1. Introduction

Early work on the dynamics of pay suggested that being in low paid employment increases the chances of both future low paid employment and unemployment (Stewart and Swaffield, 1999, and Stewart, 2007). However, this literature does not consider the possibility that low pay may also lead to higher pay. As we show below, following individuals over time between 1991 and 2008 using data from the British Household Panel Study (BHPS), about 26 (40) per cent of low-paid women (men) are in higher paying jobs in the subsequent year. Despite these high percentages, presently, the literature has paid little attention to the empirical possibility that low pay itself may have a low-pay to higher-pay stepping stone effect. The core objective of this paper is to develop and estimate a dynamic multinomial logit model of employment which will allow us to examine the dynamic relationship between no-pay, low-pay and higher-pay outcomes simultaneously. For the sake of completeness we also include in the analysis self-employment, an employment status typically ignored in the relevant literature. The policy contribution of this paper is that it will inform the debate surrounding welfare policies designed to facilitate the transition from welfare to work.

We show that both state-dependence and stepping stone effects of low pay are present among British workers after observed and unobserved individual heterogeneity has been accounted for. Our 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 not in the labour force. However, we also show that people on low pay are not more likely to become jobless in the future than their higher pay counterparts. Simply put, the paper looks for but does not find any evidence for a low pay-no pay cycle among British workers.

The paper is arranged as follows: Section 2 briefly reviews the literature; Section 3 describes the econometric model and estimation strategy; Section 4 discusses the data and model specification; Section 5 presents the estimation results; ~~and~~ Section 6 tests for and discusses panel attrition bias, and Section 7 sets out the conclusion.

2. Literature review

Whether there is a low wage-no wage cycle or whether low paid jobs act as stepping stones to higher paid jobs are essentially empirical issues. However, there are some theoretical underpinnings based on human capital, signalling and job search effects. Acemoglu (1995) assumes that human capital deteriorates during unemployment spells and its maintenance is costly and non-observable, so that employers tend to avoid hiring unemployed workers. This results in the probability of exiting from unemployment declining with its duration

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(unemployment persistence).Hence, Vishwanath (1989) suggests firms may use unemployment duration as an indicator of employability simply because higher ability workers are more likely to have shorter unemployment spells. In contrast, Pissarides (1990) argues that unemployment does not have to be stigmatising. As there are generally fewer high quality jobs around than low quality ones it may pay the more highly skilled to wait for an appropriate high skilled vacancy to appear and employers may anticipate such a strategy.

~~2.~~ Whether having a low paid job is better than no job at all depends on factors such as age, gender and level of education (Mostav, 2014). If employee skills are improved through low wage employment this may well result in a stepping stone effect into higher paid jobs, However, the accumulation of human capital in such jobs is often limited and employers may interpret such jobs as providing a negative signal, particularly in the case of those who are more highly qualified. In such an environment McCormick (1990) discusses why redundant skilled workers may be reluctant to accept interim low skilled jobs. If skilled work is more satisfying or less arduous for highly productive workers, then such workers will tend to invest more in moving quickly between skilled jobs. Consequently, high productivity workers tend to engage in on-the-job search rather than take up interim jobs. If individual differences in productivity are known to the worker but not to the potential employer, then this type of search strategy may be used as a signal of productivity. Imperfect information is a key issue in all these models.

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; Clark~~e~~ 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; Clark~~e~~ and Kanellopoulos 2013; and Fok et al. 2015) even after individual heterogeneity is controlled for.

However, there is another possible effect 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 possibility 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 if it is low paid, such as the work-first approach to welfare recipients, have a chance of improving the financial well-being of welfare recipients over time and should therefore be considered as potentially welfare-improving policies. This study extends the literature by

estimating a dynamic multinomial logit model to examine both the state-dependence and the 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 there exists genuine state-dependence of low pay as well as of 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 present 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. 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, as well as 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 their model takes into account potential endogeneity of initial low pay, initial unemployment is assumed to be exogenous. Given that 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, 2008a, Cappellari and Jenkins, 2008b). ~~Our present study examines this issue as well~~But evidence from modelling results is still mixed.

Cappellari and Jenkins (2008b) find that for the UK men, low pay experience has only a modest (and statistically insignificant) 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) and Cai (2015a) for Australian workers. 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.~~,~~ However, ~~but different from~~ Stewart (2007) ~~for Britain who~~ concludes that for ~~the~~ UK men 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. This current paper adds further evidence on this issue.

Besides state dependence, another important aspect of low pay dynamics, which has not drawn much research attention in the literature, is duration dependence of low pay. Duration dependence addresses the question how duration on low pay affects the probability of exit from low pay. Using the BHPS data, Phimister and Theodossiou (2009) present evidence of negative duration dependence of low pay for UK workers - that is, the longer a worker is on low pay, the less likely he/she will exit from it. Cai (2015b) shows a similar result for Australian workers using the Household, Income and Labour Dynamics in Australia Survey. As examining duration dependence of low pay requires a different modelling framework (i.e. duration models) from the current study, this issue is not analysed further ~~out of the scope~~ here.

3. The model and 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

[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.

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) $\mu_{i,j} = L_{i,0}\lambda_j + \bar{z}_i\theta_j + \nu_{i,j}$, *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 Σ_ν. The parameters in Σ_ν 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]

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.

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

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 ν_2, ν_3, ν_4 and ν_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 Σ_ν,

(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 $G(\nu_{2,}\nu_3, \nu_{4,}\nu_5)$; ν_2^r, ν_3^r, ν_4^r and ν_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 authors 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 C_i*=(Xi, Zi)*, conditional on unobserved heterogeneity ν_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 ν_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 C_i*=(Xi, Zi)*, conditional on unobserved heterogeneity ν_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 $SS = \frac{1}{N}\sum_{i=1}^{N} SS_i$.

4. Data and model specification

Data source and low pay definition

This paper uses data from the 18 waves of the 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 t~~The additional samples~~, from Scotland and Wales~~ together with individuals who joined the households in the survey sample through marriage, are included in the analysis~~, those from Northern Ireland are not~~.

Commented [SP2]: Scotland and Wales, but not Northern Ireland are included?

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 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

[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.

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 64,310~~939~~ observations, representing 9,04873~~9~~ individuals; the female sample has 71,03535~~5~~ observations, representing 9,6709~~7~~ individuals.[6] 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

[6] There are 238,966 observations from the 18 wave responding person data files. The 135,345 observations used in this study are reached after the following exclusions: 1,536 are excluded due to missing values of the region variable or living in Channel Islands; 5,780 observations are excluded because they were individuals who appeared in only one wave of the survey; the age restrictions exclude 57,192 observations; 8,335 observations are dropped because of missing values of the dependent variable; 10,807 observations are dropped due to missing values of explanatory variables (mostly missing education); 20,001 observations are dropped since they are the first waves of the included individuals; 30 observations are dropped due to missing values in the estimated probability of remaining in the survey, which is used for testing panel attrition bias.

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 using the BHPS, where low pay is defined as a binary variable. But they used a shorter panel of the BHPS than we do in this current study. Attrition becomes more of an issue the longer a panel survey lasts. We test and discuss attrition bias in Section 6.

~~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).~~

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.[7]

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.

5. Estimation results

The main results are shown in panel (b) of Table 3. To facilitate discussion of the results, the mean predicted transition probabilities of the sample are presented in panel (a) of Table 3. The coefficient estimates of the models can be found in Appendix Table A2.

[7] We experimented using the employment to population ratio as an alternative measure of regional labour market conditions. This is perhaps a better measure of labour demand than the unemployment rate, but the estimates on all other variables are virtually the same~~very similar~~.

Stepping stone effects

The estimates for the stepping stone effects are shown in column V of panel (b) in Table 3. 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 1~~1~~2 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 8~~7~~.6~~5~~ 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 3. 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 123 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.

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 3 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 98 percentage point lower probability of moving out of the labour force, and a 104 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. Low pay-no pay cycle implies that low paid employees are more likely to move into jobless (either unemployment or NILF) than higher pay employees. What can we learn from our estimates on this issue if we take NILF and unemployment as no-pay states? Column II of panel (b) in Table 3 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 and 0.2 percentage points for males and females respectively) 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) and Cai (2015a) for Australians. Furthermore, the results in column I of panel (b) in Table 3 indicate that for males, those who are on low pay are slightly more ~~or less equally~~ likely to transition into NILF ~~as~~than those who are on higher pay, but again this difference is not statistically significant. ~~; while~~ On the other hand, F~~f~~emales on low pay are less likely to transition into NILF than females on higher pay but~~and~~ the difference is not statistically significant either. Therefore, overall the results here do not appear to support a low pay – no pay cycle after observed and unobserved heterogeneity is accounted for.

The finding that low paid workers do not have a higher probability of becoming unemployed or moving out of the labour force than higher paid workers does not support the notion that employers may take low paid employment as a signal of low productivity. On the contrary, this result, combined with the evidence on the stepping stone effects of low pay, suggests that low paid employment helps job seekers build up skills to improve their employment prospects and opportunities in the labour market.

How do we reconcile our~~this~~ result here with those in Fok et al. (2015), which concludes that low paid workers are more likely to move into unemployment in Australia? 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. This is likely to result in sample selection bias in the estimates. 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. Indeed the magnitude of their marginal estimates is small and 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 may depend on the particular way they deal with unobserved heterogeneity.

Using also the BHPS, but with a much shorter panel, Stewart (2007) concludes that low-wage employment in the previous year has almost as large an adverse effect as unemployment in the previous on the probability of employment of the current year for the UK men. It turns out that this conclusion is based on the result that the estimate for the one-year lagged low pay dummy is not statistically significantly different from the estimate for the one-year lagged unemployment dummy in his dynamic Probit model where current unemployment status is the dependent variable. However, the partial effect estimates indicate that those who were in low-wage employment in the previous year have only a 1.5 to 2 percentage point higher probability of moving into unemployment this year than those in higher-wage employment in the previous year, depending on whether continuing spells are included or not. In contrast, the probability of being unemployed in this year conditional on being unemployed in the previous year is 3.5 to 15 percentage point higher than the probability of moving into unemployment in this year of those in higher wage employment in the previous year. In addition to a different modelling framework, Stewartd (2007) includes only labour force participants in his sample; so sample selection bias may potentially be present in his study.

The period of analysis is also relevant. In the UK a welfare-to-work programme, with the stated purpose of reducing unemployment by providing training, subsidised employment and voluntary work for the unemployed, was introduced by the new Labour government in 1998. Separate elements were the New Deal for Young People, New Deal 25 plus, New Deal for Lone Parents, New Deal for the Disabled and New Deal 50 plus. –There was also the power to withdraw benefits for those who refused offers of reasonable employment. Thus,Stafford et al. (2007) report that there was a concerted drive to get the disabled off disability benefits. Over the period July 2001 to November 2006 over 260,000 disabled persons registered under the scheme and of these 43% had found jobs by November 2006..Blundell et al. (2016) examined the case of lone mothers for whom major increases in in-work benefits or tax credits occurred between 1999 and 2002.They find that the employment rates for secondary and high school educated lone mothers increased by between 4 and 5.5 % points above the employment rates of similar single women without children. Following the introduction of the New Deals UK unemployment overall fell from 6.3% to 5.2% between Spring 1998 and Winter 2000.It seems plausible, therefore, that the introduction of these policies could explain why we do not find evidence of a low-pay-no pay cycle in our study, since the studies that do find evidence in favour cover in the main a period

before such policies were introduced, while a substantial part of our period analysed is affected by such changes.

Low pay and self-employment

Earlier studies have rarely examined the relationship between low pay and self-employment, although a substantial proportion of workers are self-employed as shown in Table 1. The model in this study provides an opportunity to look at this issue.

Interestingly the results show that for both males and females, those on loway paid employment have a higher chance (25 and 12 percentage points for males and females respectively) of 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.

The results also show that those ion low paid employment have a lower chance of moving out of the labour force than those who are self-employed, although the chance of moving into unemployment is not statistically significantly different between low paid employees and self-employed workers. Furthermore, for males self-employment appears to be stickier (i.e. less likely to move out of the state) than low paid employment, while for females the opposite appears to hold.

Heterogeneity in state-dependence and stepping stone effects

To examine heterogeneity in state-dependence and stepping effects of low paid employment, we split each gender sample by age and level of education and estimated the model separately for each of the sub-samples. ForAlong age we estimated the model separately for those under 45 years and those 45 years and over. ForAlong education levels we estimated the model for the following three groups: (a) those with a degree or higher qualification, (b) those with a non-degree qualification (i.e. A-level, O-level and other qualifications), and (c) those without qualification.

The results by age are presented in Table 4. For both males and females, the stepping stone effects of low pay relative to both NILF and unemployment appear to be much larger among those aged 45 years and over than among the younger ones. While state-dependence of low pay seems to be smaller among the older group than among the young one for males, the opposite appears to hold for females, but the differences in state-dependence of low pay between the older and the young groups do not appear to be statistically significant.

The results ~~B~~by education level are presented in Table 5.~~,~~ ~~f~~For males the stepping stone effect (state-dependence) of low pay appears to be larger (smaller) among degree holders and those without a qualification than among those with a non-degree qualification. For females the stepping stone effect of low pay is largest among those without a qualification, followed by those with a non-degree qualification, and smallest among those degree holders. While state-dependence of low pay relative to NILF and unemployment for females is largest among those without a qualification, followed by those with a non-degree qualification, and smallest among those degree holders, state-dependence of low pay relative to higher pay for females is larger among those without a qualification than among those degree holders and those with a non-degree qualification.

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.[8] 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 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 6~~5~~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

[8] 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.

period than in the second one, particularly for males, but the differences between the two periods are not statistically significant. ~~On the other hand, s~~State-dependence of low pay relative to other labour market states does not appear~~s~~ to be ~~larger in the second than in the first period for both genders, but again the differences are~~ statistically significantly different ~~insignificant~~ between the two periods either. 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.

The Great Recession and low pay dynamics

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It would be useful to know how state-dependence and stepping stone effects of low pay vary with macroeconomic conditions, in particular whether and to what extent the Great Recession changed these effects. However, the BHPS does not allow such an issue to be examined using the same data source since the BHPS stopped in 2008 when the Great Recession started. Instead, we use the first five wave Understanding Society data to re-estimate the model and calculate the estimated transition probabilities and state-dependence and stepping stone effects.[9]

The results are presented in Table 7. These results are compared with the estimates from waves 9 to 18 of the BHPS since this period was just before the Great Recession. Comparing the results, we can see that for both males and females the stepping stone effects of low pay are smaller during the Great Recession than in the earlier period, and this is mainly due to that the probability of transitioning to higher pay from low pay is much smaller during recession than in the earlier period, particularly for males.

As for state-dependence of low pay, it appears to be smaller during the Great Recession than in the earlier period for both males and females ,when low pay is compared with either NILF or unemployment. However, compared with higher pay, for males state-dependence of low pay is similar between the two periods, while for females it is slightly smaller during the Great Recession. These results are not because the probability of remaining in low pay becomes much smaller during the Great Recession; rather, it is because the probability of transitioning to low pay from higher pay has increased from the second period of the BHPS to the Great Recession.

[9] We use the entire Understanding Society sample rather than the BHPS sample in the Understanding Society because the BHPS sample were not invited to join the Understanding Society until wave 2 and less than 6,700 of the over 8000 BHPS sample invited to join did so.

6. Attribution bias

To test for attrition bias, we use the simple variable-addition tests as suggested by Verbeek and Nijman (1992). We use the following test variables: (a) an indicator of~~n~~ whether attrition occurred in the following wave (attrition indicator); (b) a variable on the proportion of time an individual responded to the survey since he/she first entered the survey; ~~number of waves that the individual is observed in the survey~~ (prop time responding~~number of waves~~); and (c) an indicator on whether the individual is in the survey all the time~~balanced sample~~ (~~balance~~all time indicator).[10] The estimates for these variables are presented in Table 8~~6~~. From the table there is evidence of attrition bias as about half of these variables are statistically significant. Nonetheless, the coefficient estimates of these variable-addition models are very similar to those of the main model. As a result, the simulated transition matrices and the estimates on state-dependence and stepping stone effects of low pay are very similar as well.[11]

The variable-addition models are for testing the presence of potential attrition bias rather than for correcting the bias. To further investigate attribution bias, we adopt an inverse probability weighted estimator proposed by Wooldridge (2002~~b,c~~) and recently applied in Contoyannis, Jones, and Rice (2004) and Clark and Kanellopoulos (2013). ~~However,~~It should be noted that such an estimator can only be applied to a pooled model that does not account for unobserved individual heterogeneity (Contoyannis, Jones, and Rice, 2004). In our case it is equivalent to estimating a multinomial logit model using the pooled data and the log-likelihood function of each observation is weighted by the inverse of an estimated probability of responding to the survey in each wave. The estimates from the weighted model are compared with the estimates from an unweighted model also applied to the pooled data to assess attrition bias.

This comparison does not provide a precise measure of attrition bias for the main model that

[10] The test variables (b) and (c) are a variation to what Verbeek and Nijman (1992) propose to reflect the fact that some individuals entered the survey later (i.e. after the first wave in 1991), as discussed in Section 4. The variable (b) is equivalent to the variable on the total number of waves an individual responded to the survey that is proposed by Verbeek and Nijman (1992); and the variable (c) is equivalent to the variable indicating if an individual is in the balanced panel that is proposed by Verbeek and Nijman (1992). The basic rationale for Verbeek and Nijman (1992) to propose the two variables is that they are a function of the indicator whether an individual responds to the survey in each wave. The two equivalent variables (b) and (c) in this study meet this requirement as well.

[11] These results are not presented in the paper, but can be obtained from authors on request.

accounts for unobserved individual heterogeneity, but it can be regarded as an upper bound estimate of the bias. This is because attrition bias in the main model should not be larger than in the pooled model since the main model may correct for attrition bias to some extent if attrition is affected by unobserved heterogeneity as well.

To obtain the probability of responding to the survey, we estimate Probit equations for responding to the survey versus attrition for each wave from the second wave conditional on a set of variables measured at the first wave. The set of variables includes those used in the main model as well as additional variables on general health of an individual and the total number of calls to the household for the survey. These additional variables are expected to predict attrition.

~~Inconsistent with~~Despite the evidence from the variable-addition models in Table 8, the inverse probability weighted estimator ~~does not~~ shows little evidence of attrition bias. The coefficient estimates are very similar between the weighted and unweighted models, as shown in the appendix Table A3~~xx~~. A Hausman test cannot reject the hypothesis that the two sets of coefficient estimates are equal.[12] Importantly the simulated transition probabilities and estimated state-dependence and stepping stone effects of low pay are ~~very~~ similar as well between the two models, as shown in ~~(see~~ Table 9~~Axx in the appendix)~~. Therefore, the overall evidence suggests that attrition bias is not a serious issue even if it may be present.

~~6.~~7. 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. However, it is also the case that, other things being equal, those who are on low pay are more

[12] The test statistics χ^2= 124.21for males; χ^2= 116.44 for females, both with degree of freedom 192.

likely to move into higher pay in the future than those who are either not in the labour force or unemployed.

There is also evidence that there is heterogeneity in the stepping stone effects of low pay. The effects tend to be larger for old people than the younger ones. And the effects appear to be larger for those with a non-degree qualification than among degree holders and those without a qualification.

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.

It would be interesting to see how the dynamics of low pay varied during the Great Financial Crisis (GFC). However, the data used for this study do not cover the period. Future research could examine this issue by combining different data sources such as the BHPS and the Understanding Society. Another limitation of the current study is that the modelling framework could not examine the effects of job characteristics on the dynamics of low pay because information on these variables is missing for those who are not employed. This issue may be picked up in future research using a different modelling framework.

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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**					**Number of observations**
	Not in labour force	Unemploy-ment	Self-employment	Low pay	Higher pay	
	Males					
Not in labour force	87.56	5.39	1.85	1.95	3.25	6,606
Unemployment	14.96	48.38	6.02	12.07	18.57	3,704
Self-employment	1.98	1.89	84.92	4.75	6.46	8,899
Low pay	2.56	5.79	7.52	43.79	40.33	5,889
Higher pay	1.58	1.85	1.93	4.29	90.35	37,571
All	11.58	5.35	14.47	8.28	60.32	62,669
	Females					
Not in labour force	81.69	3.19	1.51	6.78	6.82	17,940
Unemployment	35.84	27.65	2.14	17.14	17.23	2,246
Self-employment	8.08	1.63	74.27	8.48	7.53	3,253
Low pay	8.58	2.68	2.56	59.99	26.19	13,155
Higher pay	4.97	1.17	0.85	7.88	85.13	32,703
All	26.66	2.86	4.83	17.82	47.82	69,297

Table 3: Model estimated transition probabilities, state-dependence and stepping stone effects

Males

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

		Labour/earnings state, t				
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay
(1)	NILF	0.2492	0.0999	0.1279	0.0865	0.4365
	s.e.	*0.021*	*0.035*	*0.036*	*0.020*	*0.041*
(2)	Unemploy	0.161	0.155	0.134	0.110	0.440
	s.e.	*0.016*	*0.050*	*0.035*	*0.026*	*0.045*
(3)	Self-employ	0.098	0.063	0.396	0.141	0.303
	s.e.	*0.014*	*0.036*	*0.072*	*0.029*	*0.056*
(4)	Low pay	0.073	0.052	0.123	0.196	0.556
	s.e.	*0.009*	*0.036*	*0.033*	*0.039*	*0.052*
(5)	Higher pay	0.067	0.048	0.058	0.071	0.756
	s.e.	*0.007*	*0.026*	*0.027*	*0.017*	*0.040*

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

		I	II	III	IV	V
(6)	=(4)-(1)	-0.177	-0.048	-0.005	0.109	0.119
	s.e.	*0.013*	*0.014*	*0.012*	*0.020*	*0.022*
(7)	=(4)-(2)	-0.088	-0.103	-0.011	0.085	0.116
	s.e.	*0.012*	*0.050*	*0.014*	*0.021*	*0.036*
(8)	=(4)-(3)	-0.026	-0.010	-0.273	0.055	0.253
	s.e.	*0.007*	*0.019*	*0.045*	*0.026*	*0.028*
(9)	=(4)-(5)	0.006	0.004	0.066	0.125	-0.200
	s.e.	*0.004*	*0.017*	*0.011*	*0.023*	*0.022*

Females

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

		Labour/earnings state, t				
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay
(1)	NILF	0.431	0.046	0.040	0.147	0.337
	s.e.	*0.024*	*0.020*	*0.011*	*0.026*	*0.022*
(2)	Unemploy	0.340	0.105	0.038	0.174	0.343
	s.e.	*0.026*	*0.046*	*0.016*	*0.028*	*0.026*
(3)	Self-employ	0.244	0.045	0.184	0.223	0.304
	s.e.	*0.027*	*0.038*	*0.043*	*0.040*	*0.032*
(4)	Low pay	0.167	0.028	0.044	0.333	0.428
	s.e.	*0.017*	*0.019*	*0.014*	*0.046*	*0.034*
(5)	Higher pay	0.181	0.027	0.023	0.151	0.619
	s.e.	*0.015*	*0.016*	*0.009*	*0.032*	*0.034*

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

		I	II	III	IV	V
(6)	=(4)-(1)	-0.264	-0.017	0.004	0.186	0.091
	s.e.	*0.011*	*0.005*	*0.008*	*0.022*	*0.018*
(7)	=(4)-(2)	-0.172	-0.077	0.006	0.159	0.085
	s.e.	*0.016*	*0.030*	*0.009*	*0.031*	*0.021*
(8)	=(4)-(3)	-0.077	-0.017	-0.141	0.111	0.124
	s.e.	*0.018*	*0.021*	*0.040*	*0.024*	*0.024*
(9)	=(4)-(5)	-0.013	0.002	0.021	0.182	-0.191
	s.e.	*0.008*	*0.007*	*0.010*	*0.020*	*0.018*

Table 4: Estimation by age

	Males	**Aged 18-44 years**					**Aged 45 plus**				
		(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1									
		Labour/earnings state, t									
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	Highe pay
(1)	NILF	0.110	0.114	0.122	0.105	0.550	0.437	0.073	0.128	0.066	0.29
	s.e.	0.018	0.063	0.047	0.032	0.063	0.046	0.068	0.071	0.023	0.04
(2)	Unemploy	0.056	0.152	0.119	0.125	0.549	0.318	0.180	0.148	0.080	0.27
	s.e.	0.014	0.098	0.044	0.047	0.070	0.045	0.107	0.072	0.031	0.05
(3)	Self-employ	0.034	0.068	0.374	0.154	0.371	0.172	0.049	0.494	0.124	0.16
	s.e.	0.008	0.054	0.093	0.051	0.080	0.038	0.079	0.112	0.042	0.05
(4)	Low pay	0.022	0.051	0.108	0.215	0.605	0.156	0.046	0.163	0.162	0.47
	s.e.	0.004	0.050	0.038	0.046	0.067	0.029	0.070	0.072	0.060	0.07
(5)	Higher pay	0.021	0.055	0.052	0.076	0.796	0.136	0.035	0.046	0.056	0.72
	s.e.	0.005	0.061	0.028	0.023	0.064	0.019	0.051	0.045	0.027	0.06
		(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)									
		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.088	-0.063	-0.014	0.110	0.055	-0.281	-0.027	0.035	0.096	0.17
	s.e.	0.014	0.029	0.017	0.018	0.023	0.024	0.038	0.027	0.041	0.04
(7)	=(4)-(2)	-0.034	-0.101	-0.011	0.090	0.056	-0.162	-0.134	0.015	0.082	0.19
	s.e.	0.012	0.080	0.020	0.026	0.050	0.040	0.083	0.034	0.046	0.07
(8)	=(4)-(3)	-0.012	-0.017	-0.266	0.061	0.234	-0.016	-0.003	-0.331	0.038	0.31
	s.e.	0.006	0.038	0.065	0.028	0.047	0.018	0.040	0.061	0.055	0.04
(9)	=(4)-(5)	0.001	-0.004	0.056	0.139	-0.191	0.020	0.011	0.116	0.106	-0.25
	s.e.	0.002	0.029	0.017	0.026	0.034	0.014	0.034	0.037	0.037	0.04

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

	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	Highe pay
(1)	NILF	0.343	0.049	0.041	0.166	0.401	0.624	0.038	0.049	0.103	0.18
	s.e.	0.025	0.023	0.019	0.032	0.027	0.070	0.051	0.052	0.041	0.04
(2)	Unemploy	0.295	0.117	0.027	0.189	0.373	0.446	0.088	0.048	0.148	0.27
	s.e.	0.032	0.059	0.031	0.033	0.033	0.059	0.062	0.035	0.051	0.05
(3)	Self-employ	0.229	0.026	0.221	0.223	0.302	0.317	0.049	0.296	0.180	0.16
	s.e.	0.028	0.030	0.047	0.045	0.038	0.077	0.075	0.145	0.075	0.06
(4)	Low pay	0.154	0.032	0.038	0.329	0.446	0.185	0.024	0.054	0.332	0.40
	s.e.	0.022	0.022	0.026	0.058	0.046	0.042	0.072	0.046	0.091	0.07
(5)	Higher pay	0.179	0.025	0.017	0.139	0.640	0.155	0.030	0.014	0.172	0.62
	s.e.	0.017	0.019	0.013	0.036	0.035	0.036	0.035	0.023	0.062	0.08
		(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)									
		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.189	-0.017	-0.003	0.163	0.046	-0.439	-0.015	0.005	0.229	0.22
	s.e.	0.009	0.007	0.010	0.030	0.024	0.038	0.034	0.021	0.057	0.04
(7)	=(4)-(2)	-0.140	-0.085	0.011	0.140	0.074	-0.261	-0.064	0.006	0.184	0.13
	s.e.	0.018	0.040	0.015	0.048	0.028	0.031	0.040	0.029	0.050	0.04
(8)	=(4)-(3)	-0.074	0.006	-0.183	0.106	0.145	-0.131	-0.025	-0.242	0.153	0.24
	s.e.	0.016	0.017	0.038	0.030	0.029	0.057	0.033	0.112	0.059	0.05
(9)	=(4)-(5)	-0.025	0.008	0.021	0.190	-0.194	0.030	-0.007	0.040	0.160	-0.22
	s.e.	0.010	0.009	0.020	0.033	0.030	0.023	0.045	0.027	0.045	0.04

Table 5: Estimation by education

		Males					**Females**				
		Degree or higher					**Degree or higher**				
		(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1									
		Labour/earnings state, t									
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	Higher pay
(1)	NILF	0.188	0.076	0.120	0.082	0.533	0.295	0.049	0.058	0.115	0.48
	s.e.	0.020	0.082	0.047	0.033	0.054	0.024	0.042	0.031	0.033	0.03
(2)	Unemploy	0.130	0.115	0.156	0.086	0.514	0.221	0.088	0.080	0.124	0.48
	s.e.	0.021	0.142	0.057	0.036	0.090	0.025	0.053	0.044	0.040	0.05
(3)	Self-employ	0.069	0.051	0.440	0.095	0.346	0.156	0.039	0.260	0.162	0.38
	s.e.	0.011	0.090	0.093	0.032	0.059	0.024	0.089	0.069	0.052	0.05
(4)	Low pay	0.044	0.028	0.125	0.142	0.662	0.103	0.017	0.062	0.261	0.55
	s.e.	0.007	0.058	0.037	0.049	0.061	0.013	0.034	0.036	0.047	0.04
(5)	Higher pay	0.039	0.025	0.046	0.048	0.842	0.111	0.014	0.024	0.089	0.76
	s.e.	0.005	0.073	0.036	0.025	0.059	0.015	0.031	0.026	0.038	0.04
		(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)									
		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.144	-0.049	0.005	0.060	0.128	-0.191	-0.031	0.004	0.146	0.07
	s.e.	0.015	0.043	0.029	0.020	0.038	0.014	0.016	0.015	0.022	0.02
(7)	=(4)-(2)	-0.086	-0.088	-0.031	0.056	0.148	-0.118	-0.070	-0.018	0.138	0.06
	s.e.	0.019	0.127	0.037	0.028	0.093	0.019	0.042	0.025	0.028	0.03
(8)	=(4)-(3)	-0.024	-0.023	-0.315	0.046	0.316	-0.052	-0.021	-0.198	0.099	0.17
	s.e.	0.007	0.062	0.075	0.033	0.042	0.016	0.064	0.056	0.034	0.03
(9)	=(4)-(5)	0.005	0.003	0.079	0.094	-0.181	-0.007	0.003	0.038	0.172	-0.20
	s.e.	0.005	0.064	0.025	0.029	0.065	0.009	0.012	0.021	0.022	0.02
		Other qualification					**Other qualification**				
		(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1									
		Labour/earnings state, t									

	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	Highe pay
(1)	NILF	0.249	0.105	0.128	0.087	0.432	0.441	0.039	0.037	0.186	0.29
	s.e.	0.043	0.065	0.064	0.043	0.064	0.047	0.029	0.021	0.041	0.03
(2)	Unemploy	0.147	0.162	0.131	0.126	0.433	0.353	0.098	0.027	0.206	0.31
	s.e.	0.033	0.095	0.074	0.065	0.079	0.043	0.052	0.043	0.036	0.03
(3)	Self-employ	0.074	0.060	0.353	0.196	0.318	0.278	0.052	0.169	0.244	0.25
	s.e.	0.022	0.059	0.124	0.115	0.071	0.053	0.055	0.058	0.056	0.04
(4)	Low pay	0.059	0.053	0.129	0.243	0.516	0.169	0.033	0.040	0.367	0.39
	s.e.	0.016	0.077	0.061	0.069	0.077	0.036	0.031	0.028	0.068	0.05
(5)	Higher pay	0.061	0.052	0.075	0.078	0.734	0.173	0.039	0.021	0.173	0.59
	s.e.	0.019	0.110	0.065	0.035	0.107	0.034	0.039	0.025	0.047	0.06

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

		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.190	-0.052	0.002	0.156	0.084	-0.272	-0.006	0.002	0.181	0.09
	s.e.	0.029	0.037	0.017	0.035	0.038	0.016	0.010	0.012	0.030	0.02
(7)	=(4)-(2)	-0.088	-0.110	-0.001	0.117	0.082	-0.184	-0.065	0.012	0.161	0.07
	s.e.	0.021	0.088	0.027	0.035	0.055	0.026	0.037	0.033	0.056	0.03
(8)	=(4)-(3)	-0.015	-0.007	-0.224	0.047	0.198	-0.109	-0.019	-0.129	0.123	0.13
	s.e.	0.010	0.042	0.076	0.065	0.041	0.027	0.030	0.041	0.033	0.03
(9)	=(4)-(5)	-0.002	0.001	0.054	0.165	-0.219	-0.004	-0.006	0.019	0.194	-0.20
	s.e.	0.006	0.050	0.019	0.038	0.050	0.013	0.015	0.027	0.047	0.03

No qualification **No qualification**

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

Labour/earnings state, t

	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	Highe pay
(1)	NILF	0.427	0.155	0.110	0.106	0.203	0.697	0.052	0.018	0.147	0.08
	s.e.	0.114	0.114	0.090	0.058	0.074	0.157	0.093	0.112	0.083	0.04
(2)	Unemploy	0.297	0.230	0.103	0.132	0.238	0.556	0.135	0.022	0.181	0.10
	s.e.	0.083	0.171	0.167	0.100	0.082	0.171	0.153	0.112	0.098	0.04

(3)	Self-employ	0.201	0.139	0.332	0.161	0.167	0.399	0.185	0.091	0.234	0.09
	s.e.	0.086	0.176	0.170	0.108	0.092	0.154	0.293	0.295	0.101	0.04
(4)	Low pay	0.198	0.107	0.104	0.229	0.363	0.325	0.038	0.025	0.415	0.19
	s.e.	0.079	0.146	0.120	0.109	0.128	0.112	0.085	0.143	0.144	0.09
(5)	Higher pay	0.167	0.100	0.052	0.129	0.552	0.275	0.054	0.014	0.296	0.36
	s.e.	0.062	0.093	0.090	0.085	0.137	0.103	0.076	0.140	0.099	0.13
	(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)										
		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.229	-0.049	-0.005	0.123	0.160	-0.372	-0.014	0.007	0.268	0.11
	s.e.	0.041	0.059	0.072	0.059	0.069	0.068	0.048	0.051	0.079	0.05
(7)	=(4)-(2)	-0.100	-0.123	0.002	0.097	0.125	-0.231	-0.097	0.003	0.234	0.09
	s.e.	0.065	0.236	0.103	0.062	0.081	0.078	0.089	0.079	0.077	0.05
(8)	=(4)-(3)	-0.003	-0.032	-0.228	0.068	0.195	-0.074	-0.147	-0.066	0.180	0.10
	s.e.	0.031	0.088	0.155	0.114	0.066	0.117	0.323	0.181	0.123	0.07
(9)	=(4)-(5)	0.030	0.006	0.052	0.100	-0.189	0.050	-0.016	0.011	0.119	-0.16
	s.e.	0.031	0.083	0.054	0.060	0.074	0.046	0.034	0.045	0.078	0.07

Table 6: NMWs and low pay dynamics

	Males	**Wave 1-8**					**Wave 9-18**				
		(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1									
		Labour/earnings state, t									
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	Hig pa
(1)	NILF	0.208	0.149	0.103	0.070	0.469	0.247	0.072	0.138	0.090	0.4
	s.e.	0.039	0.105	0.056	0.035	0.081	0.020	0.031	0.036	0.022	0.0
(2)	Unemploy	0.130	0.177	0.128	0.091	0.475	0.172	0.113	0.140	0.116	0.4
	s.e.	0.028	0.157	0.070	0.054	0.094	0.019	0.042	0.038	0.028	0.0
(3)	Self-employ	0.074	0.087	0.460	0.084	0.294	0.107	0.051	0.329	0.161	0.3
	s.e.	0.024	0.106	0.109	0.045	0.086	0.012	0.031	0.055	0.046	0.0
(4)	Low pay	0.063	0.055	0.103	0.187	0.593	0.081	0.046	0.132	0.178	0.5
	s.e.	0.015	0.127	0.062	0.075	0.102	0.009	0.028	0.033	0.033	0.0
(5)	Higher pay	0.066	0.058	0.050	0.068	0.759	0.078	0.044	0.073	0.077	0.7
	s.e.	0.013	0.075	0.039	0.034	0.080	0.007	0.026	0.030	0.021	0.0
		(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)									
		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.146	-0.095	0.000	0.117	0.124	-0.166	-0.026	-0.006	0.089	0.1
	s.e.	0.026	0.055	0.025	0.045	0.041	0.013	0.013	0.014	0.017	0.0
(7)	=(4)-(2)	-0.068	-0.123	-0.025	0.096	0.118	-0.091	-0.066	-0.008	0.062	0.1
	s.e.	0.028	0.219	0.047	0.071	0.114	0.013	0.025	0.017	0.019	0.0
(8)	=(4)-(3)	-0.012	-0.033	-0.357	0.103	0.299	-0.026	-0.005	-0.197	0.017	0.2
	s.e.	0.013	0.068	0.067	0.044	0.062	0.007	0.018	0.036	0.031	0.0
(9)	=(4)-(5)	-0.004	-0.003	0.053	0.119	-0.166	0.003	0.003	0.059	0.101	-0.1
	s.e.	0.007	0.072	0.036	0.047	0.048	0.005	0.017	0.015	0.017	0.0

	Females	(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1									
		Labour/earnings state, t									
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	Hig pa

(1)	NILF	0.407	0.044	0.036	0.170	0.344	0.399	0.044	0.042	0.141	0.3
	s.e.	0.047	0.053	0.033	0.056	0.038	0.030	0.029	0.012	0.025	0.0
(2)	Unemploy	0.316	0.103	0.039	0.175	0.368	0.345	0.090	0.034	0.161	0.3
	s.e.	0.046	0.082	0.036	0.053	0.048	0.029	0.047	0.021	0.026	0.0
(3)	Self-employ	0.275	0.050	0.167	0.185	0.323	0.241	0.033	0.165	0.235	0.3
	s.e.	0.050	0.081	0.086	0.070	0.054	0.030	0.040	0.039	0.041	0.0
(4)	Low pay	0.186	0.027	0.040	0.320	0.428	0.175	0.028	0.045	0.305	0.4
	s.e.	0.037	0.051	0.042	0.082	0.056	0.022	0.028	0.015	0.046	0.0
(5)	Higher pay	0.194	0.036	0.026	0.164	0.580	0.195	0.024	0.024	0.152	0.6
	s.e.	0.033	0.047	0.028	0.057	0.053	0.018	0.025	0.010	0.028	0.0
		(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)									
		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.221	-0.017	0.004	0.150	0.083	-0.225	-0.017	0.004	0.164	0.0
	s.e.	0.018	0.021	0.015	0.033	0.025	0.012	0.008	0.006	0.024	0.0
(7)	=(4)-(2)	-0.130	-0.076	0.001	0.145	0.060	-0.170	-0.062	0.011	0.144	0.0
	s.e.	0.022	0.054	0.036	0.046	0.030	0.017	0.035	0.022	0.031	0.0
(8)	=(4)-(3)	-0.089	-0.024	-0.127	0.135	0.104	-0.067	-0.006	-0.120	0.070	0.1
	s.e.	0.030	0.041	0.057	0.039	0.037	0.015	0.018	0.030	0.024	0.0
(9)	=(4)-(5)	-0.008	-0.009	0.014	0.156	-0.152	-0.021	0.003	0.021	0.153	-0.1
	s.e.	0.013	0.016	0.023	0.034	0.030	0.008	0.009	0.007	0.023	0.0

Table 7: Estimation results using the Understanding Society data

Males

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

		Labour/earnings state, t				
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay
(1)	NILF	0.106	0.070	0.173	0.239	0.412
	s.e.	0.042	0.171	0.076	0.099	0.113
(2)	Unemploy	0.069	0.129	0.169	0.202	0.432
	s.e.	0.035	0.200	0.075	0.100	0.131
(3)	Self-employ	0.075	0.052	0.270	0.237	0.367
	s.e.	0.035	0.153	0.110	0.108	0.122
(4)	Low pay	0.059	0.046	0.151	0.272	0.472
	s.e.	0.025	0.162	0.071	0.107	0.120
(5)	Higher pay	0.062	0.049	0.127	0.160	0.601
	s.e.	0.024	0.153	0.061	0.078	0.127

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

		I	II	III	IV	V
(6)	=(4)-(1)	-0.047	-0.024	-0.022	0.032	0.060
	s.e.	0.019	0.036	0.017	0.023	0.027
(7)	=(4)-(2)	-0.010	-0.083	-0.017	0.070	0.041
	s.e.	0.014	0.070	0.027	0.031	0.041
(8)	=(4)-(3)	-0.016	-0.006	-0.118	0.034	0.106
	s.e.	0.013	0.047	0.055	0.041	0.042
(9)	=(4)-(5)	-0.003	-0.004	0.024	0.112	-0.129
	s.e.	0.006	0.033	0.024	0.035	0.037

Females

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

		Labour/earnings state, t				
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay
(1)	NILF	0.3262	0.0627	0.0589	0.1798	0.3723
	s.e.	0.0336	0.0251	0.0277	0.0389	0.0342
(2)	Unemploy	0.2935	0.1305	0.0556	0.164	0.3564
	s.e.	0.0387	0.0437	0.0285	0.043	0.0391
(3)	Self-employ	0.2349	0.0387	0.1473	0.2761	0.303
	s.e.	0.0313	0.0214	0.053	0.0573	0.042
(4)	Low pay	0.2133	0.036	0.0633	0.2894	0.398
	s.e.	0.0279	0.0197	0.034	0.0525	0.0437
(5)	Higher pay	0.2706	0.0334	0.0382	0.1815	0.4763
	s.e.	0.0262	0.0183	0.0211	0.0359	0.0328

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

		I	II	III	IV	V
(6)	=(4)-(1)	-0.1129	-0.0267	0.0044	0.1096	0.0257
	s.e.	0.0121	0.0138	0.0111	0.0219	0.0155
(7)	=(4)-(2)	-0.0802	-0.0945	0.0076	0.1255	0.0416
	s.e.	0.0198	0.0299	0.0135	0.0285	0.0223
(8)	=(4)-(3)	-0.0216	-0.0026	-0.0841	0.0134	0.0949
	s.e.	0.017	0.0184	0.0298	0.0284	0.0224
(9)	=(4)-(5)	-0.0573	0.0027	0.025	0.1079	-0.0784
	s.e.	0.0096	0.0097	0.0151	0.023	0.0185

Table 8: Variable-addition test results

	Unemploy	Self-employ	Low-pay	Higher-pay
	Males			
Attrition indicator	0.074	-0.226*	-0.180	-0.219*
s.e.	0.118	0.134	0.123	0.115
Prop time responding	0.063	-0.221*	-0.183	-0.233**
s.e.	0.118	0.133	0.121	0.115
All time indicator	-0.360***	-0.218**	-0.240***	-0.122
s.e.	0.088	0.099	0.086	0.084
	Females			
Attrition indicator	0.243**	-0.293**	-0.049	-0.134*
s.e.	0.100	0.140	0.080	0.081
Prop time responding	0.247**	-0.286**	-0.047	-0.124
s.e.	0.100	0.140	0.080	0.081
All time indicator	-0.335***	-0.293***	-0.004	-0.087
s.e.	0.065	0.098	0.054	0.056

*** indicates significant at 1%; ** 5%; and * 10% respectively.

Table 9: Comparison between unweighted and weighted results from pooled models

	Males	**Unweighted**					**Weighted**				
		(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1									
		Labour/earnings state, t									
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	High pa
(1)	NILF	0.402	0.096	0.089	0.074	0.339	0.402	0.099	0.093	0.078	0.3
	s.e.	0.031	0.032	0.025	0.013	0.030	0.018	0.016	0.014	0.012	0.0
(2)	Unemploy	0.161	0.294	0.104	0.118	0.323	0.165	0.271	0.097	0.124	0.3
	s.e.	0.020	0.057	0.028	0.023	0.040	0.012	0.038	0.013	0.022	0.0
(3)	Self-employ	0.046	0.036	0.736	0.075	0.107	0.050	0.035	0.736	0.075	0.1
	s.e.	0.011	0.017	0.053	0.020	0.032	0.006	0.008	0.027	0.010	0.0
(4)	Low pay	0.047	0.052	0.095	0.326	0.481	0.046	0.056	0.095	0.325	0.4
	s.e.	0.007	0.028	0.024	0.033	0.044	0.003	0.013	0.014	0.024	0.0
(5)	Higher pay	0.042	0.031	0.024	0.055	0.848	0.041	0.034	0.024	0.054	0.8
	s.e.	0.005	0.017	0.012	0.011	0.026	0.004	0.009	0.006	0.010	0.0
		(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)									
		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.355	-0.045	0.006	0.252	0.142	-0.356	-0.043	0.002	0.248	0.1
	s.e.	0.025	0.014	0.010	0.023	0.027	0.015	0.013	0.017	0.018	0.0
(7)	=(4)-(2)	-0.114	-0.242	-0.010	0.208	0.158	-0.120	-0.216	-0.002	0.202	0.1
	s.e.	0.016	0.053	0.014	0.022	0.033	0.010	0.035	0.013	0.021	0.0
(8)	=(4)-(3)	0.001	0.016	-0.641	0.251	0.374	-0.004	0.021	-0.641	0.250	0.3
	s.e.	0.007	0.018	0.041	0.025	0.035	0.004	0.012	0.027	0.019	0.0
(9)	=(4)-(5)	0.005	0.021	0.071	0.270	-0.368	0.005	0.022	0.071	0.271	-0.3
	s.e.	0.004	0.015	0.014	0.025	0.026	0.003	0.010	0.014	0.019	0.0
	Females	(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1									

		Labour/earnings state, t									
	Labour/earnings state, t-1	NILF	Unemploy	Self-employ	Low pay	Higher pay	NILF	Unemploy	Self-employ	Low pay	High pa
(1)	NILF	0.594	0.046	0.028	0.113	0.219	0.600	0.047	0.028	0.109	0.2
	s.e.	0.027	0.017	0.012	0.021	0.015	0.016	0.011	0.006	0.012	0.0
(2)	Unemploy	0.369	0.175	0.031	0.180	0.246	0.380	0.171	0.031	0.178	0.2
	s.e.	0.032	0.040	0.013	0.026	0.023	0.020	0.033	0.008	0.018	0.0
(3)	Self-employ	0.142	0.030	0.588	0.128	0.112	0.137	0.031	0.591	0.133	0.1
	s.e.	0.027	0.021	0.077	0.035	0.025	0.016	0.013	0.048	0.021	0.0
(4)	Low pay	0.115	0.028	0.032	0.496	0.329	0.118	0.028	0.033	0.497	0.3
	s.e.	0.015	0.013	0.014	0.044	0.031	0.007	0.007	0.008	0.026	0.0
(5)	Higher pay	0.105	0.018	0.010	0.110	0.757	0.105	0.018	0.010	0.110	0.7
	s.e.	0.010	0.010	0.007	0.019	0.022	0.005	0.005	0.003	0.011	0.0
		(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)									
		I	II	III	IV	V	I	II	III	IV	V
(6)	=(4)-(1)	-0.479	-0.018	0.004	0.383	0.110	-0.482	-0.019	0.005	0.387	0.1
	s.e.	0.015	0.007	0.006	0.026	0.024	0.010	0.005	0.003	0.015	0.0
(7)	=(4)-(2)	-0.254	-0.147	0.001	0.317	0.084	-0.262	-0.144	0.002	0.319	0.0
	s.e.	0.021	0.031	0.008	0.026	0.022	0.016	0.027	0.004	0.014	0.0
(8)	=(4)-(3)	-0.028	-0.002	-0.556	0.369	0.218	-0.020	-0.003	-0.558	0.363	0.2
	s.e.	0.024	0.016	0.071	0.032	0.032	0.015	0.010	0.045	0.020	0.0
(9)	=(4)-(5)	0.010	0.010	0.022	0.387	-0.428	0.012	0.010	0.023	0.387	-0.4
	s.e.	0.009	0.005	0.009	0.027	0.017	0.005	0.003	0.006	0.016	0.0

Table A1: Summary statistics

	All	Out of labour force	Unemployed	Self-employed	Low-paid	Higher paid
		Males				
Out of labour force, t-1	12.82	80.10	16.21	3.27	6.18	2.84
Unemployed, t-1	5.76	7.48	50.11	2.41	8.29	1.78
Self-employed, t-1	13.84	2.38	4.70	81.68	7.84	1.49
Low pay, t-1	9.16	2.04	9.54	4.79	47.82	6.14
Higher pay, t-1	58.42	8.00	19.44	7.85	29.87	87.75
Age 18-24	8.76	1.80	21.36	3.05	27.05	7.74
Age 25-34	23.50	6.19	25.67	19.15	24.44	27.52
Age 35-44	26.53	12.93	21.48	28.60	17.75	30.34
Age 45-54	22.86	21.94	17.59	28.17	16.09	23.19
Age 55 plus	18.35	57.14	13.90	21.03	14.67	11.21
1st degree or higher	15.70	7.46	8.11	13.08	7.68	19.73
Other higher degree	31.26	22.26	20.02	30.74	24.01	35.15
A-level(s)	12.80	10.97	10.79	12.96	14.70	13.03
O-level(s)	16.81	13.33	18.18	18.93	20.23	16.36
Other qualifications	7.58	9.73	10.49	8.15	10.62	6.34
No qualification	15.85	36.25	32.41	16.14	22.76	9.39
Married or partnered	74.86	71.32	54.53	81.96	58.48	78.00
Disability	12.84	56.04	20.22	7.18	9.57	5.70
London	6.76	5.11	7.91	7.44	4.45	7.12
South East	10.47	6.48	7.77	12.19	6.73	11.59
Other regions	82.77	88.41	84.32	80.37	88.82	81.29
Unemployment rate	6.25	6.21	6.97	6.19	6.15	6.22
Youngest child 0-2	10.85	2.96	12.78	11.37	9.98	12.18
Youngest child 3-4	4.70	1.77	4.22	4.93	3.50	5.41
Youngest child 5-11	11.86	6.39	9.42	14.29	7.66	13.14
Youngest child 12-16	7.22	5.48	5.48	8.84	4.91	7.65
Youngest child 17-18	2.45	1.97	1.87	3.20	1.46	2.55
No children under 19	62.92	81.43	66.23	57.37	72.49	59.07
Total children under 19	0.67	0.36	0.66	0.82	0.50	0.72
Number of observations	64,310	7,403	3,576	9,252	5,393	38,686
		Females				
Out of labour force, t-1	27.70	79.78	33.50	9.78	12.32	5.89
Unemployed, t-1	3.16	4.26	29.29	1.41	3.03	1.14
Self-employed, t-1	4.58	1.39	2.50	70.79	2.17	0.72
Low pay, t-1	18.52	5.97	16.60	9.87	62.18	10.16
Higher pay, t-1	46.04	8.60	18.11	8.15	20.30	82.09
Age 18-24	9.03	6.61	20.33	2.64	14.73	8.19
Age 25-34	25.54	24.69	25.00	20.60	21.20	28.17
Age 35-44	28.56	24.38	22.97	34.07	28.30	30.77
Age 45-54	24.34	22.42	22.03	31.09	24.90	24.66
Age 55 plus	12.53	21.90	9.67	11.60	10.87	8.21

1st degree or higher	14.26	7.13	8.96	20.39	4.33	21.66
Other higher degree	27.02	18.07	19.25	34.84	23.76	32.93
A-level(s)	11.24	8.91	11.79	11.49	12.50	12.01
O-level(s)	21.22	21.74	22.41	16.85	24.57	20.05
Other qualifications	8.99	12.28	11.65	7.53	11.24	6.29
No qualification	17.27	31.87	25.94	8.90	23.60	7.06
Married or partnered	73.58	75.69	46.70	79.99	72.24	73.94
Disability	14.03	30.17	20.42	9.93	9.57	6.71
London	6.76	5.54	9.20	9.52	2.92	8.44
South East	10.79	8.72	10.33	12.77	10.24	11.97
Other regions	82.45	85.74	80.47	77.71	86.84	79.59
Unemployment rate	6.24	6.27	6.55	6.16	6.18	6.23
Youngest child 0-2	12.45	23.50	10.14	9.43	7.82	8.48
Youngest child 3-4	6.12	8.54	5.75	6.01	5.58	5.01
Youngest child 5-11	17.04	16.58	14.29	18.90	20.63	15.93
Youngest child 12-16	10.63	8.10	8.63	12.07	13.05	11.11
Youngest child 17-18	3.36	2.62	2.88	3.34	4.05	3.54
No children under 19	50.40	40.66	58.31	50.25	48.87	55.93
Total children under 19	0.92	1.22	0.73	0.95	0.94	0.75
Number of observations	71,035	18,897	2,120	3,413	12,692	33,913

Table a2: Coefficient estimates

	Unweighted				Weighted			
	Unemploy	Self-employ	Low-pay	Higher-pay	Unemploy	Self-employ	Low-pay	Higher-pay
Males								
Unemployed, t-1	1.498***	1.052***	1.280***	0.978***	0.666***	0.615***	0.899***	0.830***
Self-employed, t-1	1.473***	4.153***	2.722***	1.710***	0.929***	3.072***	1.984***	1.221***
Low pay, t-1	1.859***	2.847***	3.810***	3.298***	1.445***	2.282***	2.851***	2.918***
Higher pay, t-1	1.875***	1.978***	2.862***	4.116***	1.882***	1.668***	2.380***	3.700***
Age 18-24	1.602***	0.649***	2.193***	1.180***	1.754***	0.504***	2.417***	1.210***
Age 25-34	0.702***	0.664***	0.978***	0.738***	0.811***	0.704***	1.142***	0.869***
Age 45-54	-0.922***	-1.116***	-1.060***	-1.293***	-1.128***	-1.425***	-1.270***	-1.645***
Age 55 plus	-2.398***	-2.863***	-2.602***	-3.351***	-2.637***	-3.373***	-2.998***	-3.886***
1st degree or higher	-0.194	0.850***	-0.216	1.394***	-0.236*	1.037***	0.058	1.830***
Other higher degree	-0.457***	0.546***	-0.307***	0.788***	-0.525***	0.695***	-0.106	1.063***
A-level(s)	-0.568***	0.333**	-0.371**	0.419***	-0.512***	0.394***	-0.071	0.647***
O-level(s)	-0.261*	0.549***	-0.077	0.612***	-0.391***	0.695***	0.189*	0.832***
Other qualifications	-0.393**	0.230	-0.280*	0.151	-0.276**	0.428***	-0.081	0.299**
Married or partnered	-0.054	0.489***	0.244	0.444***	0.183**	0.689***	0.449***	0.692***
Disability	-1.044***	-1.716***	-1.579***	-1.809***	-0.977***	-1.882***	-1.755***	-2.038***
London	0.011	0.684***	-0.132	0.395**	0.082	0.576***	-0.208	0.175
South East	0.165	0.339**	-0.188	0.335**	0.075	0.274**	-0.169	0.392***
Unemployment rate	4.611	-9.437**	-2.862	-6.227*	3.714	-7.616**	-2.518	-3.467
Youngest child 0-2	0.265	0.053	-0.213	-0.042	0.184	-0.135	-0.373***	-0.248**
Youngest child 3-4	0.075	0.035	-0.180	0.073	0.212	0.059	-0.160	0.025
Youngest child 5-11	0.200	0.383*	0.061	0.308*	0.312**	0.446***	0.125	0.334***
Youngest child 12-16	0.664***	0.715***	0.616***	0.811***	0.894***	0.951***	0.727***	0.937***
Youngest child 17-18	0.567**	0.377	0.172	0.440**	0.735***	0.558***	0.242	0.558***
Total children under 19	-0.265***	-0.292***	-0.260***	-0.327***	-0.374***	-0.364***	-0.318***	-0.413***
Married or partnered: Mean	-0.642***	-0.046	-0.190	0.148	-1.498***	-0.383***	-0.472***	-0.132

Disability: Mean	-2.055***	-3.797***	-2.817***	-3.648***	-2.855***	-4.850***	-3.989***	-4.873***
Total children: mean	0.397***	0.347***	0.319***	0.242***	0.621***	0.454***	0.392***	0.315***
Unemployed, t0	1.609***	0.874***	0.689***	0.189	2.280***	1.147***	0.688***	0.144
Self-employed, t0	1.147***	4.464***	1.516***	1.291***	2.001***	6.440***	2.135***	1.771***
Low pay, t0	1.233***	1.896***	2.003***	1.610***	2.208***	2.895***	2.934***	2.285***
Higher pay, t0	0.509***	1.487***	1.004***	1.945***	0.589***	1.899***	1.376***	2.805***
Wave 3	-0.291	-0.200	-0.049	-0.192	-0.494***	-0.464**	-0.279	-0.483***
Wave 4	-0.264	-0.293	0.099	-0.132	-0.534***	-0.607***	-0.170	-0.469***
Wave 5	-0.798***	-0.506**	-0.164	-0.373*	-1.218***	-0.894***	-0.512***	-0.785***
Wave 6	-0.598***	-0.303	0.102	-0.294	-1.086***	-0.730***	-0.262	-0.722***
Wave 7	-1.019***	-0.862***	-0.213	-0.470**	-1.554***	-1.228***	-0.547***	-0.811***
Wave 8	-1.031***	-0.919***	-0.155	-0.509**	-1.681***	-1.317***	-0.584***	-0.880***
Wave 9	-1.647***	-1.690***	-0.849***	-1.271***	-2.353***	-2.183***	-1.270***	-1.679***
Wave 10	-1.343***	-1.175***	-0.345	-0.904***	-2.038***	-1.588***	-0.688***	-1.211***
Wave 11	-1.021***	-0.910***	-0.056	-0.656***	-1.744***	-1.341***	-0.452**	-1.008***
Wave 12	-1.181***	-1.084***	-0.442*	-0.815***	-1.805***	-1.385***	-0.662***	-1.043***
Wave 13	-0.935***	-0.723**	-0.074	-0.567**	-1.668***	-1.197***	-0.617***	-1.100***
Wave 14	-1.878***	-1.557***	-0.964***	-1.363***	-2.825***	-2.075***	-1.524***	-1.816***
Wave 15	-1.181***	-0.851***	-0.034	-0.787***	-2.142***	-1.380***	-0.540**	-1.267***
Wave 16	-1.303***	-0.871***	-0.360	-0.841***	-2.159***	-1.402***	-0.994***	-1.368***
Wave 17	-1.580***	-1.001***	-0.519*	-0.934***	-2.669***	-1.717***	-1.197***	-1.522***
Wave 18	-1.120***	-0.960***	-0.333	-0.902***	-1.963***	-1.348***	-0.837***	-1.229***
Constant	0.850*	-0.781	-0.154	1.023**	1.978***	-0.331	0.800**	1.819***
c11	1.675***				2.757***			
c21	1.515***				2.329***			
c22	1.835***				2.885***			
c31	1.363***				2.073***			
c32	0.541***				1.290***			
c33	1.146***				1.969***			
c41	1.148***				1.328***			

c42	0.699***				1.180***			
c43	0.644***				1.126***			
c44	1.140***				1.735***			
Log-likelihood	-35227.09							
Females								
Unemployed, t-1	1.348***	0.366*	0.650***	0.480***	0.545***	0.025	0.474***	0.220***
Self-employed, t-1	0.935***	3.382***	1.519***	0.927***	0.512***	2.877***	1.320***	0.665***
Low pay, t-1	1.077***	1.840***	2.738***	2.231***	0.969***	1.702***	2.348***	1.993***
Higher pay, t-1	0.911***	0.905***	1.710***	2.893***	0.690***	0.531***	1.455***	2.402***
Age 18-24	0.815***	-0.485***	1.037***	0.381***	0.758***	-0.377***	1.059***	0.197***
Age 25-34	0.289***	0.041	0.199***	0.250***	0.142**	0.134**	0.107***	0.177***
Age 45-54	-0.706***	-0.746***	-0.612***	-0.913***	-0.783***	-0.784***	-0.630***	-0.953***
Age 55 plus	-1.921***	-2.126***	-1.867***	-2.546***	-2.174***	-2.351***	-2.047***	-2.809***
1st degree or higher	0.197	2.122***	-0.030	2.395***	0.590***	2.591***	0.093	2.690***
Other higher degree	0.143	1.741***	0.433***	1.671***	0.484***	2.101***	0.666***	1.746***
A-level(s)	0.177	1.324***	0.459***	1.508***	0.278***	1.538***	0.658***	1.573***
O-level(s)	0.093	0.905***	0.309***	1.071***	0.329***	1.147***	0.423***	1.071***
Other qualifications	-0.032	0.544***	0.064	0.563***	0.109	0.549***	0.081	0.466***
Married or partnered	-0.540***	0.204	-0.165**	-0.131*	-0.458***	0.252***	-0.172***	-0.081*
Disability	-0.318***	-0.605***	-0.750***	-0.883***	-0.392***	-0.701***	-0.801***	-0.951***
London	0.071	0.484**	-0.621***	0.271**	0.118	0.269**	-0.796***	0.313***
South East	0.444***	0.344**	0.206**	0.434***	0.715***	0.517***	0.378***	0.543***
Unemployment rate	9.459***	-8.452**	2.564	2.851	13.085***	-8.065***	7.698***	7.239***
Youngest child 0-2	-2.395***	-2.671***	-2.790***	-3.000***	-2.663***	-3.080***	-3.220***	-3.324***
Youngest child 3-4	-1.622***	-1.791***	-1.685***	-1.878***	-1.923***	-2.062***	-2.011***	-2.159***
Youngest child 5-11	-1.081***	-1.156***	-0.751***	-1.027***	-1.303***	-1.349***	-0.993***	-1.222***
Youngest child 12-16	-0.391***	-0.522***	-0.076	-0.084	-0.545***	-0.620***	-0.159***	-0.102*
Youngest child 17-18	0.009	-0.184	0.195	0.248**	0.061	-0.246	0.155*	0.296***
Total children under 19	-0.141**	0.212***	0.085**	-0.121***	-0.180***	0.271***	0.130***	-0.158***

Married or partnered: Mean	-0.594***	-0.058	0.001	-0.033	-0.978***	0.071	-0.080	-0.197**
Disability: Mean	-1.141***	-2.058***	-2.076***	-2.750***	-1.340***	-2.884***	-2.597***	-3.541***
Total children: mean	0.067	-0.208***	-0.091**	-0.089**	0.104**	-0.268***	-0.064**	-0.053
Unemployed, t0	1.037***	0.363	0.459***	0.298**	1.798***	0.732***	0.748***	0.548***
Self-employed, t0	0.441**	3.869***	0.761***	0.476***	1.095***	4.889***	1.142***	0.874***
Low pay, t0	0.664***	0.836***	1.592***	1.286***	0.714***	1.112***	1.996***	1.567***
Higher pay, t0	0.610***	0.789***	0.764***	2.292***	0.700***	1.050***	0.918***	2.802***
Wave 3	0.054	0.200	0.155	0.213*	0.007	0.144	0.101	0.139
Wave 4	0.021	0.208	0.214*	0.211*	0.025	0.196	0.237**	0.194*
Wave 5	0.171	-0.048	0.206*	0.241**	0.170	-0.105	0.236**	0.231**
Wave 6	0.131	0.025	0.352***	0.198	0.089	-0.009	0.406***	0.195*
Wave 7	0.048	-0.038	0.223	0.322**	0.040	-0.078	0.333***	0.373***
Wave 8	0.080	-0.297	0.348**	0.308**	0.038	-0.343*	0.449***	0.376***
Wave 9	0.138	-0.289	0.215	0.147	0.129	-0.242	0.344***	0.242**
Wave 10	0.479**	0.024	0.348**	0.374***	0.492***	0.038	0.493***	0.484***
Wave 11	0.236	-0.353	0.422***	0.393***	0.238	-0.328	0.559***	0.503***
Wave 12	0.257	-0.297	0.366**	0.379***	0.358**	-0.256	0.511***	0.473***
Wave 13	0.382*	-0.181	0.190	0.418***	0.365**	-0.212	0.303**	0.528***
Wave 14	0.273	-0.371	0.141	0.347**	0.325*	-0.323	0.280**	0.507***
Wave 15	0.325	-0.234	0.219	0.381**	0.302*	-0.195	0.317***	0.485***
Wave 16	0.252	0.021	0.302*	0.457***	0.267	0.017	0.406***	0.525***
Wave 17	0.239	-0.057	0.309*	0.432***	0.172	-0.012	0.402***	0.541***
Wave 18	0.280	-0.199	0.207	0.364**	0.158	-0.238	0.299***	0.454***
Constant	-1.806***	-3.650***	-1.178***	-1.663***	-2.195***	-4.136***	-1.471***	-1.623***
c11[(a)]	1.136***				1.993***			
c21	0.850***				1.571***			
c22	-1.934***				2.423***			
c31	0.975***				0.981***			
c32	-0.205***				0.489***			
c33	-1.059***				1.747***			

c41	0.891***	0.939***
c42	-0.186***	0.551***
c43	-0.687***	1.120***
c44	1.288***	1.845***
Log-likelihood	-47757.93	

Note: (a). c11-c44 are estimates for the elements of the lower-triangular matrix of the Cholesky decomposition of the variance-covariance matrix of ra
effects.

Table A3: Pooled model estimates, accounting for panel attrition

	Males				Females			
	Unweighted		Weighted		Unweighted		Weighted	
Covariates	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Unemployment								
Unemployed, t-1	2.542***	0.074	2.402***	0.034	2.038***	0.073	1.975***	0.039
Self-employed, t-1	2.136***	0.137	1.955***	0.073	1.298***	0.174	1.357***	0.108
Low pay, t-1	2.505***	0.116	2.576***	0.060	1.550***	0.079	1.511***	0.045
Higher pay, t-1	2.225***	0.087	2.316***	0.047	1.322***	0.081	1.272***	0.049
Age 18-24	1.406***	0.127	1.467***	0.059	0.671***	0.100	0.659***	0.055
Age 25-34	0.632***	0.095	0.660***	0.046	0.311***	0.078	0.184***	0.046
Age 45-54	-0.535***	0.088	-0.563***	0.049	-0.624***	0.083	-0.706***	0.047
Age 55 plus	-1.608***	0.093	-1.571***	0.050	-1.527***	0.106	-1.646***	0.063
1st degree or higher	-0.369***	0.106	-0.449***	0.061	0.062	0.104	0.077	0.061
Other higher degree	-0.432***	0.077	-0.427***	0.040	0.003	0.080	0.041	0.047
A-level(s)	-0.570***	0.096	-0.666***	0.051	0.086	0.094	-0.041	0.053
O-level(s)	-0.242***	0.083	-0.270***	0.045	-0.015	0.075	0.002	0.045
Other qualifications	-0.366***	0.101	-0.428***	0.055	-0.085	0.089	-0.061	0.052
Married or partnered	-0.162	0.137	-0.004	0.064	-0.501***	0.098	-0.320***	0.054
Disability	-0.830***	0.086	-0.732***	0.039	-0.224***	0.085	-0.284***	0.051
London	0.117	0.131	0.120	0.073	0.072	0.114	0.059	0.065
South East	0.178	0.110	0.185***	0.062	0.329***	0.098	0.357***	0.061
Unemployment rate	4.466	3.014	5.091***	1.827	8.970***	2.849	12.427***	1.749
Youngest child 0-2	0.353**	0.153	0.239***	0.082	-1.818***	0.121	-1.858***	0.072
Youngest child 3-4	0.217	0.189	0.280***	0.108	-1.157***	0.139	-1.248***	0.085
Youngest child 5-11	0.232	0.152	0.223**	0.093	-0.789***	0.117	-0.821***	0.069
Youngest child 12-16	0.470***	0.141	0.434***	0.088	-0.292**	0.114	-0.360***	0.074
Youngest child 17-18	0.331	0.216	0.279*	0.144	-0.031	0.160	-0.074	0.105
Total children under	-0.203***	0.076	-0.231***	0.044	-0.182***	0.063	-0.205***	0.041

Married or partnered: Mean	-0.404***	0.156	-0.483***	0.076	-0.500***	0.117	-0.578***	0.065
Disability: Mean	-1.142***	0.133	-1.337***	0.065	-0.729***	0.131	-0.771***	0.081
Total children: mean	0.263***	0.072	0.293***	0.040	0.102*	0.057	0.112***	0.037
Unemployed, t0	0.725***	0.081	0.787***	0.042	0.638***	0.081	0.764***	0.041
Self-employed, t0	0.287**	0.126	0.310***	0.067	0.191	0.181	0.184	0.122
Low pay, t0	0.486***	0.110	0.425***	0.053	0.261***	0.076	0.271***	0.046
Higher pay, t0	0.040	0.085	-0.015	0.049	0.231***	0.077	0.131***	0.044
Wave 3	0.073	0.169	0.073	0.139	0.133	0.152	0.144	0.128
Wave 4	0.107	0.169	0.116	0.136	0.045	0.156	0.091	0.128
Wave 5	-0.260	0.176	-0.250*	0.135	0.189	0.159	0.256**	0.125
Wave 6	0.021	0.180	0.038	0.138	0.164	0.168	0.237*	0.130
Wave 7	-0.411**	0.195	-0.392***	0.144	0.051	0.182	0.174	0.135
Wave 8	-0.393**	0.200	-0.380***	0.145	0.071	0.189	0.181	0.139
Wave 9	-0.829***	0.205	-0.805***	0.147	0.147	0.189	0.255*	0.139
Wave 10	-0.646***	0.195	-0.631***	0.143	0.451**	0.177	0.581***	0.132
Wave 11	-0.260	0.205	-0.257*	0.148	0.262	0.191	0.422***	0.140
Wave 12	-0.410**	0.200	-0.280**	0.138	0.262	0.188	0.515***	0.129
Wave 13	-0.117	0.208	0.003	0.144	0.394**	0.196	0.559***	0.133
Wave 14	-0.934***	0.218	-0.952***	0.147	0.296	0.202	0.500***	0.136
Wave 15	-0.333	0.220	-0.393***	0.147	0.349*	0.203	0.522***	0.133
Wave 16	-0.412*	0.214	-0.278**	0.141	0.275	0.197	0.445***	0.132
Wave 17	-0.675***	0.220	-0.809***	0.144	0.264	0.203	0.398***	0.134
Wave 18	-0.201	0.211	-0.103	0.138	0.317	0.193	0.417***	0.130
Constant	-0.571*	0.340	-0.618***	0.217	-2.139***	0.320	-2.412***	0.208
Self-employment								
Unemployed, t-1	1.527***	0.114	1.377***	0.060	0.747***	0.173	0.727***	0.108
Self-employed, t-1	5.689***	0.108	5.544***	0.055	5.057***	0.092	5.161***	0.061
Low pay, t-1	3.377***	0.121	3.362***	0.069	2.248***	0.089	2.282***	0.056
Higher pay, t-1	2.414***	0.093	2.397***	0.054	1.410***	0.094	1.416***	0.059

Age 18-24	0.724***	0.147	0.699***	0.073	-0.447***	0.150	-0.526***	0.091
Age 25-34	0.596***	0.100	0.617***	0.051	0.021	0.079	-0.035	0.049
Age 45-54	-0.651***	0.093	-0.648***	0.053	-0.610***	0.083	-0.642***	0.055
Age 55 plus	-1.920***	0.097	-1.865***	0.054	-1.578***	0.112	-1.611***	0.074
1st degree or higher	0.573***	0.106	0.669***	0.064	1.568***	0.110	1.653***	0.071
Other higher degree	0.364***	0.085	0.440***	0.050	1.310***	0.099	1.405***	0.066
A-level(s)	0.186*	0.104	0.215***	0.057	1.053***	0.115	1.008***	0.073
O-level(s)	0.382***	0.097	0.429***	0.060	0.650***	0.107	0.692***	0.075
Other qualifications	0.119	0.118	0.182***	0.069	0.373***	0.130	0.393***	0.091
Married or partnered	0.221	0.145	0.294***	0.078	0.086	0.126	0.212***	0.076
Disability	-1.332***	0.105	-1.298***	0.059	-0.430***	0.120	-0.405***	0.077
London	0.613***	0.131	0.654***	0.075	0.490***	0.128	0.468***	0.076
South East	0.170	0.108	0.162***	0.062	0.232**	0.096	0.359***	0.060
Unemployment rate	-9.553***	3.190	-9.512***	1.998	-6.487**	3.100	-3.775*	2.079
Youngest child 0-2	0.159	0.162	0.108	0.093	-1.940***	0.142	-2.026***	0.089
Youngest child 3-4	0.037	0.192	0.096	0.116	-1.293***	0.157	-1.403***	0.098
Youngest child 5-11	0.278*	0.152	0.289***	0.095	-0.828***	0.133	-0.974***	0.085
Youngest child 12-16	0.486***	0.145	0.444***	0.094	-0.451***	0.127	-0.553***	0.087
Youngest child 17-18	0.140	0.208	0.119	0.143	-0.201	0.184	-0.269**	0.131
Total children under 19	-0.235***	0.079	-0.231***	0.048	0.101	0.070	0.133***	0.046
Married or partnered: Mean	0.122	0.170	0.138	0.090	0.016	0.149	-0.059	0.092
Disability: Mean	-2.209***	0.164	-2.295***	0.095	-1.402***	0.176	-1.553***	0.114
Total children: mean	0.243***	0.074	0.260***	0.044	-0.114*	0.066	-0.120***	0.043
Unemployed, t0	0.339***	0.114	0.282***	0.060	0.125	0.158	0.040	0.092
Self-employed, t0	1.802***	0.109	1.749***	0.065	1.449***	0.098	1.395***	0.068
Low pay, t0	0.923***	0.125	0.877***	0.067	0.432***	0.087	0.397***	0.055
Higher pay, t0	0.684***	0.094	0.710***	0.056	0.381***	0.081	0.275***	0.050
Wave 3	0.237	0.189	0.213	0.159	0.568***	0.183	0.563***	0.161

Wave 4	0.132	0.189	0.107	0.156	0.572***	0.174	0.600***	0.149
Wave 5	0.061	0.197	0.073	0.154	0.395**	0.184	0.431***	0.152
Wave 6	0.295	0.200	0.267*	0.156	0.486***	0.185	0.551***	0.151
Wave 7	-0.282	0.212	-0.304*	0.160	0.408**	0.199	0.495***	0.157
Wave 8	-0.314	0.216	-0.323**	0.161	0.188	0.209	0.289*	0.161
Wave 9	-0.852***	0.219	-0.886***	0.163	0.202	0.213	0.356**	0.160
Wave 10	-0.473**	0.211	-0.513***	0.158	0.381*	0.201	0.494***	0.157
Wave 11	-0.180	0.220	-0.217	0.164	0.081	0.208	0.204	0.161
Wave 12	-0.325	0.212	-0.237	0.155	0.149	0.205	0.254	0.156
Wave 13	-0.026	0.223	-0.048	0.158	0.281	0.214	0.357**	0.160
Wave 14	-0.734***	0.230	-0.774***	0.162	0.102	0.221	0.247	0.163
Wave 15	-0.146	0.231	-0.227	0.162	0.205	0.222	0.343**	0.161
Wave 16	-0.167	0.224	-0.217	0.157	0.396*	0.215	0.430***	0.156
Wave 17	-0.308	0.230	-0.472***	0.157	0.309	0.219	0.376**	0.158
Wave 18	-0.198	0.221	-0.194	0.153	0.138	0.209	0.127	0.152
Constant	-1.488***	0.369	-1.560***	0.240	-3.260***	0.354	-3.515***	0.248
Low paid employment								
Unemployed, t-1	1.903***	0.097	1.850***	0.046	1.117***	0.075	1.122***	0.043
Self-employed, t-1	3.371***	0.123	3.198***	0.066	1.912***	0.099	2.059***	0.065
Low pay, t-1	4.809***	0.109	4.765***	0.060	3.617***	0.045	3.642***	0.027
Higher pay, t-1	3.359***	0.084	3.307***	0.046	2.287***	0.047	2.329***	0.029
Age 18-24	1.862***	0.130	1.789***	0.063	0.783***	0.069	0.762***	0.041
Age 25-34	0.853***	0.097	0.872***	0.048	0.207***	0.046	0.139***	0.029
Age 45-54	-0.616***	0.092	-0.553***	0.052	-0.519***	0.054	-0.555***	0.034
Age 55 plus	-1.754***	0.095	-1.668***	0.052	-1.371***	0.068	-1.347***	0.041
1st degree or higher	-0.340***	0.103	-0.210***	0.059	-0.213***	0.070	-0.139***	0.041
Other higher degree	-0.334***	0.076	-0.278***	0.041	0.265***	0.050	0.347***	0.031
A-level(s)	-0.390***	0.094	-0.323***	0.048	0.244***	0.060	0.182***	0.035
O-level(s)	-0.148*	0.087	-0.063	0.049	0.121**	0.049	0.153***	0.032
Other qualifications	-0.245**	0.104	-0.180***	0.058	-0.012	0.058	0.023	0.036
Married or	0.049	0.136	0.104	0.070	-0.150**	0.068	-0.068*	0.040

partnered								
Disability	-1.237***	0.092	-1.143***	0.048	-0.576***	0.061	-0.561***	0.037
London	-0.044	0.133	-0.006	0.075	-0.534***	0.088	-0.570***	0.053
South East	-0.116	0.109	-0.089	0.062	0.157***	0.058	0.233***	0.035
Unemployment rate	-1.193	3.005	-2.138	1.857	3.727**	1.703	6.904***	1.080
Youngest child 0-2	-0.002	0.158	0.040	0.085	-2.043***	0.077	-2.166***	0.045
Youngest child 3-4	-0.033	0.191	0.047	0.116	-1.156***	0.087	-1.285***	0.051
Youngest child 5-11	0.089	0.153	0.155	0.096	-0.468***	0.073	-0.615***	0.044
Youngest child 12-16	0.433***	0.142	0.377***	0.092	-0.028	0.073	-0.107**	0.045
Youngest child 17-18	-0.026	0.213	-0.056	0.145	0.139	0.106	0.100	0.072
Total children under 19	-0.225***	0.079	-0.259***	0.047	0.040	0.035	0.057**	0.023
Married or partnered: Mean	-0.033	0.157	0.049	0.080	0.101	0.081	0.087*	0.048
Disability: Mean	-1.570***	0.143	-1.720***	0.077	-1.361***	0.094	-1.462***	0.060
Total children: mean	0.231***	0.073	0.245***	0.043	-0.058*	0.034	-0.032	0.022
Unemployed, t0	0.283***	0.095	0.203***	0.048	0.236***	0.071	0.261***	0.038
Self-employed, t0	0.667***	0.115	0.494***	0.069	0.392***	0.097	0.345***	0.068
Low pay, t0	0.967***	0.107	0.858***	0.055	0.752***	0.043	0.750***	0.027
Higher pay, t0	0.345***	0.084	0.298***	0.049	0.286***	0.044	0.187***	0.027
Wave 3	0.290	0.190	0.279*	0.158	0.277***	0.100	0.274***	0.087
Wave 4	0.419**	0.189	0.404***	0.154	0.272***	0.100	0.298***	0.085
Wave 5	0.280	0.196	0.260*	0.153	0.286***	0.103	0.331***	0.084
Wave 6	0.577***	0.197	0.537***	0.154	0.443***	0.105	0.507***	0.085
Wave 7	0.233	0.206	0.183	0.157	0.276**	0.114	0.363***	0.088
Wave 8	0.323	0.210	0.230	0.158	0.415***	0.115	0.510***	0.088
Wave 9	-0.199	0.212	-0.253	0.158	0.308***	0.117	0.423***	0.089
Wave 10	0.177	0.205	0.107	0.155	0.406***	0.115	0.520***	0.088
Wave 11	0.519**	0.212	0.420***	0.159	0.531***	0.118	0.658***	0.090
Wave 12	0.191	0.208	0.258*	0.150	0.448***	0.117	0.549***	0.086
Wave 13	0.570***	0.217	0.438***	0.156	0.317***	0.123	0.420***	0.086

Wave 14	-0.187	0.223	-0.292*	0.159	0.308**	0.127	0.426***	0.090
Wave 15	0.601***	0.224	0.499***	0.158	0.363***	0.126	0.460***	0.089
Wave 16	0.335	0.218	0.187	0.154	0.439***	0.124	0.527***	0.086
Wave 17	0.208	0.224	0.109	0.154	0.431***	0.126	0.503***	0.087
Wave 18	0.438**	0.217	0.288*	0.150	0.325***	0.122	0.405***	0.085
Constant	-1.675***	0.349	-1.596***	0.229	-1.814***	0.196	-2.143***	0.132
Higher paid employment								
Unemployed, t-1	1.343***	0.084	1.405***	0.042	0.814***	0.079	0.782***	0.045
Self-employed, t-1	2.337***	0.111	2.245***	0.062	1.326***	0.104	1.376***	0.068
Low pay, t-1	3.737***	0.101	3.802***	0.059	2.648***	0.047	2.630***	0.027
Higher pay, t-1	4.822***	0.066	4.896***	0.041	3.929***	0.039	3.938***	0.023
Age 18-24	1.179***	0.125	1.193***	0.060	0.453***	0.068	0.385***	0.038
Age 25-34	0.640***	0.090	0.676***	0.046	0.243***	0.041	0.164***	0.025
Age 45-54	-0.790***	0.082	-0.768***	0.047	-0.734***	0.052	-0.770***	0.032
Age 55 plus	-2.372***	0.084	-2.300***	0.047	-1.839***	0.064	-1.832***	0.037
1st degree or higher	0.912***	0.088	1.012***	0.053	1.589***	0.060	1.661***	0.034
Other higher degree	0.522***	0.069	0.586***	0.039	1.168***	0.051	1.254***	0.031
A-level(s)	0.235***	0.086	0.246***	0.047	1.024***	0.061	0.930***	0.035
O-level(s)	0.400***	0.080	0.428***	0.047	0.693***	0.052	0.732***	0.034
Other qualifications	0.099	0.096	0.084	0.056	0.352***	0.063	0.377***	0.039
Married or partnered	0.148	0.126	0.209***	0.065	-0.165**	0.066	-0.042	0.038
Disability	-1.396***	0.079	-1.398***	0.042	-0.668***	0.058	-0.663***	0.036
London	0.406***	0.113	0.383***	0.066	0.128*	0.072	0.054	0.043
South East	0.244***	0.091	0.306***	0.053	0.299***	0.054	0.403***	0.033
Unemployment rate	-5.432**	2.674	-4.612***	1.682	4.489***	1.631	8.500***	1.018
Youngest child 0-2	0.115	0.146	0.085	0.083	-2.213***	0.067	-2.272***	0.039
Youngest child 3-4	0.176	0.174	0.214**	0.107	-1.276***	0.083	-1.400***	0.047
Youngest child 5-11	0.304**	0.139	0.347***	0.089	-0.682***	0.071	-0.829***	0.040
Youngest child 12-16	0.624***	0.127	0.580***	0.083	-0.081	0.072	-0.163***	0.046

Youngest child 17-18	0.246	0.187	0.247*	0.128	0.126	0.103	0.091	0.071
Total children under 19	-0.282***	0.070	-0.307***	0.042	-0.075**	0.033	-0.066***	0.021
Married or partnered: Mean	0.283*	0.146	0.294***	0.076	0.114	0.078	0.050	0.045
Disability: Mean	-2.189***	0.121	-2.243***	0.066	-1.744***	0.091	-1.817***	0.057
Total children: mean	0.175***	0.065	0.207***	0.038	-0.066**	0.032	-0.049**	0.020
Unemployed, t0	0.001	0.088	-0.001	0.044	0.239***	0.074	0.221***	0.039
Self-employed, t0	0.566***	0.105	0.457***	0.062	0.391***	0.101	0.325***	0.070
Low pay, t0	0.724***	0.102	0.636***	0.053	0.606***	0.045	0.595***	0.027
Higher pay, t0	0.809***	0.075	0.801***	0.045	1.057***	0.040	0.908***	0.024
Wave 3	0.176	0.159	0.156	0.133	0.324***	0.096	0.297***	0.084
Wave 4	0.231	0.161	0.225*	0.131	0.287***	0.097	0.293***	0.083
Wave 5	0.116	0.167	0.114	0.130	0.337***	0.098	0.367***	0.081
Wave 6	0.239	0.169	0.235*	0.132	0.339***	0.102	0.395***	0.083
Wave 7	0.007	0.177	0.026	0.135	0.415***	0.110	0.512***	0.086
Wave 8	-0.014	0.183	-0.005	0.137	0.402***	0.111	0.526***	0.085
Wave 9	-0.617***	0.185	-0.599***	0.137	0.265**	0.113	0.396***	0.085
Wave 10	-0.357**	0.177	-0.349***	0.133	0.452***	0.110	0.580***	0.084
Wave 11	-0.067	0.186	-0.070	0.138	0.516***	0.114	0.671***	0.086
Wave 12	-0.173	0.180	-0.011	0.129	0.479***	0.112	0.594***	0.083
Wave 13	0.064	0.188	-0.001	0.134	0.539***	0.117	0.682***	0.083
Wave 14	-0.606***	0.194	-0.575***	0.137	0.468***	0.119	0.628***	0.084
Wave 15	-0.129	0.196	-0.136	0.137	0.473***	0.120	0.584***	0.084
Wave 16	-0.156	0.190	-0.172	0.133	0.536***	0.118	0.612***	0.083
Wave 17	-0.262	0.195	-0.334**	0.134	0.496***	0.119	0.586***	0.083
Wave 18	-0.154	0.189	-0.128	0.130	0.419***	0.115	0.473***	0.080
Constant	-0.425	0.307	-0.620***	0.203	-2.191***	0.189	-2.503***	0.125