examines low pay dynamics of German men and finds that while there exists genuine state-dependence of low pay as well as in non-employment, there is also evidence of a stepping stone effect of low pay as compared with non-employment. However, unlike Uhlendorff (2006) who treats unemployment and not in the labour force (NILF) as one labour force state (i.e., non-employment), our current study models the two non-employment states separately. The distinction between NILF and unemployment is particularly important in estimating the stepping stone effect of low pay since the stepping stone effect may differ, depending on whether low paid employment is compared with NILF or with unemployment.

Fok et al. (2015) examine the dynamics of low paid employment in Australia, using the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Both state dependent and stepping stone effects of low pay are found in that study and they also find there is heterogeneity in these effects between different groups of workers. Although that study uses an extended definition of unemployment to include those who are marginally attached to the labour market in the analysis, it excludes those who are not in the labour force and not marginally attached to the labour market and those who are self-employed, which may lead to sample selection bias in their estimation.

In a dynamic probit model framework and using the German SOEP, Knabe and Plum (2013) examine the stepping stone effect of low pay relative to unemployment by including both lagged unemployment and lagged low pay as the explanatory variables. They find that low pay can act as a stepping stone to better paid employment, particularly for those who do not have a college degree, who have been unemployed more often in the past and whose low paid job carries relatively high social status. While the model takes into account potential endogeneity of initial low pay, initial unemployment is assumed to be exogenous. Given their estimation results show that initial low pay is not in fact exogenous, it is likely that initial unemployment is endogenous. Consequently, the estimates of their model are likely to be biased.

A related theme of research on low pay dynamics examines whether low paid employment and unemployment are inter-related. This question arises due to the concern that low paid workers may cycle between low pay and unemployment (or non-employment) with little hope of moving up the labour market ladder. For example, descriptive analyses tend to show that low paid workers are more likely than higher paid workers to move into joblessness in the future (e.g. Stewart and Swaffield, 1999; Cappellari and Jenkins, 2008). This study will examine this issue as well.

Cappellari and Jenkins (2008) find that for the UK men, low pay experience has only a modest effect on the probability of experiencing unemployment in the future when individual heterogeneity is accounted for. This result is similar to that found in Buddelmeyer et al. (2010) for Australian workers, but different from Stewart (2007) for Britain who concludes that low wage employment has almost as large an adverse impact as unemployment on future employment prospects and that low wage jobs act as the main conduit for repeated unemployment. Uhlendorff (2006) finds that for German men those on low pay have a higher probability of becoming jobless than those on higher pay, although the difference is not statistically significant. For Australia Fok et al. (2015) conclude that low paid employment increases the probability of unemployment relative to higher paid employment. As detailed later, this conclusion could be due to incorrect inference.

The contribution of this study is several fold. First, all earlier studies examining low paid employment have excluded those who are self-employed for the reason that it is difficult to define their low (or higher) pay status. This convenience comes with a cost – the choice of self-employment is unlikely to be independent of the potential earnings of being an employee. As such, omitting those who are self-employed from the analysis could lead to sample selection bias and consequently incorrect inferences. For this reason this study includes self-employment as a separate labour market state in estimating state-dependence and stepping stone effects of low pay. Second, this is the first study that uses a random effects dynamic multinomial logit model to examine the low pay dynamics in Britain. Early studies on low pay dynamics in the UK use a binary dependent variable - low pay or not. Third, unlike most of the earlier studies that tend to exclude females from their analyses, this current study examines low pay dynamics of both males and females. Fourth, in a multinominal logit modelling framework inferences on state-dependence, stepping stone effects and the low pay – no pay cycle need to be based on the marginal effects of the lagged dependent variables on the probability of being each of the labour market states modelled. Calculating the marginal effects under this modelling framework is not straightforward particularly in the presence of unobserved heterogeneity. Further, it is difficult to calculate the standard errors of the marginal effects in this type of models. To facilitate inferences, in this study we attempt to address these challenges. Fifth, we examine whether and to what extent the introduction of the national minimum wage (NMW) has affected the dynamics of low paid employment. This issue has not been investigated in earlier studies.

The results from the current study show that both state-dependence and stepping stone effects of low pay are present among British workers after observed and unobserved individual heterogeneity is accounted for. The results also show that, other things being equal, people who are on low pay are more likely to be in employment in the future than those who are either unemployed or NILF. On the other hand, people on low pay do not appear to be more likely to become jobless in the future than those on higher pay. In other words, the evidence provided in this study does not support a low pay-no pay cycle among British workers. The introduction of the NMW does not appear to have affected state-dependence and stepping stone effects of low pay.

## 2. Estimation strategy

*Econometric model*

The key question in this study is whether, and to what extent, current labour force/earnings status, particularly that of low pay, affects future labour force/earnings status. To answer this question, we need to model the transitions of the labour force/earnings states - NILF, unemployment, self-employment, low pay and higher pay - over time. Self-employment is included as a separate state to address any potential sample selection bias.

The five labour force/earnings states do not have a natural order from an individual perspective. One statistical model that is often used to model labour market outcomes that do not have a natural order is the multinomial logit model. Under this modelling framework, at a point of time *t*, an individual *i* occupies one of the five mutually exclusive labour force/earnings states: NILF, unemployment, self-employment, low pay and higher pay (denoted by $k$ =*1,2,3,4 and 5*). The probability of individual *i* occupying a state *k* at time *t* (i.e., $P_{i,k,t}$) is assumed to be determined by the individual's previous labour force/earnings status and a vector of other observed and unobserved individual characteristics,

$$(1) \qquad P_{i,k,t}\left(\mu_{i,j}, j = 1,2,3,4,5\right) = \frac{\exp\left(L_{i,t-1}\alpha_k + x_{i,t}\beta_k + \mu_{i,k}\right)}{\sum_{j=1}^{4} \exp\left(L_{i,t-1}\alpha_j + x_{i,t}\beta_j + \mu_{i,j}\right)}; k = 1,2,3,4,5;\ t = 1, \dots, T.$$

Where $L_{i,t}$ is a (row) vector of dummy variables indicating labour force/earnings states of individual *i* at time *t*; $x_{i,t}$ is a (row) vector of observed characteristics of the individual at time *t*, such as education level, marital status and age; $\mu_{i,k}$ summarizes unobserved individual factors that could affect the probability of occupying state $k$ and that do not change over time (i.e., unobserved individual heterogeneity); and $(\alpha_j, \beta_j; j = 1,2,3,4,5)$ are the coefficient parameters to be estimated.

The model in equation (1) differs from a conventional multinomial logit model in three aspects. First, lagged labour force/earnings status is included as an explanatory variable. The coefficient estimates on the lagged dependent variables will allow us to infer the extent of state-dependence and stepping stone effects of low paid employment. Second, the model controls for unobserved individual heterogeneity (i.e., $\mu_{i,j}$). If unobserved heterogeneity exists, but is not controlled for, the estimation results will be biased. This is because the coefficient estimates on the explanatory variables, particularly the lagged dependent variables, that are correlated with unobserved heterogeneity will be biased. Third, the model allows $\mu_{i,j}$ and $\mu_{i,k\neq j}$ to be freely correlated with each other. This relaxes the Independence of Irrelevant Alternatives (IIA) assumption in the conventional multinomial logit model (Greene 2002).[1]

The inclusion of unobserved individual heterogeneity in the model, and the fact that the data do not provide information on individuals from the beginning of their working life, imply that the initial labour force/earnings status observed in the data (i.e., $L_{i,0}$) is unlikely to be random and exogenous. This causes the initial condition problem for the dynamic model as specified in equation (1) (Heckman 1981). A solution proposed by Heckman is to separately specify a reduced form model for the initial labour force/earnings status and then jointly estimate the initial condition model with the dynamic model.

Alternatively, Wooldridge (2005) suggests modelling the distribution of unobserved individual heterogeneity ($\mu_{i,j}$) conditional on the initial value of the dependent variable ($L_{i,0}$) and other exogenous explanatory variables. This study adopts the Wooldridge approach since it is easier to implement than the Heckman approach. In addition, to relax the assumption in a typical random effects model that the observed explanatory variables and unobserved individual heterogeneity are independent, we take the Mundlak (1978) approach to specify [2]

(2) $\quad \mu_{i,j} = L_{i,0}\lambda_j + \bar{z}_i\theta_j + \nu_{i,j}, j=1,2,3,4,5,$

where $\bar{z}_i$ is a (row) vector containing the means (over time) of the exogenous variables ($z_{i,t}$). $z_{i,t}$ is typically a subset of the time varying variables in $x_{i,t}$. $\nu_{i,1}, \nu_{i,2}$, $\nu_{i,3}$ , $\nu_{i,4}$ and $\nu_{i,5}$ represent the random effects independent of any observed explanatory variables and are assumed to follow a multivariate normal distribution with mean zero and a covariance matrix $\Sigma_\nu$. The parameters in $\Sigma_\nu$ are to be estimated along with all the coefficient parameters in the model $\Theta = (\alpha_j, \beta_j, \lambda_j, \theta_j; j = 1,2,3,4,5)$.

For model identification purposes, one set of the coefficient parameters and one random effect associated with a particular labour force/earnings state choice have to be normalised to zero. We normalise the set of the parameters and the random effects associated with NILF to zero.[3]

[1] This IIA assumption states that the odds of any two alternatives do not depend on the inclusion or exclusion of other alternatives. In our case, this is equivalent to assuming that the relative probabilities of being unemployed and taking a low pay job do not change if NILF is included as an additional choice. This obviously cannot be true.

[2] In the multinomial logit model framework it is infeasible to estimate a fixed effects model. On the other hand, the assumption that unobserved heterogeneity is independent of all observed variables in a random effects model is often too strong. The unobserved heterogeneity specified in equation (2) is a compromise between fixed effects and random effects models.

[3] That is $\alpha_1 = \beta_1 = \gamma_1 = \theta_1 = \lambda_1 = \nu_{.,1} = 0$.

*Model estimation strategy*

The probability of observing individual $i$ to take a sequence of labour force/earnings states over the time period from *t=1 to T*, conditional on the random effects $(\nu_{i,j}; j = 2,3,4,5)$, can be written as

(3) $$P_i(\nu_{i,j}, j = 2,3,4,5) = \prod_{t=1}^{T} \prod_{k=1}^{4} [P_{i,k,t}(\nu_{i,j}, j = 2,3,4,5)]^{D_{i,k,t}},$$

where $D_{i,k,t} = 1$, if labour force/earnings state $k$ is taken by individual $i$, and $D_{i,k} = 0$ otherwise.

The unconditional probability can then be written as,

(4) $$L_i = \int P_i(\nu_{2,}\nu_3, \nu_4, \nu_5)dG(\nu_{2,}\nu_3, \nu_4, \nu_5)$$

where $G(\nu_{2,}\nu_3, \nu_{4,}, \nu_5)$ is the joint distribution function of the random effects $\nu_2$, $\nu_3$, $\nu_4$ and $\nu_5$. The four-dimensional integral is evaluated using simulation methods, with $G(\nu_{2,}\nu_3, \nu_4, \nu_5)$ assumed to be normal with mean zero and a covariance matrix $\Sigma_\nu$,

(5) $$\widetilde{P_i} = \frac{1}{R}\sum_{r=1}^{R} P_i(\nu_2^r, \nu_3^r, \nu_4^r, \nu_5^r),$$

where $R$ is the number of random draws from the distribution of $G(\nu_{2,}\nu_3, \nu_{4,}\nu_5)$; $\nu_2^r, \nu_3^r$, $\nu_4^r$ and $\nu_5^r$ are the $r^{th}$ random draws from their joint distribution. We use a Halton sequence to generate 50 draws to simulate the likelihood function. It has been shown that Halton sequence draws perform much better than simple random draws in terms of approximating the objective function (Train 2003). Further, Train (2000) and Bhat (2001) have shown that for mixed logit models, the estimation results are more precise with 100 Halton draws than with 1,000 random draws. As a compromise between computation time and result accuracy, this study uses 50 Halton sequence draws. Haan and Uhlendorff (2006) have shown that for random effects multinominal logit models, 50 Halton sequence draws perform well.

The likelihood function of a sample with *N* individuals is the product of equation (5) over the sample. A Gauss program written by the author is used to estimate the parameters by maximizing the log-likelihood function of the sample.

*Estimation of state-dependence and stepping stone effects*

The non-linear nature of the multinomial logit model makes interpretation of the coefficient estimates difficult. Unlike in a linear model, the coefficient estimates from a multinomial logit model cannot be interpreted as marginal effects. In particular, state-dependence and stepping stone effects of low pay, the focus of this study, cannot be directly inferred by reading the coefficient estimates on the lagged dependent variables. This subsection therefore describes how state-dependence and stepping stone effects of low pay can be inferred from the estimated model.

As noted earlier, state-dependence refers to the positive effect of being in a state now on the probability of being in the same state in the future. Empirically, state-dependence can be estimated by the difference between the probability of remaining in a state and the probability of transitioning into the state from another state. Given the estimated coefficient parameters of the model $\widehat{\Theta}$, state-dependence of low pay, denoted as *SD*, for an individual $i$ with characteristics *Ci=(Xi, Zi),* conditional on unobserved heterogeneity $\nu_i$, can be computed as,

(6) $$SD_i(\nu_i) = \Pr\left(L_{i,t} = 4 \middle| L_{i,t-1} = 4; \widehat{\Theta}, C_{i,t}, \nu_i\right) - \Pr\left(L_{i,t} = 4 \middle| L_{i,t-1} = k;\ \widehat{\Theta}, C_{i,t}, \nu_i\right),$$

for $k$*=1, 2, 3, 5*. This is the difference between the probability of remaining in low pay and the probability of transitioning into low pay from another labour force/earnings state.

In the earlier studies that define low pay as a binary dependent variable, state-dependence of low pay is estimated as the difference between the probability of remaining in low pay and the probability of transitioning into low pay from higher pay. In our multiple-state modelling framework, the estimate of state-dependence of low pay is not unique – it varies depending on the comparative labour force/earnings state, as shown in equation (6).

Following the same strategy of estimating the model, the conditioning on unobserved heterogeneity can be integrated out through simulation by repeatedly drawing from the estimated distribution of $\nu_i$ to estimate unconditional state-dependence of low pay as $SD_i = \frac{1}{R}\sum_{r=1}^{R} SD_i(\nu_i^r)$.

As discussed earlier, stepping stone effects of low pay refer to the higher probability of transitioning into higher pay from low pay than from non-employment. Therefore, the stepping stone effect of low pay can be estimated by the difference between the probability of transitioning into higher pay from low pay and the probability of transitioning into higher pay from unemployment or from NILF. For an individual $i$ with characteristics *Ci=(Xi, Zi)*, conditional on unobserved heterogeneity $\nu_i$, the stepping stone effect can be computed as,

(7) $$SS_i(\nu_i) = \Pr\left(L_{i,t} = 5 \middle| L_{i,t-1} = 4;\ \widehat{\Theta}, C_{i,t}, \nu_i\right) - \Pr\left(L_{i,t} = 5 \middle| L_{i,t-1} = k;\ \widehat{\Theta}, C_{i,t}, \nu_i\right),$$

where $k$*=0 or 1*. Unobserved heterogeneity is integrated out in the same way as in estimating state-dependence of low pay, so that $SS_i = \frac{1}{R}\sum_{r=1}^{R} SS_i(\nu_i^r)$.

In the results section, the sample means of the estimated state-dependence and stepping stone effects are reported. That is, $SD = \frac{1}{N}\sum_{i=1}^{N} SD_i$; and $SS = \frac{1}{N}\sum_{i=1}^{N} SS_i$.

## 3. Data and model specification

*Data source and low pay definition*

This paper uses data from the 18 waves of the British Household Panel Survey (BHPS), covering years 1991 to 2008.[4] Taylor (1996) documents details of this survey. In the first wave around 5,500 households and 10,300 individuals were drawn from 250 areas of Great Britain. Subsequent interviews for later waves were conducted about one year apart. In 1999 additional household samples (1,500 each) from Scotland and Wales were added; and in 2001 a sample of 2,000 household in Northern Ireland was added to make the survey suitable for UK-wide research. While the additional samples from Scotland and Wales are included in the analysis, those from Northern Ireland are not.

The BHPS contains detailed information on individual characteristics, labour market outcomes and activity. Information on labour force status and earnings is used to define the dependent variable, labour force/earnings status (i.e., NILF, unemployment, self-employment, low pay and higher pay). Classification of people into NILF and unemployment follows the conventional approach in labour economics: a person is unemployed if he or she does not have a job, but had looked for work in the past four weeks and is available for work; and those who are not employed and not actively seeking a job are classified as NILF.

However, there is not a consensus on how to define low pay (and consequently its counterpart, higher pay). First, there is the issue whether monthly earnings or hourly earnings should be used to define low pay. The BHPS provides information on monthly earnings. However, using monthly earnings to define low pay is problematic for those who work part-time – they are likely to be classified as on low pay, simply because they work fewer hours and the low hours worked are out of their own choice. To avoid this problem, in this study hourly earnings are used to define low pay status and hourly earnings are derived by using monthly earnings and weekly hours worked.[5]

Another issue in defining low pay is where to set the low pay threshold, the hourly earnings level

[4] After wave 18 BHPS respondents were absorbed into the expanded Understanding Society longitudinal data-set and the new data cover the period of the Great Recession. Thus, by ending the analysis in 2008 we avoid these complications. For an analysis of state dependence of unemployment covering the later period, but using random effects probit see Tumino (2015).

[5] Both monthly earnings and hours worked include overtime.

below which workers can be classified as on low pay. Different thresholds have been used in the literature. This study uses two thirds of the median hourly earnings, which appears to be the most popular definition for low pay (Cappellari and Jenkins 2008; Buddelmeyer *et al*. 2010). This low pay threshold is defined separately for each wave using hourly earnings of employees aged 18 year and over and is shown in Table 1, together with the proportion of employees classified to be low paid based on this threshold. The table also shows hourly national minimum wages for adult employees (NMW) from 1999 when the NMW was first introduced. The two-thirds median earnings low pay threshold is about 12 to 30 per cent higher than the NMW for the relevant years.

The sample used in this study includes individuals aged between 18 and 64 years (inclusive) for males and 18 and 60 (inclusive) for females. As hinted at earlier, self-employed persons are included in the sample, but following convention, full-time students in the age range are excluded. Observations with missing dependent and independent variables are also excluded for a self-explanatory reason. The first wave when an individual entered the BHPS is used to define the initial labour force/earnings status and thus excluded from the sample for model estimation. Since panel data models require at least two observations for each individual for identification purposes, those individuals with only one observation are excluded from the sample.

It is well established in the literature that males and females behave differently in the labour market. This study therefore models males and females separately. The male sample has 64,939 observations, representing 9,073 individuals; the female sample has 71,535 observations, representing 9,679 individuals. Summary statistics of the sample are presented in Appendix Table A1. Relatively to higher paid workers, low paid workers tend to be young, low educated, and have a disability.

The sample is an unbalanced panel and naturally there would be a concern over the potential impact of panel attrition on the estimation results. In a similar modelling framework to the current study Uhlendorff (2006) shows that panel attrition can be treated as exogenous with respect to low pay and non-employment dynamics of German workers. In addition, Cappellari and Jenkins (2008) show that panel attrition is not a concern in modelling low pay transitions of the UK workers, where low pay is defined as a binary variable.

To examine further the potential impact of ignoring panel attrition on the results, we experimented by estimating a model that took the variable-addition approach to testing attrition bias, by including a variable that indicates whether attrition has occurred in the following wave as an additional explanatory variable. Such an approach was initially suggested by Verbeek and Nijman (1992) and recently applied to the HILDA data in Wooden and Li (2014). The last non-attrition wave available (i.e., wave 18 in our case) is lost in estimating such a model since for the last non-attrition wave the attrition indicator is not defined. The coefficient estimates show that for males none of the four coefficients on the attrition indicator in the four equations is statistically significant; for females only the coefficients on the attrition indicator in the unemployment and self-employment equations are significant. However, in terms of the estimates on state-dependence and stepping stone effects of low pay, the results are very similar between the two models with and without the attrition indicator (see Appendix Table A3).

All the above evidence suggests that ignoring panel attrition should not lead to a significant bias of the estimation results. Consequently, the paper reports the results from the model that uses all the 18 waves of data available, without accounting for panel attrition.

*Transitions of labour force/earnings status*

Table 2 presents the year-on-year transitions of labour force/earning status by pooling all the waves (i.e. including wave 1). There is some indication of a stepping stone effect of low pay relative to either unemployment, NILF or self-employment, since for both males and females, those who are on low pay have a higher probability of transitioning into higher pay in the following year than those who are either unemployed, NILF or self-employed. On the other hand, there is also an indication of state-dependence of low pay since the table shows that those who are on low pay tend to have a higher probability of being in low pay in the following year than those who are not on low pay.

However, we should not draw inferences on the stepping stone effect and/or state-dependence of low pay from this simple cross-tabulation, since these results may be driven by observed and/or unobserved differences in individual characteristics. For example, the summary statistics show that those who are on low pay are less likely to have a disability than those who are unemployed or NILF, and this may explain why those on low pay are more likely to move to higher pay than those who are not employed. In addition, it is also likely that those who are on low pay have better unobserved skills (e.g., ability) than those who are not employed and therefore are more likely to move to higher pay in the future. The model described earlier controls for the differences in both observed and unobserved individual characteristics and thus allows for more accurate inferences regarding the stepping stone effect and state-dependence of low pay employment.

*Model specification*

As discussed earlier, (one year) lagged labour force/earnings states are included in the model as explanatory variables to estimate the stepping stone effect and state-dependence of low pay employment. Labour force/earnings states at the time when they first entered the BHPS are also included to address the initial condition problem.

In addition to the lagged and initial labour force/earnings status variables, the following explanatory variables are included as control variables in the model: *education* (six dummies indicating the highest education qualification obtained, including first degree or higher, other higher degrees, A-level(s), O-level(s), other qualification, and no qualification); *age* (five age category dummies); marital status (one dummy indicating whether a person is married or partnered); *disability* (one dummy indicating whether health limits work); *age of the youngest child* (six dummies indicating no dependent children under 19, youngest child aged 0-2, youngest child aged 3-4, youngest child aged 5-11, youngest child aged 12-18, and youngest child aged 17-18 ); *the total number of children aged under 19 years*; *region of residence* (two dummies representing living in London or South East), and regional unemployment rates.

Furthermore, wave dummies are included to control for the effect of time; they may also capture the impacts of macroeconomic conditions and policy settings on labour force/earnings status. For the mean variables to account for correlated random effects, the means of the time-varying variables marital status, disability status and the number of children are included in the model.

## 4. Estimation results

The main results are shown in panel (b) of Table 2. To facilitate discussion of the results, the mean predicted transition probabilities of the sample are presented in panel (a) of Table 2. The coefficient estimates of the models can be found in Appendix Table A2.

*Stepping stone effects*

The estimates for the stepping stone effects are shown in column V of panel (b) in Table 2. As discussed earlier, they are the differences between the probability of transitioning into higher pay from low pay and the probability of transitioning into higher pay from unemployment and NILF. The estimates indicate a statistically significant stepping stone effect of low paid employment for both males and females. For males, compared with those who are out of the labour force, those who are on low pay have an 11 percentage point higher probability of transitioning into higher pay in the following year. The stepping stone effect of low pay relative to unemployment is similar to that relative to NILF. The stepping stone effects of low pay for females appear to be lower than that for males. For females, the stepping stone effect of low pay relative to NILF is about 9 percentage points, slightly higher than the effect relative to unemployment (at 7.6 percentage points), but the difference is not statistically significant.

For German men, Uhlendorff (2006) estimates that those on low pay have a 5 to 6 percentage point higher probability of transitioning into higher pay in the following year compared with those who are not employed. Therefore, the stepping stone effects of low pay for UK workers appear to be larger than that for German workers.

In their main modelling results Fok et al. (2015) find that the stepping stone effects of low pay relative to unemployment in Australia is 4.4 percentage points for males and 11.3 percentage points for females. So the effect is smaller for males but larger for females in Fok et al. (2015) for Australia than in this current study for British employees.

Interestingly the results show that for both males and females, those on lay paid employment have a higher chance moving to a higher paid job than the self-employed if the latter were to become employees. This may suggest that the work experience of the self-employed may not be valued as much as that of an employee, even if she or he is low paid.

*State-dependence*

The estimates for state-dependence of low pay are shown in column IV of panel (b) in Table 2. The results show that relative to other labour force/earnings states, those who are on low pay have a higher probability of being on low pay in the following year, an indication of state-dependence of low paid employment. For example, men who are on low pay have an 11 (or 9) percentage point higher probability of being on low pay in the following year, compared to men who are out of the labour force (or unemployed). Most previous studies infer state-dependence of low pay as compared to higher pay and focus on men. The results here show that, compared to men who are on higher pay, state-dependence of low pay is found to be just over 13 percentage points. This estimate is similar to that found in Clarke and Kanellopoulos (2009) for UK men (14 percentage points) and comparable to that found in Stewart and Swaffield (1999), which ranges from 14 to 25 percentage points depending on the models and definitions of low pay.

The estimates of state-dependence of low pay for females are generally larger than for males, echoing the smaller stepping stone effects of low pay for females than for males.

However, the state-dependence estimates for low paid employment as compared to NILF and unemployment need to be interpreted with caution. This is because for those who are NILF or unemployed, their lower probability of transitioning into low pay relative to those who are on low pay is not because the former have a better chance of transitioning into higher pay than the latter, rather it is because the former have a higher probability of remaining not employed than the latter. For example, the estimates in columns I and II of panel (b) in Table 2 indicate that for males, compared with those who are out of the labour force, those who are on low pay have a 18 percentage point lower probability of moving out of the labour force, and a 5 percentage point lower probability of becoming unemployed in the following year. Compared with those who are unemployed, those who are on low pay have a 8 percentage point lower probability of moving out of the labour force, and a 11 percentage point lower probability of becoming unemployed in the following year.

As a result, those who are on low pay have a higher probability of remaining employed in the following year than those who are either unemployed or NILF. If, from a society's perspective, employment, even low paid, is a more desirable outcome than non-employment (e.g., due to lower welfare spending and higher tax revenue), low pay employment is preferable to non-employment for its impact on future employment.

*Does low pay lead to joblessness?*

As discussed earlier, empirical evidence on the low pay – no pay cycle has so far been mixed in the literature. What can we learn from our estimates on this issue? Column II of panel (b) in Table 2 shows the difference between the probability of transitioning to unemployment from low pay and the probability of transitioning to unemployment from other labour force/earnings states. The results indicate that those who are on low pay have a slightly higher probability of transitioning to unemployment than those who are on higher pay for both males and females. However, these transition probability differences are very small in magnitude (i.e., around 0.4 percentage points) and statistically insignificant, indicating that those who are on low pay are roughly equally likely to transition into unemployment as those who are on higher pay, a result consistent with that of Buddelmeyer *et al*. (2010) for Australia. Furthermore, the results in column I of panel (b) in Table 2 indicate that for males, those who are on low pay are more or less equally likely to transition into NILF as those who are on higher pay; while females on low pay are less likely to transition into NILF than females on higher pay. Therefore, overall the results here do not appear to support a low pay – no pay cycle after observed and unobserved heterogeneity is accounted for.

How do we reconcile this result with those in Fok et al. (2015)? First, this study is for Britain and the labour market institutions are different between Britain and Australia, so that we should not necessarily expect a similar result for the two countries. Second, Fok et al. (2015) do not include people who are out of labour force and not marginally attached to the labour market in the sample, let alone the self-employed. Third, while this study employs a commonly used low pay threshold of two-thirds of median hourly earnings, Fok et al. (2015) use a low pay definition based on Australia's national minimum wage. Fourth, the inference on the low pay – no pay cycle in Fok et al. (2015) is based on the significance of the coefficient estimates. In a non-linear model like the multinominal logit model, a significant coefficient does not mean the marginal effect estimate is significant as well. But they do not provide standard errors for the marginal effect estimates. So we cannot infer whether the marginal effect estimates are statistically significant. Further, it is not clear how they have dealt with unobserved heterogeneity when calculating the marginal effects. It is likely they have just assumed it to be zero – but it is not stated anywhere in their paper. Again, since this is a non-linear model and the marginal effects are affected by unobserved heterogeneity, their results depend on the particular way they deal with unobserved heterogeneity.

*The impacts of the NMWs on low pay dynamics*

The British Government introduced the NMW in April 1999. A large volume of research has been devoted to assess the impacts of the NMW on various labour market outcomes, but there does not seem to have been any research on the impacts of the NMW on low pay dynamics.[6] We examine this issue by estimating the model separately for the periods before (1991-98) and after (1999-2008) the introduction of the NMW to see whether state dependence and stepping stone effects of low pay have changed between the two periods. Since the NMW only applied to adult employees aged 22 years and above, we excluded those aged under 22 year from the sample for the analysis in this section.

It is not straightforward to expect *a priori* how the introduction of the NMW affects state-dependence and stepping stone effects of low pay between the two periods. On one hand, the introduction of the NMW might mean the average skill level of low paid workers becomes higher if NMWs price the lowest skilled workers out of employment. This may in turn means that the introduction of the NMW reduces state-dependence but increases the stepping stone effects of low paid employment. On the other hand, if the NMWs are set at a relatively low level

[6] See, for example, Machin et al. (2003), Stewart (2004), and Dickens, Riley and Wilkinson (2015) on the impacts of NMWs on employment rates; and Stewart and Swaffield (2008) on the impacts of NMWs on hours worked.

and have therefore little impact on employment, then the introduction of the NMW should not have much an impact on low pay dynamics.

The empirical results are shown in Table 4. For both males and females the stepping stone effects of low pay, relative to both NILF and unemployment, appear to be larger in the first period than in the second one, but the differences between the two periods are not statistically significant. On the other hand, state-dependence of low pay relative to other labour market states appears to be larger in the second than in the first period for both genders, but again the differences are statistically insignificant between the two periods. Therefore, overall the introduction of the NMW does not seem to have affected the dynamics of low paid employment in terms of its state-dependence and stepping stone effects.

## 5. Conclusions

Using the 18 wave BHPS survey, this study examined whether and to what extent low pay is genuinely persistent (i.e., state-dependence of low pay), and whether and to what extent low pay leads to higher pay (i.e., stepping stone effects of low pay). To this end, a dynamic random effects multinomial logit model was estimated separately for males and females in Britain to account for observed and unobserved individual heterogeneity, and state-dependence and stepping stone effects of low pay were then computed from the estimated models.

The results show that both state-dependence and stepping stone effects of low pay are present after observed and unobserved individual heterogeneity is accounted for. That is, other things being equal, those employees who are on low pay are more likely to be found on low pay in the future, compared with those who are not in the labour force, unemployed or on higher pay. On the other hand, other things being equal, those who are on low pay are more likely to move into higher pay in the future than those who are either not in the labour force or unemployed.

While there is evidence on state-dependence of low paid employment, people who are on low pay are found to be more likely to be in employment in the future than those who are either unemployed or not in the labour force. In addition, those who are on low pay do not appear to be more likely to move out of employment than those who are on higher pay. These results suggest that there is not a low pay – no pay cycle among British workers, once observed and unobserved individual heterogeneity is accounted for.

The findings that low pay acts as a stepping stone to higher pay and does not lead to non-employment provide supportive evidence for the work-first approach in welfare reforms and also suggest that minimum wages should be set at an appropriate level that promotes employment, even if the jobs created are low paid. This in turn suggests that the new Living Wage being introduced by the British Government at a level above the minimum wage may be unhelpful if it leads to a loss of employment for marginal groups of workers.

Consistent with many other studies that find the introduction the national minimum wage has little impact on employment, this study finds the introduction of the national minimum wage has little impact on state-dependence and stepping stone effects of low pay.

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**Table 1: low pay thresholds and proportions of low paid employees**

| Year | Low pay thresholds (£) | NMW (£) | % of employees aged 18 plus low paid: Males | Females | All employees |
|---|---|---|---|---|---|
| 1991 | 3.28 | | 11.43 | 30.13 | 20.45 |
| 1992 | 3.54 | | 11.28 | 29.56 | 20.32 |
| 1993 | 3.57 | | 12.69 | 29.87 | 21.20 |
| 1994 | 3.74 | | 13.67 | 30.72 | 22.25 |
| 1995 | 3.85 | | 13.82 | 29.71 | 21.71 |
| 1996 | 4.04 | | 14.87 | 31.75 | 23.34 |
| 1997 | 4.14 | | 13.22 | 28.77 | 20.89 |
| 1998 | 4.33 | | 12.83 | 28.62 | 20.57 |
| 1999 | 4.55 | 3.60 | 13.11 | 28.55 | 20.77 |
| 2000 | 4.83 | 3.70 | 13.64 | 28.84 | 21.04 |
| 2001 | 5.08 | 4.10 | 13.54 | 29.77 | 21.61 |
| 2002 | 5.26 | 4.20 | 12.80 | 29.82 | 21.20 |
| 2003 | 5.39 | 4.50 | 14.30 | 25.97 | 20.04 |
| 2004 | 5.59 | 4.85 | 12.80 | 26.58 | 19.69 |
| 2005 | 5.86 | 5.05 | 15.57 | 26.17 | 20.83 |
| 2006 | 6.08 | 5.35 | 15.17 | 25.92 | 20.54 |
| 2007 | 6.26 | 5.52 | 13.46 | 26.53 | 20.10 |
| 2008 | 6.42 | 5.73 | 14.64 | 25.55 | 22.10 |

**Table 2: Year-on-year transitions of labour force/earnings status (row percentage)**

| **Labour force/earnings status at t-1** | **Labour force/earnings status at t**: Not in labour force | Unemploy-ment | Self-employment | Low pay | Higher pay | **Number of observations** |
|---|---|---|---|---|---|---|
| | **Males** | | | | | |
| Not in labour force | 83.56 | 5.21 | 2.02 | 2.47 | 6.75 | 7,139 |
| Unemployment | 15.20 | 48.23 | 6.01 | 12.02 | 18.54 | 3,711 |
| Self-employment | 2.33 | 1.89 | 84.59 | 4.74 | 6.44 | 8,938 |
| Low pay | 3.51 | 5.71 | 7.46 | 43.35 | 39.97 | 5,952 |
| Higher pay | 2.31 | 1.84 | 1.91 | 4.25 | 89.7 | 37,853 |
| | **Females** | | | | | |
| Not in labour force | 80.71 | 3.13 | 1.51 | 7.03 | 7.62 | 18,442 |
| Unemployment | 35.94 | 27.59 | 2.13 | 17.15 | 17.19 | 2,251 |
| Self-employment | 8.47 | 1.62 | 73.93 | 8.40 | 7.58 | 3,272 |
| Low pay | 9.22 | 2.66 | 2.54 | 59.58 | 26.00 | 13,239 |
| Higher pay | 5.45 | 1.17 | 0.84 | 7.84 | 84.7 | 32,872 |

**Table 3: Model estimated transition probabilities**

**Males**

(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1

| | | Not in labour force, t | Unemployment, t | Self-employment, t | Low pay, t | Higher pay, t |
|---|---|---|---|---|---|---|
| (1) | Not in labour force, t-1 | 0.2652 | *0.0944* | 0.1160 | *0.0879* | 0.4365 |
| | *s.e.* | 0.0200 | *0.0280* | 0.0313 | *0.0223* | 0.0309 |
| (2) | Unemployment, t-1 | *0.1636* | 0.1597 | *0.1329* | 0.1078 | *0.4359* |
| | *s.e.* | *0.0148* | 0.0482 | *0.0410* | 0.0295 | *0.0372* |
| (3) | Self-employment, t-1 | *0.0950* | 0.0676 | *0.3803* | 0.1474 | 0.3098 |
| | *s.e.* | *0.0149* | 0.0397 | *0.0693* | 0.0372 | 0.0510 |
| (4) | Low pay, t-1 | *0.0852* | 0.0475 | *0.1192* | 0.2007 | *0.5475* |
| | *s.e.* | *0.0096* | 0.0239 | *0.0311* | 0.0414 | *0.0431* |
| (5) | Higher pay, t-1 | 0.0840 | 0.0440 | 0.0576 | 0.0689 | 0.7456 |
| | *s.e.* | 0.0095 | 0.0320 | 0.0211 | 0.0166 | 0.0384 |
| | (b). Differences in predicted transition probabilities (relative to transition probabilities from low pay) | | | | | |
| | | I | II | III | IV | V |
| (6) | =(4)-(1) | -0.1800 | *-0.0469* | 0.0031 | *0.1128* | 0.1109 |
| | *s.e.* | 0.0116 | *0.0129* | 0.0118 | *0.0210* | 0.0212 |
| (7) | =(4)-(2) | *-0.0784* | -0.1122 | *-0.0138* | 0.0928 | *0.1116* |
| | *s.e.* | *0.0104* | 0.0478 | *0.0200* | 0.0199 | *0.0308* |
| (8) | =(4)-(3) | *-0.0098* | -0.0201 | *-0.2611* | 0.0533 | 0.2377 |
| | *s.e.* | *0.0085* | 0.0214 | *0.0438* | 0.0236 | 0.0284 |
| (9) | =(4)-(5) | *0.0012* | 0.0035 | *0.0616* | 0.1318 | *-0.1981* |
| | *s.e.* | *0.0035* | 0.0162 | *0.0131* | 0.0262 | *0.0175* |

**Females**

(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1

| | | Not in labour force, t | Unemployment, t | Self-employment, t | Low pay, t | Higher pay, t |
|---|---|---|---|---|---|---|
| (1) | Not in labour force, t-1 | 0.4363 | *0.0419* | 0.0390 | *0.1450* | 0.3378 |
| | *s.e.* | 0.0263 | *0.0179* | 0.0134 | *0.0274* | 0.0226 |

| | | | | | | |
|---|---|---|---|---|---|---|
| (2) | Unemployment, t-1 | *0.3284* | 0.1119 | *0.0230* | 0.1883 | *0.3485* |
| | *s.e.* | *0.0281* | 0.0404 | *0.0098* | 0.0282 | *0.0279* |
| (3) | Self-employment, t-1 | *0.2545* | 0.0225 | *0.2186* | 0.2112 | 0.2932 |
| | *s.e.* | *0.0281* | 0.0235 | *0.0565* | 0.0429 | 0.0354 |
| (4) | Low pay, t-1 | *0.1739* | 0.0327 | *0.0428* | 0.3262 | *0.4243* |
| | *s.e.* | *0.0200* | 0.0197 | *0.0159* | 0.0465 | *0.0349* |
| (5) | Higher pay, t-1 | 0.1897 | *0.0284* | 0.0199 | *0.1470* | 0.6150 |
| | *s.e.* | 0.0178 | *0.0159* | 0.0107 | *0.0312* | 0.0340 |
| | (b). Differences in predicted transition probabilities (relative to transition probabilities from low pay) | | | | | |
| | | I | II | III | IV | V |
| (6) | =(4)-(1) | -0.2624 | *-0.0091* | 0.0038 | *0.1812* | 0.0865 |
| | *s.e.* | 0.0096 | *0.0058* | 0.0067 | *0.0215* | 0.0186 |
| (7) | =(4)-(2) | *-0.1545* | -0.0792 | *0.0198* | 0.1380 | *0.0759* |
| | *s.e.* | *0.0146* | 0.0246 | *0.0096* | 0.0316 | *0.0195* |
| (8) | =(4)-(3) | *-0.0806* | 0.0102 | *-0.1758* | 0.1151 | 0.1311 |
| | *s.e.* | *0.0176* | 0.0091 | *0.0462* | 0.0218 | 0.0266 |
| (9) | =(4)-(5) | *-0.0158* | 0.0043 | *0.0229* | 0.1792 | *-0.1907* |
| | *s.e.* | *0.0079* | 0.0066 | *0.0093* | 0.0220 | *0.0169* |

**Table 4: NMWs and low pay dynamics**

| | | Males Waves 1-8 | | | | |
|---|---|---|---|---|---|---|
| | (a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1 | | | | | |
| | | Not in labour force, t | Unemployment, t | Self-employment, t | Low pay, t | Higher pay, t |
| (1) | Not in labour force, t-1 | 0.2311 | 0.1237 | 0.1020 | 0.0620 | 0.4812 |
| | *s.e.* | 0.0457 | 0.0892 | 0.0432 | 0.0381 | 0.0736 |
| (2) | Unemployment, t-1 | 0.1469 | 0.1931 | 0.1281 | 0.0758 | 0.4560 |
| | *s.e.* | 0.0289 | 0.1302 | 0.0621 | 0.0494 | 0.0804 |
| (3) | Self-employment, t-1 | 0.0921 | 0.0827 | 0.4014 | 0.0786 | 0.3452 |
| | *s.e.* | 0.0316 | 0.0862 | 0.0938 | 0.0468 | 0.0813 |
| (4) | Low pay, t-1 | 0.0880 | 0.0502 | 0.1161 | 0.1361 | 0.6096 |
| | *s.e.* | 0.0227 | 0.0854 | 0.0498 | 0.0559 | 0.0823 |
| (5) | Higher pay, t-1 | 0.0861 | 0.0486 | 0.0614 | 0.0610 | 0.7430 |
| | *s.e.* | 0.0200 | 0.0571 | 0.0310 | 0.0368 | 0.0705 |
| | (b). Differences in predicted transition probabilities (relative to transition probabilities from low pay) | | | | | |
| | | I | II | III | IV | V |
| (6) | =(4)-(1) | -0.1431 | -0.0735 | 0.0140 | 0.0741 | 0.1284 |
| | *s.e.* | 0.0260 | 0.0324 | 0.0218 | 0.0384 | 0.0345 |
| (7) | =(4)-(2) | -0.0590 | -0.1429 | -0.0120 | 0.0603 | 0.1536 |
| | *s.e.* | 0.0271 | 0.1517 | 0.0351 | 0.0567 | 0.0732 |
| (8) | =(4)-(3) | -0.0041 | -0.0325 | -0.2854 | 0.0575 | 0.2644 |
| | *s.e.* | 0.0150 | 0.0442 | 0.0593 | 0.0349 | 0.0511 |
| (9) | =(4)-(5) | 0.0019 | 0.0016 | 0.0547 | 0.0751 | -0.1334 |
| | *s.e.* | 0.0083 | 0.0431 | 0.0317 | 0.0336 | 0.0379 |
| | | **Waves 9-18** | | | | |
| | (a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1 | | | | | |

| | | Not in labour force, t | Unemployment, t | Self-employment, t | Low pay, t | Higher pay, t |
|---|---|---|---|---|---|---|
| (1) | Not in labour force, t-1 | 0.3595 | 0.0378 | 0.0674 | 0.1089 | 0.4264 |
| | *s.e.* | 0.0314 | 0.0236 | 0.0154 | 0.0235 | 0.0309 |
| (2) | Unemployment, t-1 | 0.3125 | 0.0764 | 0.0726 | 0.1114 | 0.4271 |
| | *s.e.* | 0.0282 | 0.0356 | 0.0242 | 0.0218 | 0.0340 |
| (3) | Self-employment, t-1 | 0.1980 | 0.0395 | 0.2204 | 0.1680 | 0.3741 |
| | *s.e.* | 0.0257 | 0.0410 | 0.0392 | 0.0333 | 0.0405 |
| (4) | Low pay, t-1 | 0.1572 | 0.0220 | 0.0746 | 0.2332 | 0.5130 |
| | *s.e.* | 0.0192 | 0.0189 | 0.0201 | 0.0398 | 0.0403 |
| (5) | Higher pay, t-1 | 0.1644 | 0.0216 | 0.0441 | 0.1152 | 0.6548 |
| | *s.e.* | 0.0170 | 0.0184 | 0.0126 | 0.0255 | 0.0315 |
| | (b). Differences in predicted transition probabilities (relative to transition probabilities from low pay) | | | | | |
| | | I | II | III | IV | V |
| (6) | =(4)-(1) | -0.2022 | -0.0158 | 0.0072 | 0.1242 | 0.0866 |
| | *s.e.* | 0.0143 | 0.0079 | 0.0092 | 0.0195 | 0.0164 |
| (7) | =(4)-(2) | -0.1552 | -0.0544 | 0.0020 | 0.1218 | 0.0858 |
| | *s.e.* | 0.0186 | 0.0294 | 0.0262 | 0.0266 | 0.0292 |
| (8) | =(4)-(3) | -0.0407 | -0.0175 | -0.1458 | 0.0652 | 0.1389 |
| | *s.e.* | 0.0139 | 0.0261 | 0.0266 | 0.0228 | 0.0242 |
| (9) | =(4)-(5) | -0.0071 | 0.0004 | 0.0305 | 0.1180 | -0.1418 |
| | *s.e.* | 0.0063 | 0.0070 | 0.0095 | 0.0173 | 0.0133 |

**Females**

**Waves 1-8**

(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1

| | | Not in labour force, t | Unemployment, t | Self-employment, t | Low pay, t | Higher pay, t |
|---|---|---|---|---|---|---|
| (1) | Not in labour force, t-1 | 0.4185 | 0.0371 | 0.0349 | 0.1566 | 0.3529 |
| | *s.e.* | 0.0499 | 0.0482 | 0.0294 | 0.0624 | 0.0404 |

| | | | | | | |
|---|---|---|---|---|---|---|
| (2) | Unemployment, t-1 | 0.3249 | 0.0954 | 0.0471 | 0.1805 | 0.3521 |
| | *s.e.* | 0.0486 | 0.0774 | 0.0390 | 0.0631 | 0.0498 |
| (3) | Self-employment, t-1 | 0.2775 | 0.0574 | 0.1538 | 0.1668 | 0.3446 |
| | *s.e.* | 0.0507 | 0.0867 | 0.0846 | 0.0687 | 0.0554 |
| (4) | Low pay, t-1 | 0.2036 | 0.0267 | 0.0384 | 0.2910 | 0.4404 |
| | *s.e.* | 0.0416 | 0.0619 | 0.0330 | 0.0902 | 0.0625 |
| (5) | Higher pay, t-1 | 0.2067 | 0.0293 | 0.0276 | 0.1640 | 0.5724 |
| | *s.e.* | 0.0328 | 0.0531 | 0.0288 | 0.0545 | 0.0574 |
| | (b). Differences in predicted transition probabilities (relative to transition probabilities from low pay) | | | | | |
| | | I | II | III | IV | V |
| (6) | =(4)-(1) | -0.2149 | -0.0104 | 0.0035 | 0.1344 | 0.0875 |
| | *s.e.* | 0.0176 | 0.0226 | 0.0126 | 0.0354 | 0.0294 |
| (7) | =(4)-(2) | -0.1214 | -0.0687 | -0.0087 | 0.1105 | 0.0883 |
| | *s.e.* | 0.0239 | 0.0456 | 0.0193 | 0.0438 | 0.0360 |
| (8) | =(4)-(3) | -0.0739 | -0.0307 | -0.1154 | 0.1242 | 0.0958 |
| | *s.e.* | 0.0318 | 0.0464 | 0.0734 | 0.0431 | 0.0404 |
| (9) | =(4)-(5) | -0.0031 | -0.0027 | 0.0109 | 0.1269 | -0.1320 |
| | *s.e.* | 0.0182 | 0.0206 | 0.0142 | 0.0488 | 0.0415 |
| | | **Waves 9-18** | | | | |
| | (a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1 | | | | | |
| | | Not in labour force, t | Unemploy-ment, t | Self-employment, t | Low pay, t | Higher pay, t |
| (1) | Not in labour force, t-1 | 0.4133 | 0.0372 | 0.0406 | 0.1337 | 0.3752 |
| | *s.e.* | 0.0357 | 0.0300 | 0.0122 | 0.0262 | 0.0293 |
| (2) | Unemployment, t-1 | 0.3635 | 0.0775 | 0.0445 | 0.1379 | 0.3767 |
| | *s.e.* | 0.0331 | 0.0441 | 0.0198 | 0.0245 | 0.0320 |
| (3) | Self-employment, t-1 | 0.2427 | 0.0411 | 0.1738 | 0.2110 | 0.3314 |
| | *s.e.* | 0.0328 | 0.0507 | 0.0385 | 0.0379 | 0.0385 |
| (4) | Low pay, t-1 | 0.1920 | 0.0226 | 0.0460 | 0.2829 | 0.4565 |
| | *s.e.* | 0.0240 | 0.0242 | 0.0165 | 0.0424 | 0.0395 |
| (5) | Higher pay, t-1 | 0.2043 | 0.0227 | 0.0242 | 0.1482 | 0.6006 |

| | | I | II | III | IV | V |
|---|---|---|---|---|---|---|
| | *s.e.* | 0.0214 | 0.0286 | 0.0087 | 0.0291 | 0.0333 |
| | (b). Differences in predicted transition probabilities (relative to transition probabilities from low pay) | | | | | |
| | | I | II | III | IV | V |
| (6) | =(4)-(1) | -0.2213 | -0.0146 | 0.0054 | 0.1492 | 0.0813 |
| | *s.e.* | 0.0145 | 0.0092 | 0.0076 | 0.0199 | 0.0162 |
| (7) | =(4)-(2) | -0.1715 | -0.0549 | 0.0015 | 0.1450 | 0.0798 |
| | *s.e.* | 0.0192 | 0.0332 | 0.0211 | 0.0283 | 0.0273 |
| (8) | =(4)-(3) | -0.0507 | -0.0185 | -0.1278 | 0.0719 | 0.1250 |
| | *s.e.* | 0.0169 | 0.0306 | 0.0273 | 0.0250 | 0.0232 |
| (9) | =(4)-(5) | -0.0123 | -0.0001 | 0.0218 | 0.1347 | -0.1441 |
| | *s.e.* | 0.0075 | 0.0081 | 0.0083 | 0.0167 | 0.0116 |

**Table A1: Summary statistics**

| | All | Out of labour force | Unemployed | Self-employed | Low-paid | Higher paid |
|---|---|---|---|---|---|---|
| | | **Males** | | | | |
| Out of labour force, t-1 | 13.07 | 76.69 | 16.34 | 3.29 | 6.40 | 2.95 |
| Unemployed, t-1 | 5.71 | 7.09 | 50.00 | 2.41 | 8.25 | 1.78 |
| Self-employed, t-1 | 13.76 | 2.61 | 4.72 | 81.70 | 7.85 | 1.49 |
| Low pay, t-1 | 9.17 | 2.63 | 9.50 | 4.80 | 47.74 | 6.14 |
| Higher pay, t-1 | 58.29 | 10.98 | 19.44 | 7.80 | 29.76 | 87.64 |
| Age 18-24 | 8.76 | 2.20 | 21.40 | 3.05 | 27.05 | 7.75 |
| Age 25-34 | 23.49 | 7.36 | 25.70 | 19.15 | 24.39 | 27.52 |
| Age 35-44 | 26.50 | 13.56 | 21.45 | 28.59 | 17.78 | 30.34 |
| Age 45-54 | 22.89 | 22.26 | 17.57 | 28.18 | 16.12 | 23.19 |
| Age 55 plus | 18.36 | 54.62 | 13.88 | 21.03 | 14.66 | 11.20 |
| 1st degree or higher | 15.83 | 8.89 | 8.13 | 13.10 | 7.74 | 19.75 |
| Other higher degree | 31.30 | 23.34 | 20.00 | 30.73 | 24.06 | 35.13 |
| A-level(s) | 12.79 | 11.06 | 10.78 | 12.97 | 14.64 | 13.03 |
| O-level(s) | 16.77 | 13.23 | 18.21 | 18.92 | 20.28 | 16.36 |
| Other qualifications | 7.54 | 9.31 | 10.47 | 8.15 | 10.58 | 6.34 |
| No qualification | 15.77 | 34.17 | 32.41 | 16.13 | 22.70 | 9.39 |
| Married or partnered | 74.89 | 71.96 | 54.50 | 81.96 | 58.49 | 77.98 |
| Disability | 12.76 | 52.49 | 20.20 | 7.17 | 9.55 | 5.70 |
| London | 6.76 | 5.29 | 7.93 | 7.43 | 4.44 | 7.12 |
| South East | 10.54 | 7.30 | 7.77 | 12.19 | 6.72 | 11.60 |
| Other regions | 82.70 | 87.41 | 84.30 | 80.38 | 88.84 | 81.28 |
| Unemployment rate | 6.25 | 6.20 | 6.96 | 6.20 | 6.15 | 6.22 |
| Youngest child 0-2 | 10.84 | 3.40 | 12.77 | 11.37 | 9.96 | 12.19 |
| Youngest child 3-4 | 4.68 | 1.90 | 4.22 | 4.94 | 3.50 | 5.41 |
| Youngest child 5-11 | 11.87 | 6.90 | 9.41 | 14.28 | 7.64 | 13.14 |
| Youngest child 12-16 | 7.25 | 5.82 | 5.47 | 8.84 | 4.98 | 7.65 |
| Youngest child 17-18 | 2.45 | 2.07 | 1.87 | 3.20 | 1.46 | 2.55 |
| No children under 19 | 62.91 | 79.91 | 66.26 | 57.37 | 72.46 | 59.06 |
| Total children under 19 | 0.67 | 0.38 | 0.66 | 0.82 | 0.50 | 0.72 |
| Number of observations | 64,939 | 7,960 | 3,580 | 9,255 | 5,404 | 38,740 |
| | | **Females** | | | | |
| Out of labour force, t-1 | 27.82 | 78.83 | 33.56 | 9.81 | 12.37 | 5.96 |
| Unemployed, t-1 | 3.15 | 4.18 | 29.28 | 1.41 | 3.04 | 1.14 |
| Self-employed, t-1 | 4.57 | 1.43 | 2.50 | 70.83 | 2.17 | 0.73 |
| Low pay, t-1 | 18.51 | 6.31 | 16.60 | 9.84 | 62.12 | 10.14 |
| Higher pay, t-1 | 45.95 | 9.25 | 18.06 | 8.11 | 20.30 | 82.03 |
| Age 18-24 | 9.02 | 6.58 | 20.37 | 2.66 | 14.76 | 8.19 |
| Age 25-34 | 25.49 | 24.51 | 24.99 | 20.61 | 21.20 | 28.17 |
| Age 35-44 | 28.54 | 24.44 | 22.95 | 34.06 | 28.27 | 30.77 |
| Age 45-54 | 24.39 | 22.68 | 22.02 | 31.07 | 24.90 | 24.66 |
| Age 55 plus | 12.56 | 21.79 | 9.67 | 11.60 | 10.87 | 8.21 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 1st degree or higher | 14.36 | 7.63 | 8.96 | 20.41 | 4.36 | 21.67 |
| Other higher degree | 27.04 | 18.38 | 19.28 | 34.82 | 23.75 | 32.92 |
| A-level(s) | 11.23 | 8.94 | 11.79 | 11.48 | 12.49 | 12.00 |
| O-level(s) | 21.18 | 21.57 | 22.40 | 16.87 | 24.59 | 20.05 |
| Other qualifications | 8.97 | 12.13 | 11.65 | 7.53 | 11.22 | 6.29 |
| No qualification | 17.22 | 31.35 | 25.92 | 8.89 | 23.59 | 7.07 |
| Married or partnered | 73.59 | 75.71 | 46.68 | 80.00 | 72.22 | 73.93 |
| Disability | 14.00 | 29.70 | 20.41 | 9.93 | 9.58 | 6.71 |
| London | 6.75 | 5.56 | 9.19 | 9.52 | 2.91 | 8.43 |
| South East | 10.83 | 8.93 | 10.33 | 12.80 | 10.24 | 11.98 |
| Other regions | 82.42 | 85.51 | 80.48 | 77.68 | 86.85 | 79.59 |
| Unemployment rate | 6.24 | 6.27 | 6.55 | 6.16 | 6.18 | 6.23 |
| Youngest child 0-2 | 12.43 | 23.16 | 10.14 | 9.43 | 7.81 | 8.48 |
| Youngest child 3-4 | 6.11 | 8.43 | 5.75 | 6.00 | 5.58 | 5.01 |
| Youngest child 5-11 | 17.05 | 16.63 | 14.29 | 18.89 | 20.61 | 15.94 |
| Youngest child 12-16 | 10.61 | 8.11 | 8.63 | 12.06 | 13.05 | 11.11 |
| Youngest child 17-18 | 3.36 | 2.65 | 2.88 | 3.34 | 4.05 | 3.54 |
| No children under 19 | 50.44 | 41.02 | 58.31 | 50.28 | 48.90 | 55.92 |
| Total children under 19 | 0.92 | 1.21 | 0.73 | 0.95 | 0.94 | 0.75 |
| Number of observations | 71,535 | 19,360 | 2,121 | 3,415 | 12,697 | 33,942 |

**Table A2: Coefficient estimates**

| | Males | | Females | |
|---|---|---|---|---|
| | Coe. | S.e. | Coe. | S.e. |
| **Unemployment** | | | | |
| Unemployed, t-1 | 1.573*** | 0.086 | 1.510*** | 0.082 |
| Self-employed, t-1 | 1.525*** | 0.153 | 0.367** | 0.184 |
| Low pay, t-1 | 1.411*** | 0.132 | 1.168*** | 0.084 |
| Higher pay, t-1 | 1.289*** | 0.093 | 0.893*** | 0.084 |
| Age 18-24 | 1.218*** | 0.146 | 0.644*** | 0.113 |
| Age 25-34 | 0.490*** | 0.106 | 0.266*** | 0.082 |
| Age 45-54 | -0.702*** | 0.104 | -0.666*** | 0.087 |
| Age 55 plus | -1.965*** | 0.114 | -1.746*** | 0.114 |
| 1st degree or higher | -0.596*** | 0.135 | 0.105 | 0.111 |
| Other higher degree | -0.565*** | 0.105 | 0.109 | 0.086 |
| A-level(s) | -0.540*** | 0.132 | 0.158 | 0.105 |
| O-level(s) | -0.193 | 0.121 | 0.066 | 0.084 |
| Other qualifications | -0.391** | 0.158 | -0.025 | 0.104 |
| Married or partnered | -0.095 | 0.144 | -0.483*** | 0.098 |
| Disability | -0.851*** | 0.091 | -0.280*** | 0.088 |
| London | -0.081 | 0.166 | 0.030 | 0.126 |
| South East | -0.112 | 0.136 | 0.428*** | 0.106 |
| Unemployment rate | 7.079* | 3.689 | 10.589*** | 3.163 |
| Youngest child 0-2 | 0.182 | 0.176 | -2.164*** | 0.128 |
| Youngest child 3-4 | 0.027 | 0.217 | -1.409*** | 0.148 |
| Youngest child 5-11 | -0.027 | 0.178 | -0.938*** | 0.124 |
| Youngest child 12-16 | 0.349** | 0.168 | -0.311** | 0.122 |
| Youngest child 17-18 | 0.355 | 0.229 | 0.017 | 0.170 |
| Total children under 19 | -0.114 | 0.088 | -0.170** | 0.067 |
| Married or partnerred: Mean | -0.741*** | 0.177 | -0.609*** | 0.123 |
| Disability: Mean | -1.807*** | 0.169 | -1.017*** | 0.149 |
| Total children: mean | 0.303*** | 0.080 | 0.109* | 0.060 |
| Unemployed, t0 | 1.699*** | 0.137 | 0.995*** | 0.107 |
| Self-employed, t0 | 0.824*** | 0.148 | 1.088*** | 0.203 |
| Low pay, t0 | 1.165*** | 0.153 | 0.628*** | 0.089 |
| Higher pay, t0 | 0.694*** | 0.114 | 0.543*** | 0.085 |
| Wave 3 | -0.183 | 0.179 | 0.065 | 0.161 |
| Wave 4 | -0.154 | 0.185 | 0.069 | 0.167 |
| Wave 5 | -0.630*** | 0.195 | 0.192 | 0.170 |
| Wave 6 | -0.474** | 0.197 | 0.175 | 0.181 |
| Wave 7 | -0.784*** | 0.213 | 0.103 | 0.197 |
| Wave 8 | -0.829*** | 0.229 | 0.151 | 0.208 |
| Wave 9 | -1.277*** | 0.234 | 0.191 | 0.204 |
| Wave 10 | -1.028*** | 0.226 | 0.525*** | 0.194 |
| Wave 11 | -0.861*** | 0.235 | 0.299 | 0.211 |
| Wave 12 | -0.893*** | 0.234 | 0.307 | 0.204 |
| Wave 13 | -0.660*** | 0.245 | 0.467** | 0.213 |

| | | | | |
|---|---|---|---|---|
| Wave 14 | -1.460*** | 0.253 | 0.357 | 0.224 |
| Wave 15 | -0.898*** | 0.254 | 0.402* | 0.225 |
| Wave 16 | -0.972*** | 0.248 | 0.355 | 0.219 |
| Wave 17 | -1.252*** | 0.257 | 0.333 | 0.221 |
| Wave 18 | -0.806*** | 0.243 | 0.381* | 0.210 |
| Constant | 0.185 | 0.426 | -2.143*** | 0.356 |
| **Self-employment** | | | | |
| Unemployed, t-1 | 1.139*** | 0.143 | -0.105 | 0.192 |
| Self-employed, t-1 | 4.091*** | 0.113 | 3.443*** | 0.112 |
| Low pay, t-1 | 2.398*** | 0.137 | 1.757*** | 0.108 |
| Higher pay, t-1 | 1.392*** | 0.105 | 0.741*** | 0.111 |
| Age 18-24 | 0.186 | 0.172 | -0.584*** | 0.172 |
| Age 25-34 | 0.401*** | 0.114 | -0.029 | 0.099 |
| Age 45-54 | -0.831*** | 0.111 | -0.694*** | 0.100 |
| Age 55 plus | -2.303*** | 0.125 | -1.982*** | 0.138 |
| 1st degree or higher | 0.570*** | 0.156 | 1.995*** | 0.158 |
| Other higher degree | 0.464*** | 0.128 | 1.688*** | 0.128 |
| A-level(s) | 0.325** | 0.157 | 1.366*** | 0.150 |
| O-level(s) | 0.540*** | 0.145 | 0.944*** | 0.133 |
| Other qualifications | 0.297 | 0.186 | 0.487*** | 0.180 |
| Married or partnered | 0.421*** | 0.156 | 0.216 | 0.141 |
| Disability | -1.465*** | 0.118 | -0.573*** | 0.132 |
| London | 0.512*** | 0.182 | 0.463** | 0.184 |
| South East | -0.004 | 0.145 | 0.382*** | 0.137 |
| Unemployment rate | -7.674* | 4.112 | -6.614* | 3.915 |
| Youngest child 0-2 | -0.024 | 0.192 | -2.454*** | 0.176 |
| Youngest child 3-4 | -0.013 | 0.243 | -1.623*** | 0.197 |
| Youngest child 5-11 | 0.116 | 0.194 | -1.042*** | 0.162 |
| Youngest child 12-16 | 0.376** | 0.185 | -0.452*** | 0.159 |
| Youngest child 17-18 | 0.152 | 0.236 | -0.194 | 0.227 |
| Total children under 19 | -0.140 | 0.094 | 0.159* | 0.082 |
| Married or partnerred: Mean | -0.096 | 0.204 | -0.220 | 0.185 |
| Disability: Mean | -3.427*** | 0.213 | -2.080*** | 0.239 |
| Total children: mean | 0.246*** | 0.085 | -0.145* | 0.076 |
| Unemployed, t0 | 0.807*** | 0.185 | 0.618*** | 0.214 |
| Self-employed, t0 | 4.035*** | 0.187 | 3.587*** | 0.202 |
| Low pay, t0 | 1.411*** | 0.187 | 0.870*** | 0.123 |
| Higher pay, t0 | 1.357*** | 0.140 | 0.869*** | 0.117 |
| Wave 3 | -0.171 | 0.204 | 0.242 | 0.215 |
| Wave 4 | -0.241 | 0.215 | 0.299 | 0.205 |
| Wave 5 | -0.391* | 0.221 | 0.026 | 0.223 |
| Wave 6 | -0.269 | 0.225 | 0.136 | 0.227 |
| Wave 7 | -0.708*** | 0.238 | 0.074 | 0.253 |
| Wave 8 | -0.802*** | 0.254 | -0.188 | 0.245 |
| Wave 9 | -1.420*** | 0.253 | -0.211 | 0.259 |
| Wave 10 | -0.941*** | 0.252 | 0.059 | 0.247 |

| | | | | |
|---|---|---|---|---|
| Wave 11 | -0.879*** | 0.259 | -0.282 | 0.255 |
| Wave 12 | -0.889*** | 0.255 | -0.239 | 0.255 |
| Wave 13 | -0.544** | 0.267 | -0.078 | 0.266 |
| Wave 14 | -1.239*** | 0.276 | -0.280 | 0.276 |
| Wave 15 | -0.691** | 0.278 | -0.180 | 0.280 |
| Wave 16 | -0.644** | 0.265 | 0.123 | 0.268 |
| Wave 17 | -0.791*** | 0.271 | 0.030 | 0.271 |
| Wave 18 | -0.742*** | 0.262 | -0.135 | 0.256 |
| Constant | -1.257** | 0.494 | -3.552*** | 0.455 |
| **Low pay** | | | | |
| Unemployed, t-1 | 1.223*** | 0.114 | 0.804*** | 0.089 |
| Self-employed, t-1 | 2.627*** | 0.141 | 1.415*** | 0.119 |
| Low pay, t-1 | 3.328*** | 0.112 | 2.649*** | 0.049 |
| Higher pay, t-1 | 2.182*** | 0.085 | 1.602*** | 0.052 |
| Age 18-24 | 1.716*** | 0.146 | 0.850*** | 0.093 |
| Age 25-34 | 0.715*** | 0.104 | 0.173*** | 0.057 |
| Age 45-54 | -0.802*** | 0.103 | -0.578*** | 0.062 |
| Age 55 plus | -2.115*** | 0.113 | -1.729*** | 0.082 |
| 1st degree or higher | -0.538*** | 0.133 | -0.239** | 0.102 |
| Other higher degree | -0.403*** | 0.110 | 0.362*** | 0.073 |
| A-level(s) | -0.324** | 0.132 | 0.403*** | 0.088 |
| O-level(s) | 0.000 | 0.121 | 0.252*** | 0.074 |
| Other qualifications | -0.234 | 0.153 | 0.021 | 0.087 |
| Married or partnered | 0.156 | 0.142 | -0.137** | 0.069 |
| Disability | -1.353*** | 0.099 | -0.714*** | 0.064 |
| London | -0.280* | 0.166 | -0.621*** | 0.119 |
| South East | -0.377*** | 0.138 | 0.162* | 0.084 |
| Unemployment rate | 0.233 | 3.697 | 3.854* | 2.340 |
| Youngest child 0-2 | -0.267 | 0.179 | -2.597*** | 0.098 |
| Youngest child 3-4 | -0.218 | 0.229 | -1.514*** | 0.109 |
| Youngest child 5-11 | -0.198 | 0.181 | -0.630*** | 0.090 |
| Youngest child 12-16 | 0.261 | 0.170 | 0.015 | 0.086 |
| Youngest child 17-18 | -0.061 | 0.225 | 0.205* | 0.120 |
| Total children under 19 | -0.110 | 0.088 | 0.052 | 0.040 |
| Married or partnerred: Mean | -0.299* | 0.179 | 0.062 | 0.097 |
| Disability: Mean | -2.454*** | 0.184 | -2.016*** | 0.126 |
| Total children: mean | 0.251*** | 0.077 | -0.044 | 0.041 |
| Unemployed, t0 | 1.048*** | 0.151 | 0.505*** | 0.117 |
| Self-employed, t0 | 1.442*** | 0.165 | 0.861*** | 0.153 |
| Low pay, t0 | 1.961*** | 0.157 | 1.611*** | 0.073 |
| Higher pay, t0 | 1.290*** | 0.119 | 0.848*** | 0.070 |
| Wave 3 | 0.002 | 0.202 | 0.160 | 0.108 |
| Wave 4 | 0.155 | 0.204 | 0.264** | 0.116 |
| Wave 5 | -0.056 | 0.207 | 0.230* | 0.118 |
| Wave 6 | 0.157 | 0.211 | 0.394*** | 0.120 |
| Wave 7 | -0.029 | 0.224 | 0.258* | 0.132 |

| | | | | |
|---|---|---|---|---|
| Wave 8 | 0.010 | 0.236 | 0.384*** | 0.136 |
| Wave 9 | -0.535** | 0.235 | 0.229* | 0.137 |
| Wave 10 | -0.061 | 0.229 | 0.355** | 0.138 |
| Wave 11 | 0.022 | 0.239 | 0.435*** | 0.144 |
| Wave 12 | -0.207 | 0.238 | 0.378*** | 0.143 |
| Wave 13 | 0.161 | 0.248 | 0.243 | 0.152 |
| Wave 14 | -0.592** | 0.256 | 0.174 | 0.159 |
| Wave 15 | 0.175 | 0.255 | 0.240 | 0.156 |
| Wave 16 | -0.075 | 0.247 | 0.346** | 0.153 |
| Wave 17 | -0.259 | 0.255 | 0.348** | 0.156 |
| Wave 18 | -0.066 | 0.245 | 0.228 | 0.148 |
| Constant | -0.865** | 0.433 | -1.504*** | 0.264 |
| Unemployed, t-1 | 0.946*** | 0.108 | 0.555*** | 0.097 |
| Self-employed, t-1 | 1.603*** | 0.125 | 0.837*** | 0.122 |
| Low pay, t-1 | 2.782*** | 0.104 | 2.125*** | 0.055 |
| Higher pay, t-1 | 3.432*** | 0.062 | 2.765*** | 0.040 |
| Age 18-24 | 0.718*** | 0.142 | 0.194** | 0.093 |
| Age 25-34 | 0.467*** | 0.097 | 0.220*** | 0.054 |
| Age 45-54 | -1.020*** | 0.091 | -0.877*** | 0.061 |
| Age 55 plus | -2.817*** | 0.103 | -2.394*** | 0.082 |
| 1st degree or higher | 1.038*** | 0.124 | 2.213*** | 0.098 |
| Other higher degree | 0.649*** | 0.104 | 1.592*** | 0.080 |
| A-level(s) | 0.476*** | 0.127 | 1.443*** | 0.095 |
| O-level(s) | 0.664*** | 0.118 | 1.004*** | 0.082 |
| Other qualifications | 0.172 | 0.151 | 0.548*** | 0.102 |
| Married or partnered | 0.359*** | 0.129 | -0.082 | 0.067 |
| Disability | -1.539*** | 0.083 | -0.854*** | 0.063 |
| London | 0.253* | 0.143 | 0.269** | 0.113 |
| South East | 0.135 | 0.120 | 0.366*** | 0.082 |
| Unemployment rate | -3.876 | 3.414 | 3.941* | 2.346 |
| Youngest child 0-2 | -0.101 | 0.164 | -2.812*** | 0.087 |
| Youngest child 3-4 | 0.038 | 0.207 | -1.716*** | 0.102 |
| Youngest child 5-11 | 0.025 | 0.166 | -0.901*** | 0.088 |
| Youngest child 12-16 | 0.418*** | 0.155 | 0.008 | 0.086 |
| Youngest child 17-18 | 0.181 | 0.184 | 0.256** | 0.117 |
| Total children under 19 | -0.165** | 0.082 | -0.154*** | 0.039 |
| Married or partnerred: Mean | 0.034 | 0.168 | -0.003 | 0.098 |
| Disability - Mean | -3.354*** | 0.168 | -2.664*** | 0.132 |
| Total children - mean | 0.161** | 0.072 | -0.041 | 0.041 |
| Unemployed, t0 | 0.493*** | 0.144 | 0.393*** | 0.123 |
| Self-employed, t0 | 1.025*** | 0.153 | 0.674*** | 0.166 |
| Low pay, t0 | 1.468*** | 0.153 | 1.322*** | 0.080 |
| Higher pay, t0 | 2.069*** | 0.112 | 2.341*** | 0.075 |
| Wave 3 | -0.085 | 0.165 | 0.205* | 0.105 |
| Wave 4 | -0.040 | 0.174 | 0.245** | 0.115 |
| Wave 5 | -0.242 | 0.176 | 0.255** | 0.113 |

| | | | | |
|---|---|---|---|---|
| Wave 6 | -0.218 | 0.179 | 0.225* | 0.119 |
| Wave 7 | -0.264 | 0.192 | 0.336*** | 0.130 |
| Wave 8 | -0.326 | 0.208 | 0.322** | 0.135 |
| Wave 9 | -0.938*** | 0.207 | 0.140 | 0.136 |
| Wave 10 | -0.590*** | 0.203 | 0.358*** | 0.137 |
| Wave 11 | -0.552*** | 0.214 | 0.385*** | 0.142 |
| Wave 12 | -0.569*** | 0.211 | 0.352** | 0.141 |
| Wave 13 | -0.330 | 0.219 | 0.437*** | 0.148 |
| Wave 14 | -0.990*** | 0.227 | 0.344** | 0.153 |
| Wave 15 | -0.571** | 0.227 | 0.370** | 0.153 |
| Wave 16 | -0.548** | 0.219 | 0.475*** | 0.150 |
| Wave 17 | -0.657*** | 0.226 | 0.460*** | 0.153 |
| Wave 18 | -0.632*** | 0.219 | 0.358** | 0.145 |
| Constant | 0.432 | 0.396 | -1.911*** | 0.265 |
| | | | | |
| c11 | 1.550*** | 0.061 | 0.980*** | 0.055 |
| c21 | 1.026*** | 0.080 | 1.972*** | 0.066 |
| c22 | 1.808*** | 0.061 | 0.213** | 0.092 |
| c31 | 1.353*** | 0.066 | 0.620*** | 0.047 |
| c32 | 0.400*** | 0.055 | 0.269*** | 0.063 |
| c33 | 1.028*** | 0.043 | 1.244*** | 0.036 |
| c41 | 1.120*** | 0.065 | 0.701*** | 0.050 |
| c42 | 0.496*** | 0.049 | 0.068 | 0.056 |
| c43 | 0.701*** | 0.043 | 0.908*** | 0.044 |
| c44 | 1.125*** | 0.031 | 1.270*** | 0.028 |
| | | | | |
| Log-likelihood | -37247.81333 | | -48831.26157 | |

**Table A3: Estimated transition probabilities, accounting for panel attrition**

**Males**

(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1

| | | Not in labour force, t | Unemployment, t | Self-employment, t | Low pay, t | Higher pay, t |
|---|---|---|---|---|---|---|
| (1) | Not in labour force, t-1 | 0.2623 | *0.0959* | 0.1117 | *0.0903* | 0.4398 |
| | *s.e.* | 0.0216 | *0.0319* | 0.0326 | *0.0227* | 0.0335 |
| (2) | Unemployment, t-1 | 0.1641 | 0.1593 | 0.1307 | 0.1058 | 0.4401 |
| | *s.e.* | 0.0161 | 0.0486 | 0.0429 | 0.0294 | 0.0401 |
| (3) | Self-employment, t-1 | 0.0938 | 0.0646 | 0.3785 | 0.1461 | 0.3169 |
| | *s.e.* | 0.0164 | 0.0431 | 0.0753 | 0.0364 | 0.0564 |
| (4) | Low pay, t-1 | 0.0860 | 0.0466 | 0.1198 | 0.1985 | 0.5491 |
| | *s.e.* | 0.0112 | 0.0271 | 0.0334 | 0.0444 | 0.0484 |
| (5) | Higher pay, t-1 | 0.0848 | 0.0435 | 0.0585 | 0.0678 | 0.7454 |
| | *s.e.* | 0.0106 | 0.0347 | 0.0230 | 0.0161 | 0.0403 |

(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)

| | | I | II | III | IV | V |
|---|---|---|---|---|---|---|
| (6) | =(4)-(1) | -0.1763 | *-0.0494* | 0.0081 | *0.1082* | 0.1094 |
| | *s.e.* | 0.0119 | *0.0137* | 0.0108 | *0.0237* | 0.0241 |
| (7) | =(4)-(2) | -0.0782 | -0.1127 | -0.0109 | 0.0927 | 0.1090 |
| | *s.e.* | 0.0106 | 0.0469 | 0.0187 | 0.0224 | 0.0333 |
| (8) | =(4)-(3) | -0.0079 | -0.0181 | -0.2587 | 0.0524 | 0.2323 |
| | *s.e.* | 0.0091 | 0.0218 | 0.0476 | 0.0288 | 0.0318 |
| (9) | =(4)-(5) | 0.0012 | 0.0030 | 0.0614 | 0.1307 | -0.1963 |
| | *s.e.* | 0.0038 | 0.0168 | 0.0132 | 0.0300 | 0.0206 |

**Females**

(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1

| | | Not in labour force, t | Unemployment, t | Self-employment, t | Low pay, t | Higher pay, t |
|---|---|---|---|---|---|---|
| (1) | Not in labour force, t-1 | 0.4369 | *0.0419* | 0.0419 | *0.1478* | 0.3315 |
| | *s.e.* | 0.0263 | *0.0189* | 0.0199 | *0.0278* | 0.0215 |

| | | I | II | III | IV | V |
|---|---|---|---|---|---|---|
| (2) | Unemployment, t-1 | 0.341 | 0.0957 | 0.0343 | 0.1795 | 0.3495 |
| | *s.e.* | 0.0262 | 0.0361 | 0.0137 | 0.0258 | 0.0253 |
| (3) | Self-employment, t-1 | 0.2649 | 0.0321 | 0.2053 | 0.2163 | 0.2814 |
| | *s.e.* | 0.0292 | 0.0266 | 0.0648 | 0.0398 | 0.0345 |
| (4) | Low pay, t-1 | 0.1776 | 0.0286 | 0.0449 | 0.3243 | 0.4245 |
| | *s.e.* | 0.0201 | 0.0204 | 0.0206 | 0.0501 | 0.036 |
| (5) | Higher pay, t-1 | 0.1849 | 0.0293 | 0.019 | 0.1501 | 0.6167 |
| | *s.e.* | 0.0167 | 0.0197 | 0.0131 | 0.0317 | 0.0339 |
| | (b). Differences in predicted transition probabilities (relative to transition probabilities from low pay) | | | | | |
| | | I | II | III | IV | V |
| (6) | =(4)-(1) | -0.2593 | *-0.0133* | 0.003 | *0.1766* | 0.093 |
| | *s.e.* | 0.0104 | *0.0058* | 0.0066 | *0.0245* | 0.0218 |
| (7) | =(4)-(2) | -0.1634 | -0.067 | 0.0106 | 0.1448 | 0.075 |
| | *s.e.* | 0.014 | 0.0202 | 0.0112 | 0.0336 | 0.0229 |
| (8) | =(4)-(3) | -0.0873 | -0.0035 | -0.1603 | 0.1081 | 0.143 |
| | *s.e.* | 0.0184 | 0.0106 | 0.0482 | 0.0266 | 0.0289 |
| (9) | =(4)-(5) | -0.0073 | -0.0007 | 0.0259 | 0.1743 | -0.1922 |
| | *s.e.* | 0.0089 | 0.0066 | 0.0095 | 0.0269 | 0.0245 |