State-Dependence and Stepping Stone Effects of Low Pay Employment in Australia

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Abstract: Using the HILDA Survey, this study examines state-dependence and stepping stone effects of low pay in Australia. 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. The results also show that, other things being equal, people who are on low pay are more likely to be in employment in the future than those who are either unemployed or not in the labour force. On the other hand, people on low pay do not appear to be more likely to become jobless in the future than those on higher pay.

Key words: Low pay, stepping stone effects, state dependence, multinomial logit model

JEL code: J31, J38, C35

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1. Introduction

Using the first eleven waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, this study examines whether and to what extent low pay employment is 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), among Australian workers. While there is a sizable literature on persistence of low pay overseas, Australian research on this issue is limited.

Increasing earnings inequality over the last three decades or so and an emphasis on a work-first approach to welfare reform since mid-1990s have prompted an increasing number of studies on low pay employment in industrialised economies. These studies are aimed at enhancing understanding how low paid workers fare in the labour market, particularly whether low paid workers tend to stay in low pay employment or use it as a stepping stone to higher pay. Answers to these questions have important policy implications.

From a welfare policy perspective, if low pay employment acts as a stepping stone to higher pay, welfare reforms that promote employment, even it is low paid, such as the work-first approach to welfare recipients, have a good chance to improve the financial wellbeing of welfare recipients over time and are therefore justified. On the other hand, if low pay employment tends to be persistent or even leads to a vicious cycle between low pay and unemployment, an appropriate level of in work benefit provided through the welfare system may be required to alleviate financial difficulty of low paid workers (Cappellari 2002, 2007; Buddelmeyer *et al*. 2010).

From an earnings inequality perspective, transitory low pay means that earnings inequality is shared among individuals over their life-cycle, while persistent low pay implies low pay concentrates in a fraction of the population, who may be excluded from sharing economic prosperity in the long-run. Therefore, while an adequate minimum wage is a justifiable policy instrument if low pay is persistent, it may not be appropriate if low pay is transitory and acts as a stepping stone to higher pay, since a wage floor established by minimum wages may reduce the opportunity for low-skilled workers to enter employment in the first place (Cappellari 2002, 2007).[1]

Descriptive analysis of survey data tends to indicate persistence of low pay employment. However, observed persistence in low pay may have various causes, which in turn has different policy implications. For example, persistent low pay may be due to persistent individual

[1] Although empirical evidence has so far been mixed, it has been argued that an introduction or an increase of minimum wages could price out low skilled workers whose productivity is below the minimum wage. For a comprehensive review of the literature on this issue, see (Neumark and Wascher 2007).

characteristics, such as low skills (i.e., observed heterogeneity) and/or low ability (i.e., unobserved heterogeneity), and therefore has nothing to do with previous labour market or earnings experience. On the other hand, past low pay experience itself may cause low pay in the future (i.e., genuine state-dependence of low pay), leading to persistence in low pay. There are several possible reasons for genuine state-dependence in low pay employment. For example, low pay employment may not lead to accumulation or may even cause deterioration of human capital if a low paid job is of low quality; and this consequently reduces the chance of low paid workers moving into a higher paid job in the future. From an employer's perspective, past low pay employment may be viewed as a signal of low productivity of the worker, which again reduces the chance of the worker moving into a higher paid job. Obviously, persistence of low pay as a result of genuine state-dependence requires a different policy response than persistence of low pay resulting from persistent differences in individual characteristics.

With the availability of panel data, an increasing number of studies have been devoted to the dynamics of low pay employment (e.g., Gregory and Elias 1994; Sloane and Theodossiou 1998; Gosling *et al*. 1997; Stewart and Swaffield 1999; Cappellari 2002, 2007; Cappellari and Jenkins 2008; Clark and Kanellopoulos 2009; Stewart 2007). These studies examine what factors affect workers' low pay status with a particular interest in genuine state dependence of low pay. These studies estimate state-dependence of low pay by examining the difference between the probability of remaining in low pay and the probability of transitioning into low pay from higher pay, taking into account the differences in individual characteristics. Statistically significant state-dependence of low pay has been found by a number of studies even after observed and unobserved individual heterogeneity is accounted for (e.g., Cappellari and Jenkins 2008; Uhlendorff 2006; Clark and Kanellopoulos 2009; Stewart 2007).[2]

A related theme of research in low pay dynamics examines whether low pay employment and unemployment are inter-related. This question arises due to the concern that low paid workers may cycle between low pay and unemployment with little hope to move up the labour market ladder. For example, descriptive analyses by Dunlop (2001) and Perkins and Scutella (2008), while using different data sources, show that low paid workers are more likely than higher paid workers to move into joblessness in the future. As shown in Table 1 later, descriptive analysis in this current study produces a similar result. That is, on a year-on-year basis, workers on low pay

[2] Using linked employer-employee data of Germany, Mosthaf, Schnabel and Stephani (2011) examine the factors that affect the upward mobility of wages by restricting their analysis to those who were initially low paid, and find that those low paid workers who are younger, better qualified, and work in larger firms are more likely to move up the earnings ladder. Stepping stone effects and state-dependence of low pay are not examined in this study.

have a higher probability of transitioning to either unemployment or not in the labour force (NILF) than workers on higher pay for both males and females. This descriptive result has not taken into account the impacts of observed and unobserved individual heterogeneity.

Using the first seven-wave HILDA survey to examine the dynamics of unemployment, Buddelmeyer *et al*. (2010) find that relative to higher pay, low pay experience has only a modest effect on the probability of experiencing unemployment in the future when observed and unobserved individual heterogeneity is accounted for. This result is consistent with Cappellari and Jenkins (2008) for the UK men; but different from Stewart (2007) who finds that low wage employment has almost as large an adverse impact as unemployment on future employment prospects and that low wage jobs act as the main conduit for repeated unemployment. Uhlendorff (2006) finds that for German men those on low pay have a higher probability of becoming jobless than those on higher pay, although the difference is not statistically significant.

Most of the earlier studies on persistence of low pay treat low pay as a binary variable and infer state-dependence of low pay by comparing the predicted probability of remaining in low pay with the predicted probability of transitioning into low pay from higher pay (e.g., Stewart and Swaffield 1999; Cappellari and Jenkins 2008; Clark and Kanellopoulos 2009). As such, the potential stepping stone effects of low pay are often not examined by these studies, because inferring the stepping stone effects would need to compare the probability of transitioning into higher pay from low pay with the probability of transitioning into higher pay from non-employment states (i.e., unemployment and NILF).

In a dynamic Probit model framework and using the German SOEP, Knabe and Plum (2010) examine the stepping stone effect of low pay relative to unemployment by including both lagged unemployment and lagged low pay as the right hand side variables. They find that low pay can act as a stepping stone to better pay employment, particular for those who do not have a college degree, who have been unemployed more often in the past and whose low paid job carries a relatively high social status. While the model takes account potential endogeneity of initial low pay, initial unemployment is assumed to be exogenous. Given their estimation results show that initial low pay is not exogenous, it is likely that initial unemployment is endogenous. Consequently, the estimates of the model are likely to be biased.

Departing from the earlier studies on low pay persistence, this current study examines both state dependence and stepping stone effects of low pay employment by estimating a dynamic random effects multinomial logit model. It appears the only study that takes a similar approach is

Uhlendorff (2006). Using the German Socio-Economic Panel Study (SOEP) waves 1998 to 2003, Uhlendorff (2006) examines low pay dynamics of German men and finds that while there exists genuine state-dependence in low pay as well as in non-employment, there is also evidence of a stepping stone effect of low pay as compared with non-employment.

However, unlike Uhlendorff (2006) who treats unemployment and NILF as one labour force state (i.e., non-employment), this current study models the two non-employment states separately. The distinction between NILF and unemployment is particularly important in estimating the stepping stone effect of low pay since the stepping stone effect may differ depending on whether low pay employment is compared with NILF or with unemployment. A priori, one would expect that those who are unemployed are more likely than those who are out of the labour force to obtain a higher paid job. That is, the stepping stone effect of low pay employment is expected be larger when NILF than when unemployment is used as a counterfactual to low pay employment. Also, unlike the earlier studies that tend to exclude females from their analyses, this current study examines low pay dynamics of both Australian males and females.

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

2. Econometric model and estimation strategy

Econometric model

The key question of this study is whether, and to what extent, current labour force/earnings status, particularly low pay state, affects future labour force/earnings status. To answer this question, we need to model the transition of the labour force/earnings states - NILF, unemployment, low pay and higher pay - over time.

The four 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 have no 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 four mutually exclusive labour force/earnings states: NILF, unemployment, low pay and higher pay (denoted by *k =1,2,3 and 4*). 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,

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

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 $(\alpha_j, \beta_j; j = 1,2,3,4)$ 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 explanatory variables. The coefficient estimates on the lagged dependent variables will allow us to infer the extent of stepping stone effects and state-dependence of low pay employment. Second, the model controls for unobserved individual heterogeneity (i.e., $\mu_{i,j}$). If unobserved heterogeneity exists, but is not controlled for, the estimated stepping stone effects and state-dependence will be biased. This is because coefficient estimates on 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).[3]

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

[3] 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.

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's (1978) approach to specify [4]

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

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 $x_{i,t}$. $\nu_{i,1}, \nu_{i,2}$, $\nu_{i,3}$ and $\nu_{i,4}$ 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 $\Theta = (\alpha_j, \beta_j, \lambda_j, \theta_j; j = 1,2,3,4)$.

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 effect associated with NILF to zero.[5]

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 $(\nu_{i,j}; j = 2,3,4)$, can be written as

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

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

The unconditional probability can then be written as,

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

[4] 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 (3) is a compromise between fixed effects and random effects models.

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

where $G(\nu_{2,}\nu_3, \nu_4)$ is the joint distribution function of the random effects ν_2, ν_3 and ν_4. The three-dimensional integral is evaluated using simulation methods, with $G(\nu_{2,}\nu_3, \nu_4)$ assumed to be normal with mean zero and a covariance matrix Σ_ν,

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

where R is the number of random draws from the distribution of $G(\nu_{2,}\nu_3, \nu_4)$; ν_2^r, ν_3^r and ν_4^r are the r^{th} random draws from their joint distribution. We use Halton sequence to generate 50 random draws to simulate the likelihood function. It has been shown that Halton sequence draws perform better than simple random draws in terms of approximating the objective function (Train 2003). The likelihood function of a sample with N individuals is the product of equation (7) over the sample. A Gauss program written by the author is used to estimates 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 can be inferred from the estimated model.

As noted earlier, state-dependence refers to the 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 for an individual i with characteristics $C_i=(Xi, Zi)$, conditional on unobserved heterogeneity ν_i, can be computed as,

(8) $SD_i(\nu_i) = \Pr\left(L_{i,t} = 3 \middle| L_{i,t-1} = 3; \widehat{\Theta}, C_{i,t}, \nu_i\right) - \Pr\left(L_{i,t} = 3 \middle| L_{i,t-1} = k;\ \widehat{\Theta}, C_{i,t}, \nu_i\right)$,

for $k=1, 2, 4$. 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 those 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, state-dependence of low pay is not unique – it varies depending on the comparative labour force/earnings state, as shown in equation (8).

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 the unconditional state-dependence as $SD_i = \frac{1}{R}\sum_{r=1}^{R} SD_i(\nu_i^r)$.

Similarly, 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,

(9) $$SS_i(\nu_i) = \Pr\left(L_{i,t} = 4 \middle| L_{i,t-1} = 3;\ \widehat{\Theta}, C_{i,t}, \nu_i\right) - \Pr\left(L_{i,t} = 4 \middle| L_{i,t-1} = k;\ \widehat{\Theta}, C_{i,t}, \nu_i\right),$$

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

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

3. Data and model specification

Data source and low pay definition

This paper uses data from the first 11 waves of the HILDA Survey. Wooden *et al*. (2002) and Watson and Wooden (2012) document details of this survey. In the first wave, 7,683 households representing 66 per cent of all in-scope households were interviewed. This generated a sample of 15,127 persons who were 15 years or older and eligible for interviews, of whom 13,969 were successfully interviewed. Subsequent interviews for later waves were conducted about one year apart.

The HILDA survey contains detailed information on individual characteristics, labour market outcomes, activity and history. Information on labour force status and earnings is used to define the dependent variable, labour force/earnings status (i.e., NILF, unemployment, low pay and higher pay). Classification of people into NILF and unemployment follows the conventional approach in labour economics: NILF refers to individuals who are not employed and not actively seeking for a job; unemployment refers to those who are not employed but actively looking for work.

However, there is not a consensus on how to define low pay (and consequently its counterpart, higher pay). First, there is the issue whether weekly earnings or hourly earnings should be used to define low pay. Like most other household surveys, the HILDA data provide information on weekly earnings. However, using weekly 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 (e.g., they prefer leisure to work or are balancing work with caring responsibilities). To avoid this problem, in this study hourly earnings are used to define low pay status and hourly earnings are derived by dividing weekly earnings by weekly hours worked from the main job.[6] Using hourly earnings may overestimate low pay for those who reported very long working hours as a result of unpaid overtime. To partly remedy this problem, weekly working hours are top-coded at 55 hours a week.

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 low pay thresholds to test the robustness of the results: (a) two thirds of the median hourly earnings, which appears to be the most popular definition for low pay (Buddelmeyer *et al*. 2010); and (b) the first quintile of the hourly earnings distribution, which has been used in a number of studies.

The sample used in this study includes Australian employees aged between 21 and 60 years (inclusive).[7] 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.[8] 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 26,951 observations, representing 4,385 individuals; the female sample has 34,017 observations, representing 5,254 individuals.

Summary statistics of the sample are presented in Appendix Table a1. Consistent with findings

[6] Specifically, weekly earnings are taken from a derived variable on weekly gross wages and salary, including estimation from net earnings.

[7] That is, employers, self-employed, own account workers and contributing family workers are excluded from the sample since they are unlikely to be paid based on their working hours, and consequently difficult to determine their low pay status.

[8] The vast majority of the observations excluded for this reason are due to missing dependent or lagged dependent variables.

in earlier studies (e.g., Healy and Richardson 2006; McGuinness *et al*. 2007), low paid workers tend to be single, young, low educated, and migrants from non-English speaking backgrounds.

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

Transitions of labour force/earnings status

Table 1 presents the year-on-year transitions of labour force/earning status by pooling all the 11 waves of the HILDA data. For males, the transition rate from unemployment to higher pay over a year period is about 37 per cent, while the transition rate from low pay to higher pay is about 51 per cent. The difference between the two transition rates is about 14 percentage points. For females, the gap of the transition rates is higher, at about 18 percentage points. The difference in the transition rate into higher pay between those who are from low pay and those who are from NILF is around 40 percentage points for both males and females. Therefore, 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 or NILF. This suggests that low pay employment has a stepping stone effect relative to either unemployment or NILF.

On the other hand, low pay does show stickiness relative to other labour force/earnings states. That is, those who are on low pay tend to have a higher probability to be in low pay in the following year than those who are not on low pay. For example, for males the probability of remaining in low pay in the following year for those who are on low pay in this year is about 42 per cent, compared with 4, 10 and 3 per cent respectively for those who are on higher pay, unemployed and NILF in this year. A similar pattern exhibits for females.

However, we should not draw inferences on stepping stone effects 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 health condition 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 survey 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 degree or higher, diploma, certificate level 3-4, certificate level 1-2, year 12, and year 11 and below); *age* (five age category dummies); marital status (one dummy indicating whether a person is married or partnered); *health* (one dummy indicating whether long-term health condition is present); *country of birth* (three dummies indicating whether a person was born in Australia - OZ born, an immigrant from an English speaking country - ESC, or an immigrant from a non-English speaking country - NESC); *age of the youngest child* (five dummies indicating no dependent children under 18, youngest child aged 0-2, youngest child aged 3-5, youngest child aged 6-11, and youngest child aged 12-17); *the total number of children aged under 18 years*; and *region of residence* (four dummies representing cities, inner regions, outer regions and remote areas).

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, health and the number of children are included in the model.

4. Estimation result

The main results are shown in panel (b) of Table 2. To facilitate discussion of the results, the mean predicted transition probabilities of the sample are presented in panel (a) of Table 2. The coefficient estimates of the models can be found in Appendix Table a2.

Stepping stone effect

The estimates for the stepping stone effects are shown in column IV of panel (b) in Table 2. As discussed earlier, they are the differences between the probability of transitioning into higher pay from low pay and the probability of transitioning into higher pay from unemployment and NILF. The estimates indicate a statistically significant stepping stone effect of low pay employment. Also, consistent with our earlier conjecture, the stepping stone effect is larger when low pay employment is compared with NILF than when it is compared with unemployment.

The estimated stepping stone effects are quantitatively similar between the two measures of low pay for both males and females. For males, compared with those who are out of the labour force, those who are on low pay have a 13 to 15 percentage point higher probability of transitioning into higher pay in the following year; compared with those who are unemployed, those who are on low pay have a 5 to 6 percentage point higher probability of transitioning into higher pay in the following year. For females, the stepping stone effect of low pay as compared to NILF is around 14 percentage points; and the stepping stone effect as compared to unemployment is about 6 percentage points. Therefore, there does not appear to be a gender difference in the stepping stone effects of low pay employment.

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. This result is not directly comparable to that in this current study since Uhlendorff (2006) does not distinguish unemployment from NILF.

State-dependence

The estimates for state-dependence are shown in column III of panel (b) in Table 2. The results show that relative to other labour force/earnings states, those who are on low pay have a higher probability of being on low pay in the following year, an indication of state-dependence of low pay employment. For example, using the two-third median low pay definition, men who are on low pay have a 4 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. Compared to men who are on higher pay, state-dependence is found to be around 5 percentage points. The estimates for state-dependence are generally larger for females than for males for both measures of low pay.

State-dependence of low pay as compared to higher pay estimated in this study for Australian males is larger than that in Uhlendorff (2006) for German men (around 3 percentage points for the two-third median low pay definition, and around 4 percentage points for the first quintile low pay definition). The estimates for state-depedence in this current study are close to the lower end of the estimates in Clarke and Kanellopoulos (2009) for males in 12 European countries (ranging from 0.07 for Demark to 0.24 for Portugal); they are lower than that in Stwart and Swaffield (1999) for British men, which ranges from 0.14 to 0.25 depending on the models and definitions of low pay.

However, the state-dependence estimates for low pay employment as compared to NILF and unemployment need to be interpreted with caution. This is because for those who are NILF or unemployed, their lower probability of transitioning into low pay relative to those who are on low pay is not because the former have a better chance of transitioning into higher pay than the latter, rather it is because the former have a higher probability of remaining not employed than the latter. For example, the estimates in columns I and II of panel (b) in Table 2 indicate that for males, compared with those who are out of the labour force, those who are on low pay have a 15 percentage point lower probability of moving out of the labour force, and a 4 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 5 percentage point lower probability of moving out of the labour force, and 4 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 than non-employment for its impact on future employment.

Does low pay lead to joblessness?

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

5. Conclusion

Using the first 11 wave HILDA Survey, this study examined whether and to what extent low pay is 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 male and female Australians to account for observed and unobserved individual heterogeneity, and state-dependence and stepping stone effects of low pay were then computed from the estimated models.

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

While there is evidence on state-dependence of low pay 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 Australian workers, once observed and unobserved individual heterogeneity is accounted for.

The findings that low pay works as a stepping stone to higher pay and does no 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 they are low paid.

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Table 1: Year-on-year transitions of labour force/earnings status (row percentage)

Labour force/earnings status t-1	Labour force/earnings status t				Number of observations
	Not in labour force	Unemployed	Low pay	Higher pay	
		Males			
Not in labour force	80.36	6.59	3.10	9.94	2,867
Unemployed	20.08	32.55	10.32	37.05	1,066
Low pay	3.63	3.99	41.64	50.74	1,955
Higher pay	1.96	1.59	3.83	92.62	21,063
All males	11.14	3.52	6.75	78.59	26,951
		Females			
Not-in-labour force	81.34	4.34	3.07	11.25	9,584
Unemployed	30.86	25.79	10.66	32.69	1,144
Low pay	10.01	3.58	35.59	50.82	2,737
Higher pay	5.92	1.35	6.35	86.37	20,552
All females	28.34	3.20	7.93	60.54	34,017

Table 2: Predicted transition probabilities and their differences

	Males				Females			
	A. Two thirds median low pay threshold							
	(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1							
	NILF, t	Unemploy, t	Low pay, t	Higher pay, t	NILF, t	Unemploy, t	Low pay, t	Higher pay, t
(1) NILF, t-1	0.2283	0.0745	0.0752	0.6220	0.4186	0.0537	0.0577	0.4700
s.e.	*0.0224*	*0.0313*	*0.0172*	*0.0305*	*0.0198*	*0.0144*	*0.0106*	*0.0199*
(2) Unemploy, t-1	0.1258	0.0716	0.0738	0.7287	0.2930	0.0788	0.0791	0.5491
s.e.	*0.0159*	*0.0345*	*0.0222*	*0.0376*	*0.0213*	*0.0235*	*0.0176*	*0.0276*
(3) Low pay, t-1	0.0779	0.0315	0.1148	0.7759	0.1987	0.0283	0.1642	0.6088
s.e.	*0.0082*	*0.0147*	*0.0267*	*0.0297*	*0.0154*	*0.0098*	*0.0287*	*0.0268*
(4) Higher pay, t-1	0.0785	0.0308	0.0624	0.8282	0.2077	0.0244	0.0870	0.6810
s.e.	*0.0068*	*0.0132*	*0.0149*	*0.0207*	*0.0139*	*0.0087*	*0.0171*	*0.0205*
	(b). Differences in predicted transition probabilities (relative to transition probabilities from low pay)							
	I	II	III	IV	I	II	III	IV
(3)-(1)	-0.1504***	-0.0430**	0.0396**	0.1539***	-0.2228***	-0.0263***	0.1070***	0.1420***
s.e.	*0.0172*	*0.0219*	*0.0171*	*0.0208*	*0.0108*	*0.0079*	*0.0205*	*0.018*
(3)-(2)	-0.0480***	-0.0401	0.0410**	0.0472*	-0.0962***	-0.0509***	0.0853***	0.0618***
s.e.	*0.0106*	*0.0247*	*0.0167*	*0.0259*	*0.0135*	*0.0151*	*0.0176*	*0.0219*
(3)-(4)	-0.0006	0.0006	0.0523***		-0.0088	0.004	0.0772***	
s.e.	*0.005*	*0.0093*	*0.0175*		*0.008*	*0.0047*	*0.0172*	
	B. First quintile low pay threshold							
	(a). Predicted labour force/earnings state probabilities at t, conditional on labour force/earnings state at t-1							
	NILF, t	Unemploy, t	Low pay, t	Higher pay, t	NILF, t	Unemploy, t	Low pay, t	Higher pay, t
(1) NILF, t-1	0.2349	0.0800	0.1201	0.5650	0.4212	0.0535	0.1071	0.4182
s.e.	*0.0229*	*0.0311*	*0.0216*	*0.0296*	*0.0199*	*0.0135*	*0.0161*	*0.0174*
(2) Unemploy, t-1	0.1342	0.0751	0.1526	0.6380	0.2938	0.0665	0.1451	0.4946
s.e.	*0.0172*	*0.0340*	*0.0325*	*0.0422*	*0.0210*	*0.0196*	*0.0252*	*0.0253*
(3) Low pay, t-1	0.0802	0.0342	0.1876	0.6980	0.1982	0.0293	0.2402	0.5322
s.e.	*0.0084*	*0.0143*	*0.0316*	*0.0330*	*0.0160*	*0.0095*	*0.0317*	*0.0258*
(4) Higher pay, t-1	0.0771	0.0301	0.1080	0.7847	0.2081	0.0257	0.1479	0.6182
s.e.	*0.0066*	*0.0125*	*0.0205*	*0.0239*	*0.0138*	*0.0084*	*0.0223*	*0.0207*

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

		I	II	III	IV	I	II	III	IV
(3)-(1)		-0.1547***	-0.0458**	0.0675***	0.1329***	-0.2199***	-0.0254***	0.1065***	0.1388***
	s.e.	*0.0174*	*0.022*	*0.0195*	*0.0223*	*0.0114*	*0.0081*	*0.0207*	*0.0172*
(3)-(2)		-0.0540***	-0.0410*	0.0350*	0.0600**	-0.0943***	-0.0505***	0.0851***	0.0597***
	s.e.	*0.0115*	*0.0245*	*0.0208*	*0.0264*	*0.0136*	*0.0163*	*0.0178*	*0.0205*
(3)-(4)		0.0031	0.004	0.0796***		-0.0089	0.0038	0.0772***	
	s.e.	*0.0047*	*0.0085*	*0.0183*		*0.0074*	*0.0047*	*0.0168*	

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

Appendix Summary statistics and coefficient estimates

Table a1: Summary statistics of modelling samples

	Males					Females				
	NILF	Unemp	Low pay[a]	Higher pay	All	NILF	Unemp	Low pay[a]	Higher pay	All
Year 11 or below	41.45[b]	38.46	33.68	17.62	22.09	45.84	34.22	36.65	20.59	29.45
Year 12	11.33	11.49	19.29	12.95	13.14	16.06	17.39	16.21	14.38	15.1
Certificate 1 or 2	3.3	4.11	4.51	1.27	1.82	3.48	6.26	4.3	1.83	2.63
Certificate 3 or 4	25.26	25.92	25.66	30.27	29.25	13.05	20.24	21.48	15.33	15.33
Diploma	7.53	7.9	6.87	9.46	9.02	7.65	7.27	9.72	11.14	9.92
Degree or higher	11.13	12.12	10	28.43	24.68	13.93	14.63	11.65	36.73	27.57
Married/de facto	55.41	48.79	56.54	75.09	70.72	73.23	52.9	67.21	71.38	70.98
Health condition	72.14	31.61	23.68	14.53	22.16	38.05	32.84	20.85	14.91	22.51
Age 21-24	3.73	13.91	17.53	5.58	6.47	4.65	12.6	9.27	5.49	5.78
Age 25-34	11.86	27.61	30.38	27.14	25.68	23.46	29.25	23.52	24.6	24.34
Age 35-44	18.43	25.92	22.86	30.94	28.83	27.4	29.62	28.49	29.93	29.09
Age 45-54	30.76	21.81	21.1	26.96	26.8	23.06	21.16	27.82	30.19	27.69
Age 55+	35.22	10.75	8.13	9.38	12.22	21.43	7.36	10.91	9.79	13.1
Australian born	77.77	77.56	82.2	80.39	80.12	75.74	77.55	81.9	79.89	78.8
Immigrants-ESC	9.13	10.85	6.87	9.91	9.65	7.94	7.36	7.05	9.41	8.74
Immigrants-NESC	13.1	11.59	10.93	9.7	10.23	16.33	15.09	11.05	10.7	12.46
No children under 18	74.88	72.5	70.6	56.29	59.9	41.09	48.21	52.23	55.22	50.75
Youngest 0-2	6.63	11.91	11.48	13.4	12.47	25.33	11.5	7.75	8.07	13.05
Youngest 3-5	4.77	4.43	4.89	7.81	7.16	12.11	9.66	8.57	7.31	8.84
Youngest 6-11	7.53	5.8	6.98	12.34	11.21	12.33	18.31	17.21	14.84	14.43
Youngest 12-17	6.2	5.37	6.04	10.16	9.27	9.14	12.33	14.24	14.56	12.93
Number of children	0.52	0.53	0.54	0.81	0.75	1.26	0.98	0.89	0.81	0.95
s.t.	*1.06*	*1.05*	*1.00*	*1.07*	*1.07*	*1.37*	*1.14*	*1.13*	*1.04*	*1.17*
City	52.65	57.96	52.69	66.06	63.38	58.62	60.72	53.49	66.24	62.9
Inner region	29.39	24.97	29.84	22.95	24.21	26.21	25.67	28.19	22.72	24.23
Outer region	17.06	14.12	15.33	9.14	10.62	13	11.59	15.91	9.13	10.84
Remote area	0.9	2.95	2.14	1.84	1.79	2.17	2.02	2.41	1.91	2.03
No of observations	3,001	949	1,820	21,181	26,951	9,640	1,087	2,696	20,594	34,017

Note: (a) The two-third median low pay definition is used for the summary statistics. (b) Except for the variable on the number of children, statistics for all other variables are in percentage.

Table a2: Coefficient estimates of the models

	Two-third median				First quintile			
	Males		Females		Males		Females	
	Coef.	S.e.	Coef.	S.e.	Coef.	S.e.	Coef.	S.e.
	Unemployment							
Unem t-1	1.031	0.172	1.112	0.123	0.937	0.178	0.935	0.133
Low pay t-1	1.047	0.248	0.739	0.160	1.025	0.208	0.730	0.139
Higher pay t-1	0.994	0.159	0.494	0.116	0.947	0.167	0.486	0.125
Degree	-0.179	0.204	0.217	0.134	-0.159	0.210	0.221	0.146
diploma	0.173	0.216	0.147	0.158	0.259	0.222	0.145	0.172
Certificate 3-4	0.020	0.150	0.544	0.118	0.029	0.155	0.554	0.128
Certificate 1-2	0.385	0.248	0.507	0.208	0.380	0.263	0.525	0.233
Year 12	-0.191	0.208	0.134	0.120	-0.207	0.214	0.151	0.130
Age21-24	0.678	0.252	0.588	0.174	0.717	0.256	0.633	0.182
Age25-34	0.134	0.158	0.194	0.104	0.118	0.162	0.218	0.109
Age45-54	-0.404	0.159	-0.493	0.112	-0.402	0.162	-0.521	0.118
Age55+	-1.306	0.191	-1.441	0.159	-1.344	0.192	-1.462	0.167
Married/de facto	0.033	0.234	-0.623	0.159	0.040	0.235	-0.641	0.160
Health condition	-0.825	0.168	-0.027	0.129	-0.828	0.169	-0.005	0.129
Immigrants-ESC	0.159	0.205	-0.121	0.169	0.120	0.207	-0.096	0.181
Immigrants-NESC	-0.070	0.204	0.057	0.121	-0.048	0.211	0.068	0.130
Youngest 0-2	0.130	0.264	-1.300	0.151	0.131	0.263	-1.298	0.155
Youngest 3-5	0.000	0.255	-0.293	0.144	-0.022	0.260	-0.300	0.148
Youngest 6-11	0.344	0.292	0.321	0.146	0.333	0.295	0.308	0.150
Youngest 12-17	0.620	0.269	0.516	0.144	0.720	0.279	0.505	0.150
No. of children	-0.239	0.188	-0.218	0.114	-0.267	0.191	-0.205	0.116
Inner region	-0.004	0.141	-0.102	0.097	-0.013	0.145	-0.102	0.105
Outer region	-0.256	0.165	-0.076	0.128	-0.304	0.172	-0.076	0.138
Remote area	0.608	0.344	-0.256	0.265	0.551	0.349	-0.238	0.281
Wave 3	-0.305	0.240	-0.535	0.177	-0.316	0.240	-0.501	0.180
Wave 4	-0.603	0.263	-0.265	0.186	-0.628	0.265	-0.280	0.187
Wave 5	-0.278	0.264	-0.145	0.188	-0.301	0.265	-0.161	0.188
Wave 6	-0.354	0.258	-0.059	0.190	-0.375	0.260	-0.093	0.193
Wave 7	-0.628	0.282	-0.099	0.189	-0.643	0.280	-0.129	0.190
Wave 8	-0.451	0.267	-0.017	0.190	-0.477	0.267	-0.051	0.194
Wave 9	-0.170	0.268	-0.129	0.188	-0.192	0.270	-0.171	0.190
Wave 10	-0.206	0.261	0.021	0.188	-0.216	0.262	-0.009	0.192
Wave 11	-0.193	0.255	-0.175	0.190	-0.207	0.257	-0.203	0.193
Unem t0	3.167	0.219	2.850	0.145	3.334	0.234	3.031	0.165
Low pay t0	1.874	0.291	1.758	0.183	1.988	0.265	1.675	0.165
Higher pay t0	1.848	0.210	1.556	0.139	1.914	0.224	1.426	0.146
Mean (married)	-0.014	0.278	-0.097	0.191	-0.043	0.283	-0.115	0.197
Mean (health)	-0.551	0.250	-0.770	0.186	-0.488	0.255	-0.755	0.193
Mean (children)	-0.047	0.142	-0.002	0.093	-0.027	0.143	-0.007	0.096
Constant	-1.691	0.309	-1.987	0.220	-1.770	0.318	-2.117	0.231
	Low pay							
Unem t-1	1.205	0.228	1.134	0.153	1.457	0.194	1.166	0.136
Low pay t-1	2.899	0.226	2.784	0.120	2.902	0.186	2.617	0.093
Higher pay t-1	2.112	0.186	2.013	0.096	2.288	0.166	1.985	0.081
Degree	-0.554	0.210	-0.412	0.122	-0.602	0.194	-0.378	0.110
diploma	-0.159	0.223	0.038	0.132	-0.141	0.198	0.076	0.121
Certificate 3-4	-0.037	0.161	0.336	0.105	0.056	0.148	0.417	0.097
Certificate 1-2	0.025	0.340	0.349	0.192	-0.062	0.320	0.298	0.185
Year 12	0.190	0.211	-0.123	0.121	0.057	0.193	-0.007	0.109
Age21-24	0.841	0.272	0.433	0.169	0.783	0.253	0.441	0.159

Age25-34	0.168	0.161	0.001	0.099	0.109	0.148	-0.001	0.089
Age45-54	-0.379	0.157	-0.238	0.098	-0.475	0.141	-0.223	0.089
Age55+	-1.593	0.194	-1.150	0.131	-1.799	0.172	-1.161	0.119
Married/de facto	0.174	0.217	-0.450	0.134	0.099	0.201	-0.389	0.121
Health condition	-0.924	0.164	-0.478	0.103	-0.974	0.151	-0.447	0.090
Immigrants-ESC	-0.160	0.248	-0.228	0.143	-0.274	0.219	-0.200	0.131
Immigrants-NESC	-0.005	0.195	-0.240	0.119	-0.091	0.193	-0.277	0.108
Youngest 0-2	-0.095	0.281	-1.684	0.132	-0.255	0.257	-1.766	0.118
Youngest 3-5	-0.047	0.267	-0.122	0.113	-0.159	0.246	-0.075	0.099
Youngest 6-11	0.465	0.312	0.444	0.117	0.377	0.283	0.444	0.108
Youngest 12-17	0.805	0.283	0.531	0.118	0.906	0.263	0.611	0.109
No. of children	-0.473	0.185	-0.390	0.087	-0.392	0.164	-0.497	0.078
Inner region	0.247	0.139	0.030	0.085	0.124	0.128	0.024	0.076
Outer region	0.026	0.165	0.231	0.107	-0.169	0.149	0.118	0.100
Remote area	0.858	0.394	0.113	0.212	0.676	0.396	0.009	0.188
Wave 3	-0.042	0.244	-0.373	0.149	-0.113	0.222	-0.137	0.131
Wave 4	-0.143	0.259	-0.094	0.155	-0.189	0.238	-0.020	0.139
Wave 5	-0.098	0.269	0.145	0.156	-0.085	0.247	0.307	0.140
Wave 6	0.275	0.258	0.328	0.154	0.068	0.240	0.244	0.141
Wave 7	-0.014	0.265	0.276	0.155	-0.144	0.245	0.243	0.141
Wave 8	0.136	0.267	0.475	0.158	-0.011	0.244	0.384	0.146
Wave 9	0.066	0.262	0.125	0.157	-0.164	0.242	-0.008	0.144
Wave 10	-0.320	0.265	0.223	0.158	-0.332	0.243	0.163	0.144
Wave 11	-0.238	0.268	-0.077	0.158	-0.302	0.246	-0.062	0.144
Unem t0	1.807	0.283	1.467	0.177	1.695	0.262	1.399	0.167
Low pay t0	4.641	0.285	3.414	0.158	4.248	0.251	3.293	0.129
Higher pay t0	2.674	0.241	2.205	0.126	2.513	0.233	2.288	0.114
Mean (married)	0.095	0.270	0.159	0.169	0.259	0.250	0.117	0.154
Mean (health)	-0.668	0.251	-0.820	0.169	-0.821	0.230	-0.965	0.152
Mean (children)	0.123	0.138	0.210	0.076	0.044	0.123	0.274	0.066
Constant	-3.196	0.371	-2.885	0.213	-2.438	0.336	-2.400	0.196
	Higher pay							
Unem t-1	1.571	0.166	1.079	0.124	1.366	0.177	1.127	0.130
Low pay t-1	2.876	0.207	2.160	0.102	2.751	0.175	2.167	0.086
Higher pay t-1	3.064	0.118	2.334	0.059	3.162	0.126	2.395	0.064
Degree	0.643	0.173	0.957	0.101	0.711	0.170	1.054	0.103
diploma	0.400	0.197	0.631	0.119	0.471	0.190	0.666	0.118
Certificate 3-4	0.445	0.138	0.698	0.095	0.498	0.135	0.725	0.096
Certificate 1-2	-0.018	0.292	0.185	0.190	-0.007	0.280	0.077	0.194
Year 12	0.395	0.185	0.378	0.106	0.405	0.182	0.458	0.108
Age21-24	0.091	0.255	-0.016	0.159	0.048	0.250	-0.109	0.161
Age25-34	-0.046	0.144	-0.086	0.080	-0.060	0.141	-0.057	0.081
Age45-54	-0.474	0.136	-0.240	0.083	-0.439	0.133	-0.232	0.084
Age55+	-1.871	0.155	-1.393	0.108	-1.796	0.152	-1.386	0.107
Married/de facto	0.151	0.189	-0.406	0.109	0.161	0.190	-0.434	0.110
Health condition	-1.040	0.138	-0.464	0.080	-1.016	0.140	-0.477	0.082
Immigrants-ESC	-0.153	0.199	-0.162	0.125	-0.145	0.187	-0.053	0.123
Immigrants-NESC	-0.417	0.172	-0.558	0.110	-0.363	0.179	-0.533	0.108
Youngest 0-2	-0.226	0.237	-1.795	0.099	-0.147	0.235	-1.770	0.099
Youngest 3-5	-0.059	0.217	-0.072	0.085	-0.096	0.221	-0.079	0.088
Youngest 6-11	0.417	0.268	0.523	0.098	0.448	0.260	0.558	0.101
Youngest 12-17	0.794	0.238	0.771	0.103	0.930	0.239	0.805	0.106
No. of children	-0.323	0.146	-0.596	0.067	-0.362	0.146	-0.583	0.068
Inner region	-0.148	0.120	-0.278	0.075	-0.161	0.118	-0.302	0.074
Outer region	-0.482	0.145	-0.276	0.101	-0.521	0.144	-0.287	0.103
Remote area	0.691	0.357	-0.213	0.183	0.904	0.354	-0.196	0.184

Wave 3	0.009	0.207	-0.030	0.117	0.033	0.207	-0.081	0.120
Wave 4	-0.110	0.225	0.032	0.125	-0.102	0.226	0.021	0.128
Wave 5	-0.009	0.232	0.255	0.128	-0.014	0.232	0.191	0.130
Wave 6	0.062	0.229	0.271	0.128	0.109	0.230	0.308	0.129
Wave 7	-0.028	0.233	0.243	0.129	0.003	0.234	0.266	0.131
Wave 8	0.134	0.230	0.346	0.133	0.183	0.229	0.372	0.136
Wave 9	-0.012	0.233	0.045	0.131	0.062	0.234	0.096	0.133
Wave 10	-0.185	0.230	0.090	0.131	-0.150	0.230	0.093	0.134
Wave 11	-0.120	0.232	-0.032	0.131	-0.059	0.232	-0.031	0.133
Unem t0	1.716	0.237	1.523	0.167	1.765	0.239	1.461	0.171
Low pay t0	3.064	0.256	2.679	0.147	3.249	0.235	2.711	0.128
Higher pay t0	4.307	0.204	3.742	0.111	4.307	0.209	3.896	0.112
Mean (married)	0.662	0.232	0.243	0.145	0.634	0.235	0.268	0.146
Mean (health)	-1.337	0.212	-1.411	0.147	-1.238	0.215	-1.440	0.150
Mean (children)	0.046	0.112	0.275	0.058	0.054	0.112	0.245	0.059
Constant	-2.026	0.314	-1.844	0.192	-2.326	0.312	-2.126	0.195
c11[(a)]	-0.910	0.115	-0.815	0.090	-1.004	0.113	-0.973	0.094
c21	-1.393	0.131	-1.281	0.074	-1.121	0.137	-0.986	0.099
c22	0.841	0.143	0.043	0.095	-1.037	0.101	-0.880	0.091
c31	-0.832	0.133	-1.196	0.085	-0.783	0.134	-0.870	0.098
c32	0.576	0.138	-0.883	0.091	-0.571	0.108	-0.830	0.090
c33	1.123	0.067	-0.233	0.102	1.082	0.055	0.933	0.040
Log-likelihood	-10039.24		-18282.19		-11997.80		-20629.25	
Observations	26951		34017		26951		34017	

Note: c11-c33 refer to the corresponding elements in the Cholesky decomposition of the variance-covariance matrix of the random effects.