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Abstract

This paper employs a dynamic multinomial choice framework to provide new evidence on the effect of health on labour market transitions among older individuals. We consider retirement as a multi-state process and examine the effects of ill-health and health shocks on mobility between full-time employment, part-time employment, self-employment and inactivity. In order to disentangle the roles of unobserved individual heterogeneity and true state dependence, we estimate dynamic panel multinomial logit models with random effects, assuming a first order Markov process and accounting for the initial conditions problem. We also account for potential measurement error in the self-assessed health status by building a latent health stock model and employing measures of health shocks. Using data from the first nine waves of the (2001 - 2009) Household, Income and Labour Dynamics in Australia (HILDA) Survey, we find that both ill-health and health shocks greatly increase the probability of leaving full-time employment towards inactivity. We also find evidence of health-driven part-time and self-employment paths into inactivity.

JEL classifications: C23, I10, J24

Keywords: ill-health, health shocks, labour transitions, dynamic multinomial choice models

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1. Introduction

Population ageing poses a fundamental threat and a burden to the sustainability of any social security system. This demographic change combined with the generosity of national pension systems and disability benefit schemes in the majority of developed economies also has profound consequences for labour markets. Early exists from the labour market and the increased fragmentation of individuals' labour market trajectories are imposing the need to re-examine the determinants of individuals' labour market choices, particularly in the latter part of the life-cycle. The identification of both determinants and trajectories of labour transitions at older ages would allow governments and policy makers to formulate policies aimed at avoiding the loss of contribution from a potentially active labour force. Whereas the literature has established that ill-health is strongly associated with labour supply decisions, especially retirement choices (Disney *et al.*, 2006; Lindeboom, 2006a; Garcia-Gomez, 2011), there is still sparse evidence on the different labour routes followed by middle-age and older workers in ill-health before transiting into economic inactivity.

Empirical evidence consistently finds that retirement is a multi-state process and that a considerable number of individuals only partially retire (Ruhm, 1990, 1995; Peracchi and Welch, 1994; Doeringer, 1995; Jimenez-Martin *et al.*, 2006). Individuals frequently re-enter the labour force after an initial exit or move from a full-time job as an employee to a part-time job, self-employment or disability before becoming permanently inactive (Kerkhofs *et al.*, 1999; Bruce *et al.*, 2000; Blundell *et al.*, 2002). Also, in the majority of the OECD countries, a large proportion of the self-employed is middle-age or older workers (Blanchflower, 2000; Gu, 2009). Even though the study on the determinants of self-employment has received a lot of attention (Parker, 2004, 2006), very few empirical studies have explored the relationship between health and self-employment in the latter part of the life-cycle (Fuchs, 1982; Zissimopoulos and Karoly, 2007; Parker and Rougier, 2007). Furthermore, among previous studies there is no apparent consensus on the direction of the effect of health on the decision to choose self-employment versus waged employment for older individuals.

Trends of rising self-employment among older workers are especially marked in Australia, where 37 per cent of all employed individuals aged 65 and over are owner-managers of unincorporated businesses (Australian Bureau of Statistics (ABS), 2008).[1] Also, the likelihood

[1] Australian Bureau of Statistics, Australian Labour Statistics, Issue 6105.0, July 2008.

of being self-employed rises steadily with age. While around 10 per cent of the Australian employed population aged 25-29 years are self-employed, this percentage more than triples around retirement age (60-64), (ABS, 2008). Data also indicate that in recent years there has been an increase in the proportion of individuals working part-time in pre-retirement ages, especially among men (Australian Bureau of Statistics, 2011).[2] These trends suggest the presence of part-time and self-employment routes into retirement.

In this paper, we explicitly consider retirement as a multi-state process and examine the effect of ill-health and health shocks on mobility between full-time employment, part-time employment, self-employment and inactivity, using a dynamic multinomial choice framework. We devote particular attention to the notion of true state dependence. True state dependence, or scarring, arises whenever there is a causal link between past and current labour market states so that the experience of a particular state may alter preferences, prices or constraints in the way that later employment is affected (Arulampalam, 2000). In order to disentangle the effects of unobserved individual heterogeneity and true state dependence, we estimate dynamic panel multinomial logit models with random effects, assuming a first order Markov process and accounting for the initial conditions problem (Wooldridge, 2005). In this way we can distinguish between the effects of past employment experience and observable and unobservable characteristics on current employment behaviour.

Following the literature (see, for example, Bound, 1991; Bound *et al.*, 1999; Brown *et al.*, 2010; Jones *et al.*, 2010), we attempt to account for measurement error in the self-assessed health (SAH) status by building a latent health stock model, specifying SAH as a function of a set of more specific measures of health using generalised ordered probit models. Furthermore, we distinguish between gradual and sudden health deterioration (health shocks), as information on the incidence of unexpected health changes could help identifying the impact of health shocks on labour outcomes.

Models are estimated on a sample of middle-age and older individuals drawn from the first nine waves (2001-2009) of the Household, Income and Labour Dynamics in Australia Survey (HILDA). We find that ill-health and health shocks strongly influence labour market choices at latter ages. For both men and women, long-term health conditions and health shocks greatly increase the probability of leaving full-time employment and enhance the likelihood of

[2] Australian Bureau of Statistics, Australian Labour Statistics, Issue 6105.0, October 2011.

switching to inactivity. We also find evidence of part-time and self-employment paths into inactivity.

This paper presents two important contributions to the existing literature. First, it extends the knowledge of the relationship between ill-health and transitions to part-time and self-employment among older workers. Secondly, our models allow us to identify the presence of health-driven multi-state labour trajectories towards inactivity. Moreover, to the best of our knowledge, this is the first paper that proposes a dynamic multinomial framework of labour transitions for older individuals that accounts for state dependence, unobserved heterogeneity, as well as health shocks and measurement error in self-assessed health.

2. Previous literature

There are three different strands of literature relevant to this paper: studies which examine inter-temporal dependencies in labour market decisions; the empirical literature on health shocks and labour supply; and more specifically analyses of the impact of ill-health on self-employment. Within the first strand of literature, we focus on dynamic models that account for unobserved heterogeneity. Allowing for persistence in unobservables is needed to correctly identify the causal link between past and current labour supply behaviour (true state dependence) (Knights *et al.,* 2002). Previous studies find that there is a great deal of persistence in individual's labour supply. Hyslop (1999) analyses the inter-temporal labour force participation behaviour of married women using data drawn from the U.S. Panel Study of Income Dynamics (PSID). Employing a series of linear and non-linear models, he finds that women's participation decisions exhibit substantial unobserved heterogeneity and positive true state dependence.

Recently, a number of studies on labour-market transitions have focused on the estimation of dynamic multinomial choice models with unobserved heterogeneity. Uhlendorff (2006) estimates a dynamic multinomial logit model with random effects on data from the German Socio-economic Panel Study (SOEP) to analyse mobility between low paid jobs, high paid jobs and not working. His findings reveal the presence of true state dependence in low paid jobs and non-employment. On the same dataset, Haan and Uhlendorff (2007) look at inter-temporal labour supply behaviour using a mixed logit framework to account for true state dependence and unobserved effects. They find that true state dependence is present in voluntary non-participation, involuntary unemployment, full-time work and over-time work. Caliendo and Uhlendorff (2008) and Haan (2010) estimate a series of dynamic panel data multinomial models on data from the SOEP to model transitions between waged employment, self-employment and unemployment among men and the intertemporal labour supply of married women, respectively. Their results suggest evidence of true state dependence in all labour market states considered. Using data from the HILDA Survey (as in the present study), Buddelmeyer and Wooden (2008) analyse transitions from casual employment to four other labour market outcomes (permanent employment, fixed-term employment, self-employment and joblessness). They find that for both men and women, labour market choices entail a large amount of state dependence.

In the empirical literature on health and work, health shocks are commonly defined using either self-reported or clinical information on acute health events such as strokes, heart attacks or cancer (Datta Gupta and Larsen, 2007). Health shocks are also defined using differences in responses between consecutive waves on the five point self-assessed measure of health (Garcia Gomez and Lopez Nicolas, 2006) or identified as a sudden drop in a self-assessed measure of health satisfaction (Riphahn, 1999). Potentially important elements in the definition of a health shock are the measurement of its severity and the ability to define whether it is anticipated or unanticipated. Jimenez-Martin *et al.* (2006) analyse the effects of various disabilities and their severity on older workers' labour force transitions. They find that more severe shocks are associated with a larger magnitude of effect on the probability of retiring. Lindeboom *et al.* (2006b) focus on the relationship between the onset of disability and employment outcomes. Their results show that unanticipated health shocks (defined as unscheduled hospitalisation) greatly increase the likelihood of an onset of disability. Studies on Australian data, conclude that ill-health and health shocks are important determinants of labour market exits (Cai and Kalb, 2006; Zhang, *et al.* 2009; Zucchelli *et al.*, 2010) and that work disability and its severity can also explain changes in labour force decisions inside the Australian labour market (Oguzoglu, 2011).

Finally, existing evidence on ill-health and self-employment among older individuals is limited and inconclusive. Using longitudinal data drawn from the U.S. Retirement History Study (RHS), an early study by Fuchs (1982) found no impact of health on transitions to self-employment. Moreover, estimates using data from the British Retirement Study indicate a negative effect of poor health on participation in self-employment (Parker and Rougier, 2007). However, using panel data from the U.S. Health and Retirement Study (HRS) Zissimopoulos and Karoly (2007) find that the likelihood of moving to self-employment increases by 47 and 30 percentage points for men and women, respectively, with a health condition which limits their work relative to their respective counterparts without a work limiting health condition. While it is possible to conclude that these results can be partly explained by institutional factors, their inconsistencies highlight the need for further research.

3. Econometric framework

3.1 A dynamic model for labour transitions

We focus our attention on the effect of health on mobility between four alternative labour market states: full-time employment (j=1); part-time employment (j=2); self-employment (j=3); and inactivity (j=4). As an individual's choice is characterised by a set of discrete, unordered and mutually exclusive outcomes over different time periods, we describe labour transitions using panel data dynamic multinomial logit models with random effects. We assume a first order Markov process to capture state dependence and an individual random effect error component to account for unobserved heterogeneity, in order to distinguish between true and "spurious" state dependence. Multinomial logit models are consistent with the Random Utility Maximisation (RUM) assumption of consumer behaviour (Green, 2003), where each labour market outcome is associated with a given level of utility. Assume the utility for individual i from choosing labour state j in period t, V_{ijt}, is given by:

$$V_{ijt} = X_{it}\beta_j + P_{it-1}\chi_j + L_{it-1}\phi_j + \alpha_{ij} + \varepsilon_{ijt} \quad (i = 1,..., N; t = 1,..., T; j = 1,..., J), \tag{1}$$

where X_{it} and P_{it-1} are vectors containing individual observed characteristics in period t (constant, age, education, geographical origin, living in a inner or remote region) and $t-1$ (health, marital status, household income, housing tenure, having own dependent children) respectively, with unknown weights, β_j and χ_j, respectively. Individual characteristics in P_{it-1} are assumed to affect labour market decisions in lagged form, which also help to ease any potential problems of endogeneity. L_{it-1} is a vector of (J-1) binary dummy variables indicating lagged labour market states with parameter vector ϕ_j, with $L_{ijt-1} = 1$ if individual i

at time (t-1) chooses labour state j, and $L_{ijt-1} = 0$ otherwise. Individual-specific time-invariant unobserved heterogeneity is represented by α_{ij} and ε_{ijt} is the idiosyncratic error term. ε_{ijt} independently and identically follows a Type I extreme value distribution and is also assumed to be independent of observable regressors and α_{ij}. Assume at each time period an individual will choose the labour market state with the highest utility. That is, $L_{ijt} = 1$ if $V_{ijt} > V_{ikt}$ for all $k \neq j$ $(k = 1,...,J)$. Accordingly, conditional on individual random effects, the probability of an individual i choosing alternative j in period t is:

$$P_{ijt} = P(L_{ijt} = 1 \mid X_{it}, P_{it-1}, Z_{it-1}, \alpha_{i1},...,\alpha_{iJ}) = \frac{\exp(X_{it}\beta_j + P_{it-1}\chi_j + L_{it-1}\phi_j + \alpha_{ij})}{\sum_{k=1}^{J}\exp(X_{it}\beta_k + P_{it-1}\chi_k + L_{it-1}\phi_k + \alpha_{ik})}. \tag{2}$$

For identification purposes, all coefficients for the first category (j =1, for full-time employment in our case) and its unobserved heterogeneity term in equation (1) are set to zero. We also assume that the unobserved heterogeneity for the J-1 remaining choices follows a multivariate normal distribution with zero means and a variance-covariance matrix.[3] This implies a trivariate normal distribution for our application. It is important to highlight that the assumption of non-zero correlation across random effects for alternative choices in the stochastic part of utility means that this type of multinomial logit model does not exhibit the restrictive assumption of Independence from Irrelevant Alternatives (IIA)(Revelt and Train, 1998). The sample likelihood for the multinomial logit with random effects can be written as:

$$SL = \prod_{i=1}^{N}\int_{-\infty}^{\infty}\prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp(X_{it}\beta_j + P_{it-1}\chi_j + L_{it-1}\phi_j + \alpha_{ij})}{\sum_{k=1}^{4}\exp(X_{it}\beta_k + P_{it-1}\chi_k + L_{it-1}\phi_k + \alpha_{ik})}\right)^{L_{ijt}} f(\alpha)d(\alpha), \tag{3}$$

Expression (3) cannot be solved analytically and is instead approximated using simulated maximum likelihood methods (Train, 2003). The simulated sample likelihood is given by:

[3] Although the distributional assumption depends on the research question, in most applications unobserved heterogeneity is specified to be normally distributed. For a detailed explanation, see Train (2003).

$$SSL = \prod_{i=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp(X_{it}\beta_j + P_{it-1}\chi_j + L_{it-1}\phi_j + \alpha_{ij}^r)}{\sum_{k=1}^{3} \exp(X_{it}\beta_k + P_{it-1}\chi_k + L_{it-1}\phi_k + \alpha_{ik}^r)} \right)^{L_{ijt}}, \quad (4)$$

where R values are drawn from the distribution of the unobserved heterogeneity. For each of these draws the likelihood is calculated and then averaged over the R draws.[4]

3.2 Initial conditions problem

As we are estimating dynamic models, we need to account for the initial conditions problem. The initial conditions problem arises whenever the observation period of transition probabilities does not start with the stochastic process generating individual's employment dynamics (Heckman, 1981). We follow Mundlak (1978), Chamberlain (1985) and Wooldridge (2005) and model the distribution of the unobserved effect conditional on the initial values and the within individual means of any exogenous (with respect to ε_{ijt}) explanatory variables. This simply translates into including among our regressors dummy variables for the initial values of the dependent variables L_{i1} and the average over the sample period of the observations for the exogenous variables. Accordingly, we parameterize the distribution of the individual effect as:

$$\alpha_{ij} = L_{i1}\vartheta_j + \overline{PX}_i\eta_j + \mu_{ij} \ \ (i = 1,..., N;\ j = 2,..., J), \quad (5)$$

where L_{i1} is a vector for the *J*-1 values of the employment status variables in the initial period (t =1) and $\overline{PX_i}$ is the average of those exogenous variables in P_{it-1} and X_{it} that vary over the sample periods. μ_{ij} is assumed to be multivariate normally distributed, with zero means and $(J-1)\times(J-1)$ variance-covariance matrix, and independent of all the covariates, the initial conditions and the idiosyncratic error term (ε_{ijt}). Note that this approach not only addresses the initial conditions problem, but also allows for the unobserved effects to be arbitrarily

[4] Models are estimated using the *mixlogit* Stata routine that implements simulation using Halton sequences. In particular, the dynamic random effects models presented in section 5 were estimated using 250 Halton draws. As a sensitivity test, a selection of these models was also estimated using adaptive quadrature, implemented in Stata by the program *GLLAMM* (Generalized Linear Latent and Mixed Models). For a description of the mechanics of Halton sequences in the context of the estimation of mixed logit models see Train (2000). For further details on the method of adaptive quadrature, see Rabe-Hesketh *et al.* (2004).

correlated with the observed heterogeneity. Similar approaches have been used by Erdem and Sun (2001), Bjorn and Leth-Petersen (2007), Buddelmeyer and Wooden (2008) and Caliendo and Uhlendorff (2008). It should be noted that, as we are specifying a complete model for the unobserved effect, this method can be sensitive to miss-specification.

3.3 Model for self-assessed health

Self-assessed measures of health can be problematic when used to identify the causal effect of health on labour market outcomes (Anderson and Burkhauser, 1985; Bazzoli, 1985; Stern, 1989; Bound, 1991; Bound *et al.*, 1999; Au *et al.*, 2005). First, self-reported measures are based on non-comparable subjective judgements: individuals with the same underlying health may apply different thresholds when reporting their health status on a categorical scale (Lindeboom and van Doorslaer, 2004). Secondly, self-reported health might not be independent of labour market status (Garcia-Gomez and Lopez Nicholas, 2006). While measurement error caused by reporting heterogeneity will lead to an underestimation of the effect of health on labour market outcomes, endogeneity in the health-work relationship will lead to an upward bias (Bound, 1991; Bound *et al.*, 1999). Thirdly, health problems can also be systematically overstated as a means of obtaining social security benefits such as disability benefits (Kerkhofs and Lindeboom, 1995) or simply to justify being outside the labour market (justification bias). All these indicate potential endogeneity for the health status regressor in P_{it-1} in equation (1).

In this paper, we follow Stern (1989) and Bound (1991) and adopt an instrumental variable type-procedure to deal with the issues related to the endogeneity and measurement error of self-perceived health. This method involves estimating a generalised ordered probit model (GOP, Pudney and Shields, 2000) for a measure of self-assessed health (SAH) as a function of a series of more specific and thus potentially more accurate indicators of health limitations and bodily pain, to obtain a health stock measure purged of reporting bias. We then use this latent health stock variable as our measure of health in the labour transition models. This procedure simply mirrors standard methods of dealing with error-in variables (Griliches, 1974) and has been extensively used in the empirical literature on health and labour outcomes (e.g. Disney *et al.*, 2006; Brown *et al.*, 2010; Jones *et al.*, 2010). In order to check the robustness of this measure, we also make use of an alternative health indicator defined as the presence of working-limiting long-term conditions. Details for all the above mentioned health variables are reported in the following section.

4. Data

4.1 Dataset and variables of interest

This paper uses data drawn from the first 9 waves (2001-2009) of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. HILDA is a household-based longitudinal study which focuses on issues related to three major topic areas: household and family dynamics; income and welfare dynamics; and labour market dynamics (Watson and Wooden, 2007). The survey data also contain a large number of health variables which we use to build our health stock measure and a measure of health shocks.

As our interest is on the effects of health on labour market choices of older workers, we only make use of a sub-sample of individuals aged between 45 years of age to the year prior state retirement age. We thus obtain a balanced sample which consists of 2467 individuals, 1192 men, aged between 45 and 64, and 1275 women, aged between 45 and 62. The variables used in our analysis are summarised in Tables 1 and 2. Table 1 contains definitions and sample statistics of the dependent and explanatory variables used in the labour transitions model, while Table 2 presents the variables used in health stock model.

(*Tables 1 and 2 around here)*

Employment status

We look at transitions over time between four different labour market states: full-time employment; part-time employment; self-employment; and economic inactivity. Using information contained in the HILDA Survey, we distinguish between being full-time and part-time employed as an employee (*i.e.* any individual who works for a public or private employer and receives remuneration in wages/salaries). Self-employed individuals are identified using the Australian Bureau of Statistics (ABS) Employment Type classification.[5] According to this categorisation, we define self-employed individuals as those who self-

[5] Australian Labour Market Statistics, Australian Bureau of Statistics (ABS), Issue 6105.0, July 2011.

report being owner-managers of either incorporated or unincorporated enterprises.[6] Our broad definition of economic inactivity comprises individuals both voluntarily inactive (retired) and involuntarily inactive (unemployed).[7]

Health and health shocks

We define ill-health using a latent health stock measure obtained regressing a five class measure of self-assessed health (SAH) onto a series of more specific health indicators using generalised ordered probit models (Table 2). The SAH variable contained in the survey offers an ordinal ranking of perceived general health status and is derived from the question: "In general, would you say your health is excellent/very good/good/fair/poor?". The specific health measures used as covariates in the health stock model contain information on various degrees of physical functioning (limitations in the ability of performing a series of moderate and vigorous activities; lifting or carrying groceries; climbing one or several flights of stairs; walking different distances and bathing and dressing); problems with work or other daily activities caused by physical health; degrees of bodily pain and the extent to which pain interferes with normal work (see Table 2 for details on these variables). Generalised ordered probit models (GOP) also allow for different thresholds when reporting self-assessed health. In particular, we allow the SAH thresholds to be influenced by age, gender (estimating GOP models for men and women separately), ethnicity, education, employment status, income and other demographic characteristics (see lower part of Table 2).[8] In addition, we also define ill-health employing a variable which defines the presence of any long-term conditions "which limit the type or amount of work an individual can execute". This is arguably a more accurate measure of health than the general SAH variable.

We identify health shocks using self-reported information on the incidence of a serious injury or illness in the twelve months prior the interview. Accordingly, we define a dummy variable

[6] Given the purpose of our paper, it appears appropriate to include in our definition of self-employment owner managers of incorporated enterprises (OMIEs). As suggested by the ABS (Issue 6105.0, July 2011), the inclusion of OMIEs among the self-employed is justified by their greater degree of autonomy over both their business and employment conditions if compared to all other employees. For a more detailed discussion on these issues, see Blanchflower (2000).

[7] More precisely, we define as voluntarily inactive individuals who self-report being retired, disabled, unpaid volunteer and looking after an ill-person. It should also be noted that only a small minority of middle-age and older individuals in our sample are involuntarily inactive/unemployed.

[8] Following Jones *et al.*, (2010), we use specific health indicators to predict an individual's underlying health status and socioeconomic characteristics to model reporting bias (i.e. the thresholds of the self-assessed measure of health). This implicitly assumes that, conditional on the health indicators, any residual association between self-reported health and socioeconomic characteristics should only reflect reporting bias (and not genuine variation in health). In this context, this assumption does not appear to be too strong as our main objective is simply to build a measure of health that is purged of reporting bias.

which takes the value 1 if the individual has suffered a serious injury or an illness. This variable is particularly useful for the identification of the effect of a sudden health change on labour market outcomes as it captures the occurrence of an unexpected health-related negative event (serious injury).[9]

Other demographic and socioeconomic variables

A wide range of individual demographic and socioeconomic characteristics are also included as covariates in the models for labour transitions (see Table 1). These characteristics are: age, considered through a series of dummy variables defining four age classes; education, coded using three dummies for three different levels of schooling; job characteristics (if blue collar or two different levels of white collar); income (individual-specific log household income from all sources of labour and non-labour income) and home ownership. Household characteristics are captured through marital status (if married or living in a couple) and household composition (the presence of own dependent children). We also include geographical information on the country of origin (if born overseas) and area of actual residence (if living in a regional or remote area). Income, home ownership, marital status and household composition variables are reported at their lagged values to reduce concerns related to endogeneity.

4.2 Descriptive statistics

Tables 3 and 4 display observed transition probabilities between the four labour market states in the presence and absence of health shocks and long-term health conditions. The rows of the table contain previous labour market states whereas the columns show current labour market states.

(Tables 3 and 4 around here)

These tables show a strong degree of observed persistence, outlined by higher percentage values on the diagonals of each observed matrix, in labour market outcomes for both men and women. However, for individuals who suffered a health shock or have any long-term

[9] We have also attempted to use an alternative definition of health shocks based on differences between health stock values over time. More specifically, following Disney *et. al*, (2006) and Jones *et al.*, (2010), we have included in our models of labour transitions both initial (wave 1) values of the health stock as well as lagged values of the health stock. By conditioning on initial health, the coefficient on lagged health can be interpreted as a health shock, defined in terms of a deviation from the initial health status. In this case, using lagged health instead of current health might help reducing concerns about endogeneity. However, using these variables most of the dynamic multinomial logit models with random effects failed to achieve convergence.

health condition, such observed persistence appears to be lower for all labour market outcomes with the exception of inactivity. In particular, individuals previously in full-time employment experiencing a worsening of their health seem to downshift towards the other three labour market states, especially to inactivity. Further, both health shocks and long-terms health conditions increase the percentage of men shifting from full-time employment to part-time and self-employment. Any type of health deterioration (health shocks or long-term conditions) also increases the percentage of women moving from full-time employment to both part-time and self-employment. However, while having long-term health conditions seems to increase the percentage of female individuals down-shifting from full-time to part-time, health shocks seem to reduce it.

5. Results

Average marginal effects

Key results for the labour transition models are displayed separately for men and women in Tables 5 and 6. As noted earlier, we consider two alternative definitions of health: a latent health stock variable purged of reporting bias and a variable identifying long-term health conditions (models I and II in each Table, respectively). We use lagged values of these variables to further ease any concerns about endogeneity. In all models health shocks are defined using information on the occurrence of a serious injury or illness.

Each table contains average marginal effects for key variables, as well as estimated variances and correlation coefficients of the individual unobserved heterogeneity terms, together with their standard deviations, from our dynamic multinomial logit models.[10]The variances and correlation coefficients for the individual random effects (see lower parts of Tables 5 and 6) show that there is a statistically non-zero variance for the individual heterogeneity effects, justifying the random effect specification. The correlation coefficients also appear to indicate that there is a significant correlation between the individual unobserved decision effects across the three labour states. However, our results seem to suggest that while for women there is a high degree of correlation via unobservables between all labour market states, for men there appears to be only a significant correlation between part-time and inactivity choices. In addition, likelihood ratio tests performed for all specifications reject the null hypothesis of no heterogeneity. This also appears to suggest that individual unobserved

[10] In this case, average marginal effects are obtained by computing the average effects over all observations.

heterogeneity is an important element and that our models should be preferred to models without random effects.

(Table 5 and 6 around here)

We focus our attention on the average marginal effects of the health variables and the one-period lagged labour market states. For men (Table 5), the majority of marginal effects of the health and health shocks variables are negative and statistically significant on the probability for full-time employment. Accordingly, both ill-health and health shocks decrease the probability of full-time employment. In particular, the presence of long-term health appears to decrease the probability of choosing full-time employment by around 5 percentage points while the occurrence of health shocks seems to decrease the same probability by 4 to 5 percentage points. Average marginal effects of all health variables are positive and statistically significant for being in inactivity. This appears to suggest that both gradual and sudden health deteriorations (health shocks) increase the probability of inactivity. We also observe a small but positive and significant marginal effect of the long-term health variable for part-time employment (model II). However, both specifications (models I and II) also report negative and significant marginal effects of the health shocks variable for transitions to part-time employment. This might suggest that for middle-age and older men while suffering from a long-term condition marginally enhances the probability of part-time employment, health shocks decreases it. Our models also present negative, but not statistically significant, marginal effects of ill-health and health shocks for transitions to self-employment.

According to both models for men, genuine persistence appears to exist in all labour market states considered. Being employed part-time, self-employed or inactive in year t - 1 greatly increase the probability of being in the same labour market state in year t. However, being in any of these labour market states in the previous period greatly decrease the probability of choosing full-time employment in the subsequent wave. These results also present evidence of cross-mobility among labour market states, suggesting that older male individuals might fluctuate between different labour states, especially among part-time, self-employment and inactivity.

For women, average marginal effects obtained from both models (I and II, Table 6) indicate a similar role of ill-health and health shocks in determining labour market states. Ill-health and long-term health conditions consistently decrease the probability of choosing full-time employment while they increase the probability of opting for inactivity. Also, the incidence of health shocks appears to decrease the probability of being in part-time employment. Furthermore, while positive state dependence appears to be strong also for women in part-time employment, self-employment and inactivity, cross mobility appears to be concentrated mainly between the latter two.

In line with previous studies, there is some evidence that labour transitions among older individuals might be also influenced by age, education, income, type of jobs and household and geographical characteristics.[11] More specifically, for men the probability of choosing full-time employment seems to be a positive function of all age dummies as compared to the base category of over 60 years age group (with marginal effects quantitatively smaller as age increases) and a negative function of type of jobs (relative to being manager), geographical variables (relative to living in a remote area) and income (although this should be interpreted together with the negative and statistically significant marginal effect of the average household income variable that is part of our initial conditions). The probability of part-time employment seems to depend positively on higher levels of education, type of jobs and negatively on age and geographical origin (being born overseas). Being in self-employment is positively associated mainly with age and geographical variables. The likelihood of choosing inactivity appears to increase if born overseas and with higher levels of household income. The same probability appears to decrease with age (even though the marginal effects in both specifications seem to become smaller as age increases) and in the presence of a partner (marital status).

As for the models estimated for women, the larger and most consistently significant marginal effects are the ones for the age dummies (positive for both full-time and part-time employment and negative for transitions to inactivity, although with smaller marginal effects for older age categories); household income (negative for transitions to full-time and part-time employment, positive to inactivity); and marital status (negative for full-time employment but positive for both self-employment and inactivity). Also, higher levels of education are positively associated with transitions to full-time and self-employment and negatively associated with inactivity. Relative to being a manager, holding a highly ranked

[11] Tables with the full set of average marginal effects can be found at the end of the paper.

white collar job appears to decrease the likelihood of choosing full-time employment and to increase the one of opting for inactivity.

Simulating employment responses to ill-health and health shocks

In order to quantify more accurately the effects of health and health shocks on labour market transitions, we evaluate and compare average predicted transition probabilities by simulating alternatively the presence and absence of long-term health conditions and health shocks. We employ re-sampling methods to compute these transition probabilities by drawing repeated realisations from the estimated multivariate normal distribution of the correlated random effects. For each pre-determined labour market state, we then evaluate the transition probabilities for both scenarios (i.e. with and without long-term health conditions and health shocks) using average values of these random draws.[12] This is an alternative way of showing the transition probabilities for predetermined labour states for the previous time period that also has the advantage of accounting more directly for different values of the unobserved individual effect.

Table 7a compares estimated transition matrices for men in the presence and absence of health shocks (left-hand side of the table) and long-term health conditions (right-hand side of the table).

(Table 7a about here)

For full-time employed men in t - 1, suffering from a health shock decreases the average predicted probability of being so in the subsequent wave by around 6.17 percentage points. For the same group of individuals, health shocks decrease the average predicted probability of switching to part-time employment (by nearly 1.2 percentage points) while they increase the probability of choosing inactivity (around 6.7 percentage points) and, to a smaller extent, self-employment (0.63).

Similarly, if previously in full-time employment, the presence of long-term health conditions greatly decreases the predicted probability of being in the same labour market state in the following wave (by around 12.5 percentage points). Long-term health conditions have also a positive impact on the propensity to transit into part-time employment (2.10 percentage points), self-employment (1.24) and inactivity (about 9.15 percentage points).

[12] The general procedure that outlines how to compute simulated choice probabilities can be found in Train (2003).

If previously employed part-time or self-employed, men experiencing a deterioration of their health conditions (through either a health shock or long-term health conditions), appear to display particularly large average predicted probabilities of choosing inactivity at time *t* (between 13 to 17 percentage points if working part-time at *t-1*, and between 7.5 to nearly 12 percentage points if self-employed at *t-1*, respectively). This appears to suggest that for men part-time and self-employment might be stepping stones towards inactivity and that ill-health and health shocks are important determinants of these transitions.

(Table 7b around here)

Average predicted transition probabilities computed for women seem to display similar transitions patters (Table 7b). Women employed in full-time at *t*-1 experiencing a worsening of their health status, present substantially lower probabilities of staying in full-time employment (by about 10 to 11 percentage points) and higher probabilities of choosing part-time (from around 0.3 to 2 percentage points), self-employment (from 0.65 to 3 percentage points) and inactivity (between 7 to 8) in the subsequent wave. According to our transition probabilities, health shocks seem to play a larger role in determining transitions to self-employment if compared to men. Further, the heath-driven paths from part-time and self-employment towards inactivity seem to emerge also for the women sub-sample.

6. Conclusions

This study examines and quantifies the effects of different measures of ill-health and health shocks on transitions between full-time employment, part-time employment self-employment and inactivity among middle-age and older workers. Our analysis was motivated by the scarcity of knowledge around the relationship between health deterioration and transitions in and out of part-time employment and self-employment for individuals in this particular age group. From a policy perspective, this paper contributes to the debate centred on the implementation of policies targeted at containing the decline of labour force participation due to the ageing population. Differently from the majority of previous studies, our empirical analysis accounts simultaneously for state dependence, unobserved heterogeneity and potential reporting bias of the self-assessed measures of health.

Our findings indicate the presence of strong true state dependence in all labour marker states. There is also evidence of cross-mobility between part-time, self-employment and inactivity and that these movements are greatly influenced by health. In particular, both men and women experiencing a health shock have a substantially higher propensity of shifting out of full-time employment in wage and salaried work. If previously employed as an employee, health shocks significantly increase the probability of opting for economic inactivity and to a smaller degree also enhance the probability of switching to part-time and self-employment in the subsequent year, especially for women. We also find that negative changes in health greatly increase the probability of switching to inactivity for individuals already in part-time and self-employment.

Overall, these results appear to corroborate the hypothesis that health could be a push factor for older individuals to move towards part-time and self-employment. Both part-time and self-employment could be used as bridges towards permanent retirement by persons who suffered from a health deterioration. This might be also related to the perception for older workers in ill-health that self-employment provides a more flexible and accommodating work environment compared to wage and salary work (Zissimopoulos and Karoly, 2007).

Although we accounted for a number of important elements such as employment dynamics, health dynamics, the role of unobserved heterogeneity and a broad range of demographic and socioeconomic variables, our labour trajectories do not control directly for some potentially important institutional factors. For example, the structure of the social security system and the tax system might inform some of movements within and outside the labour market. However, our models strengthen results from previous empirical studies on health and inactivity and provide new evidence on the existence of heath-driven inactivity paths.

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Tables

Table 1: Variables used in the labour transitions model			
Dependent variable: labour market outcomes		*Mean*	*Std. Dev.*
Employed full-time	1 if employed as an employee either full-time, 0 otherwise	0.3425	0.4746
Employed part-time	1 if employed as an employee part-time, 0 otherwise	0.1574	0.3642
Self-employed	1 if own account worker, 0 otherwise	0.1658	0.3719
Inactive	1 if economically inactive, 0 otherwise	0.3342	0.4717
Covariates: health variables			
Health shocks	1 if suffered a serious injury or illness in the past 12 months, 0 otherwise	0.0801	0.2715
Long-term health	1 if having a long term health condition which limits type or amount of work, 0 otherwise	0.2448	0.4300
Health stock	Latent self-assessed health measure obtain from the health stock model	1.2928	0.9992
Other covariates			
Age 45-49	1 if individual is aged between 45-49, 0 otherwise	0.1264	0.3323
Age 55-59	1 if individual is aged between 50-54, 0 otherwise	0.3120	0.4633
Age 55-59	1 if individual is aged between 55-59, 0 otherwise	0.3328	0.4712
Age 60-64	1 if individual is aged between 60-62 (women) or 60-64 (men), 0 otherwise (baseline category)	0.2289	0.4201
Education/degrees	1 if individual holds a first degree or post degree qualifications, 0 otherwise	0.3199	0.4665
Education/certificate	1 if advanced diploma or certificate, 0 otherwise	0.2122	0.4089
Education 12	1 if highest education completed is year 12, 0 otherwise (baseline category)	0.4679	0.4990
White collar 1	1 if last or current job as a manager, administrator or professional, 0 otherwise	0.2822	0.4501
White collar 2	1 if clerical, sales or service worker, 0 otherwise (baseline category)	0.2067	0.4050
Blue collar	1 if tradesperson, labourer, production or transport worker, 0 otherwise	0.1781	0.3826
Log household income	Log of individual-specific total household income from all sources	10.9521	0.8669
Renting home	1 if living in a rented house, 0 otherwise	0.1458	0.3529
Own-mortgage	1 if living in a owned house with or without a mortgage, 0 otherwise (baseline category)	0.8355	0.3708
Single	1 if individual is single, 0 otherwise (baseline category)	0.2533	0.4349
Marital status	1 if married or living with a partner, 0 otherwise	0.7467	0.4349
Own dependent children	1 if having own dependent children, 0 otherwise	0.3463	0.4758
Born Australia	1 if born in Australia, 0 otherwise (baseline category)	0.7364	0.4406
Born overseas	1 if born overseas, 0 otherwise	0.2636	0.4406
Major city area	1 if living in a major city area, 0 otherwise (baseline category)	0.5740	0.4945
Regional/remote area	1 if living in a inner or remote area, 0 otherwise	0.4260	0.4945

Table 2: Variables used in the health stock model

Dependent variable	
Self-assessed health (SAH)	1: Excellent, 2: Very good, 3: Good, 4: Fair, 5: Poor
Covariates - health index	
Physical functioning	
Vigorous activities - limited a little	1 if limited a little in the ability of performing vigorous activities, 0 otherwise
Vigorous activities - limited a lot	1 if limited a lot in the ability of performing vigorous activities, 0 otherwise
Moderate activities - limited a little	1 if limited a little in the ability of performing moderate activities, 0 otherwise
Moderate activities - limited a lot	1 if limited a lot in the ability of performing moderate activities, 0 otherwise
Lifting or carrying groceries - limited a little	1 if limited a little in the ability of lifting or carrying groceries, 0 otherwise
Lifting or carrying groceries - limited a lot	1 if limited a little in the ability of lifting or carrying groceries, 0 otherwise
Climbing several flights of stairs -limited a little	1 if limited a little in the ability of climbing several flights of stairs, 0 otherwise
Climbing several flights of stairs - limited a lot	1 if limited a lot in the ability of climbing several flights of stairs, 0 otherwise
Climb one flight of stairs - limited a little	1 if limited a little in the ability of climbing one flights of stairs, 0 otherwise
Climb one flight of stairs - limited a lot	1 if limited a lot in the ability of climbing one flights of stairs, 0 otherwise
Bending, kneeling or stooping - limited a little	1 if limited a little in the ability of bending, kneeling, or stooping, 0 otherwise
Bending, kneeling or stooping - limited a lot	1 if limited a lot in the ability of bending, kneeling, or stooping, 0 otherwise
Walking one kilometre - limited a little	1 if limited a little in the ability of walking more than 1 kilometre, 0 otherwise
Walking one kilometre - limited a lot	1 if limited a lot in the ability of walking more than 1 kilometre, 0 otherwise
Walking half kilometre -limited a little	1 if limited a little in the ability of walking half a kilometre, 0 otherwise
Walking half kilometre - limited a lot	1 if limited a lot in the ability of walking half a kilometre, 0 otherwise
Walking 100 metres - limited a little	1 if limited a little in the ability of walking 100 meters, 0 otherwise
Walking 100 metres - limited a lot	1 if limited a lot in the ability of walking 100 meters, 0 otherwise
Bathing and dressing - limited a little	1 if limited a little in the ability of bathing or dressing, 0 otherwise
Bathing and dressing - limited a lot	1 if limited a lot in the ability of bathing or dressing, 0 otherwise
Role-physical (work and regular daily activities)	
Less work	1 if respondent spends less time working, 0 otherwise
Accomplish less	1 if respondent accomplishes less than he would like, 0 otherwise
Limited in the kind of work	1 if respondent is limited in the kind of work due, 0 otherwise
Difficulties working	1 if respondent has difficulties performing work, 0 otherwise
Bodily pain	
Mild bodily pain	1 if respondent suffers from very mild or mild bodily pain, 0 otherwise
Moderate bodily pain	1 if respondent suffers from moderate bodily pain, 0 otherwise
Severe bodily pain	1 if respondent suffers from severe or very severe bodily pain, 0 otherwise
Pain interferes slightly with work	1 respondent's bodily pain interferes slightly with work, 0 otherwise
Pain interferes moderately with work	1 if respondent's bodily pain interferes moderately with work, 0 otherwise
Pain interferes a lot with work	1 if respondent's bodily pain interferes quite a bit or extremely work, 0 otherwise
Covariates - SAH thresholds	
Age	Age of the respondent
Age2	Squared age of the respondent
Aboriginal	1 if the respondent is of aboriginal origin, 0 otherwise
Not aboriginal	1 if the respondent is not of aboriginal origin, 0 otherwise (baseline)
Education/degrees	1 if individual holds a first degree or post degree qualifications, 0 otherwise
Education/certificate	1 if advanced diploma or certificate, 0 otherwise
Education 12	1 if highest education completed is year 12, 0 otherwise (baseline category)
Employed	1 if the employed, 0 otherwise (baseline category)
Unemployed/inactive	1 if the individual is unemployed or inactive, 0 otherwise
Household income	Log of individual-specific total houseld income from all sources
Born Australia	1 if born in Australia, 0 otherwise (baseline category)
Born overseas	1 if born overseas, 0 otherwise
Major city area	1 if living in a major city area, 0 otherwise (baseline category)
Regional/remote area	1 if living in a inner or remote area, 0 otherwise

Table 3: Observed labour market transition probabilities in the absence and presence of health shocks											
	Men - no health shocks						**Women - no health shocks**				
	FT, t	**PT, t**	**SE, t**	**INA, t**	Total		**FT, t**	**PT, t**	**SE, t**	**INA, t**	Total
FT, t-1	88.98	3.70	3.01	4.31	100	**FT, t-1**	86.27	7.96	1.74	4.03	100
PT, t-1	15.35	63.58	6.69	14.37	100	**PT, t-1**	8.92	77.76	2.52	10.81	100
SE, t-1	6.06	2.32	87.29	4.32	100	**SE, t-1**	3.23	5.65	79.44	11.69	100
INA, t-1	3.41	4.66	3.17	88.76	100	**INA, t-1**	1.75	5.97	2.07	90.22	100
	Men - health shocks						**Women - health shocks**				
	FT, t	**PT, t**	**SE, t**	**INA, t**	Total		**FT, t**	**PT, t**	**SE, t**	**INA, t**	Total
FT, t-1	80.00	4.62	3.08	12.31	100	**FT, t-1**	78.38	2.70	5.41	13.51	100
PT, t-1	-	40.00	20.00	40.00	100	**PT, t-1**	7.41	51.85	11.11	29.63	100
SE, t-1	2.63	5.26	76.32	15.79	100	**SE, t-1**	4.35	4.35	60.87	30.43	100
INA, t-1	5.95	3.57	3.57	86.90	100	**INA, t-1**	0.95	3.81	5.71	89.52	100

Notes: FT = employed full-time; PT = employed part-time; SE = self-employed; INA = inactive

Table 4: Observed labour market transition probabilities in the absence and presence of long-term health conditions											
	Men - no long-term health						**Women - no long-term health**				
	FT, t	**PT, t**	**SE, t**	**INA, t**	Total		**FT, t**	**PT, t**	**SE, t**	**INA, t**	Total
FT, t-1	89.73	3.40	2.89	3.98	100	**FT, t-1**	87.27	7.80	1.61	3.33	100
PT, t-1	18.56	63.37	6.19	11.88	100	**PT, t-1**	9.78	77.84	2.66	9.71	100
SE, t-1	6.16	2.10	88.48	3.26	100	**SE, t-1**	3.11	5.13	81.80	9.95	100
INA, t-1	6.69	6.15	4.37	82.79	100	**INA, t-1**	2.20	7.14	2.67	87.99	100
	Men - long-term health						**Women - long-term health**				
	FT, t	**PT, t**	**SE, t**	**INA, t**	Total		**FT, t**	**PT, t**	**SE, t**	**INA, t**	Total
FT, t-1	70.78	8.44	4.55	16.23	100	**FT, t-1**	72.67	11.33	4.00	12.00	100
PT, t-1	3.09	58.76	8.25	29.90	100	**PT, t-1**	5.58	74.25	1.29	18.88	100
SE, t-1	3.57	4.08	79.59	12.76	100	**SE, t-1**	2.04	5.10	64.29	28.57	100
INA, t-1	1.00	2.69	2.19	94.12	100	**INA, t-1**	1.29	4.82	1.61	92.28	100

Notes: FT = employed full-time; PT = employed part-time; SE = self-employed; INA = inactive

Table 5: Dynamic Multinomial logit (MNL) models with random effects - Men									
	AME - Model (I)					**AME - Model (II)**			
Health Variables	**FT**	**PT**	**SE**	**INA**		**FT**	**PT**	**SE**	**INA**
Health stock (t-1)	-0.0206***	-0.0000	-0.0021	0.0227***		-	-	-	-
	(0.004)	(0.003)	(0.003)	(0.004)					
Long-term health (t-1)	-	-	-	-		-0.0500***	0.0113*	-0.0012	0.0398***
						(0.009)	(0.007)	-0.0082	(0.007)
Health shocks	-0.0169	-0.0208*	-0.0034	0.0413***		-0.0500***	-0.0284***	(0.007)	0.0574***
	(0.010)	(0.011)	(0.008)	(0.010)		(0.009)	(0.011)	(0.008)	(0.010)
Occupation at t-1									
Part-time(t-1)	-0.1941***	0.1195***	0.0407***	0.0339***		-0.1929***	0.1174***	0.0416***	0.0338***
	(0.010)	(0.007)	(0.010)	(0.009)		(0.010)	(0.007)	(0.010)	(0.009)
Self-employed(t-1)	-0.2152***	0.0261***	0.1696***	0.0194**		-0.2111***	0.0202**	0.1725***	0.0183**
	(0.009)	(0.008)	(0.007)	(0.010)		(0.009)	(0.008)	(0.007)	(0.009)
Inactive (t-1)	-0.2465***	0.0229***	0.0166*	0.2069***		-0.2403***	0.0160**	0.0178**	0.2064***
	(0.010)	(0.007)	(0.009)	(0.007)		(0.009)	(0.007)	(0.008)	(0.007)
σ_2	1.5488***					1.5167***			
	(0.172)					(0.164)			
σ_3	1.6880***					1.7640***			
	(0.197)					(0.183)			
σ_4	1.2943***					1.4334***			
	(0.173)					(0.185)			
ρ_{23}	-0.3005					-0.1372			
	(0.393)					(0.450)			
ρ_{24}	1.0392***					0.8005**			
	(0.403)					(0.379)			
ρ_{34}	0.2960					0.2690			
	(0.409)					(0.428)			
AIC	6676.4					7387.5			
BIC	7294.1					8012.9			
Log-likelihood:	-3263.2					-3618.8			
N	6974					7721			
LR test (p value)	160.1(0.000)					206.6(0.000)			
Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01									

FT = employed full-time; PT = employed part-time; SE = self-employed; INA = inactive; σ are the standard deviations of the random effects (where 2 = PT, 3 = SE, 4 = INA); ρ are the estimated correlation coefficients between random effects (where 2 = PT, 3 = SE, 4 = INA).

Table 6: Dynamic Multinomial logit (MNL) models with random effects - Women								
	AME - Model (I)				AME - Model (II)			
Health Variables	**FT**	**PT**	**SE**	**INA**	**FT**	**PT**	**SE**	**INA**
Health stock (t-1)	-0.0061	-0.0050	-0.0033	0.0145***	-	-	-	-
	(0.004)	(0.004)	(0.003)	(0.004)				
Long-term health(t-1)	-	-	-	-	-0.0282***	0.0045	-0.0085	0.0322***
					(0.009)	(0.010)	(0.006)	(0.008)
Health shocks	-0.0236*	-0.0243*	0.0017	0.0462***	-0.0198*	-0.0315**	0.0018	0.0496***
	(0.012)	(0.014)	(0.008)	(0.012)	(0.011)	(0.013)	(0.008)	(0.011)
Occupation at t-1								
Part-time(t-1)	-0.2029***	0.2056***	0.0062	-0.00887	-0.2017***	0.2013***	0.0055	-0.0050
	(0.006)	(0.008)	(0.006)	(0.010)	(0.006)	(0.008)	(0.006)	(0.009)
Self-employed(t-1)	-0.1994***	0.0240	0.1093***	0.0659***	-0.1954***	0.0141	0.1063***	0.0750***
	(0.016)	(0.019)	(0.006)	(0.014)	(0.015)	(0.018)	(0.006)	(0.013)
Inactive (t-1)	-0.2243***	-0.0065	0.0004	0.2304***	-0.2205***	-0.0159	-0.0002	0.2366***
	(0.010)	(0.011)	(0.006)	(0.009)	(0.009)	(0.011)	(0.006)	(0.009)
σ_2	1.4096***				1.5956***			
	(0.149)				(0.143)			
σ_3	2.1859***				2.3427***			
	(0.250)				(0.257)			
σ_4	1.9486***				2.0536***			
	(0.198)				(0.211)			
ρ_{23}	1.4951***				1.8540***			
	(0.521)				(0.604)			
ρ_{24}	1.8676***				2.0845***			
	(0.483)				(0.542)			
ρ_{34}	2.8180***				2.0845***			
	(0.799)				(0.542)			
AIC	7401.4				8271.6			
BIC	8020.1				8899.3			
Log-likelihood:	-3625.7				-4060.8			
N	7066				7971			
LR test (p value)	190.7(0.000)				279.3(0.000)			
Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$								

FT = employed full-time; PT = employed part-time; SE = self-employed; INA = inactive; σ are the standard deviations of the random effects (where 2 = PT, 3 = SE, 4 = INA); ρ are the estimated correlation coefficients between random effects (where 2 = PT, 3 = SE, 4 = INA).

Table 7a: Average predicted labour market transition probabilities - Men

No health shocks	FT, t	PT, t	SE, t	INA, t	Total
FT, t-1	84.52	4.7	4.48	6.28	100
PT, t-1	23.52	41.31	14.69	20.47	100
SE, t-1	9.59	5.08	77.05	8.27	100
INA, t-1	6.26	6.34	6.23	81.16	100

Health shocks	FT, t	PT, t	SE, t	INA, t	Total
FT, t-1	78.35	3.53	5.11	12.99	100
PT, t-1	20.98	30.97	14.53	33.51	100
SE, t-1	6.92	3.42	73.88	15.77	100
INA, t-1	3.11	2.59	4.14	90.16	100

Differences	FT, t	PT, t	SE, t	INA, t
FT, t-1	-6.17	-1.17	0.63	6.71
PT, t-1	-2.54	-10.34	-0.16	13.04
SE, t-1	-2.67	-1.66	-3.17	7.5
INA, t-1	-3.15	-3.75	-2.09	9

No long-term health	FT, t	PT, t	SE, t	INA, t	Total
FT, t-1	84.18	4.49	4.66	6.65	100
PT, t-1	24.35	40.79	12.94	21.9	100
SE, t-1	10.55	4.37	77.08	7.98	100
INA, t-1	9.65	7.58	7.98	74.77	100

Long-term health	FT, t	PT, t	SE, t	INA, t	Total
FT, t-1	71.7	6.59	5.9	15.8	100
PT, t-1	15.3	30.6	15.05	39.02	100
SE, t-1	5.58	5.39	69.16	19.85	100
INA, t-1	3.85	5.26	4.82	86.05	100

Differences	FT, t	PT, t	SE, t	INA, t
FT, t-1	-12.48	2.1	1.24	9.15
PT, t-1	-9.05	-10.19	2.11	17.12
SE, t-1	-4.97	1.02	-7.92	11.87
INA, t-1	-5.8	-2.32	-3.16	11.28

Notes: all values are in percentages; FT = employed-full-time; PT = employed part-time; SE = self-employed and INA = inactive

Table 7b: Average predicted labour market transition probabilities - Women

No health shocks	FT, t	PT, t	SE, t	INA, t	Total
FT, t-1	77.38	12.02	2.96	7.63	100
PT, t-1	13.4	66.03	4.54	16.01	100
SE, t-1	8.22	10.77	63.7	17.28	100
INA, t-1	4.14	9.61	3.42	82.8	100

Health shocks	FT, t	PT, t	SE, t	INA, t	Total
FT, t-1	67.33	12.31	5.49	14.85	100
PT, t-1	9.82	60.99	4.91	24.27	100
SE, t-1	6.47	7.55	63.75	22.2	100
INA, t-1	2.38	4.95	3.28	89.37	100

Differences	FT, t	PT, t	SE, t	INA, t
FT, t-1	-10.05	0.29	2.53	7.22
PT, t-1	-3.58	-5.04	0.37	8.26
SE, t-1	-1.75	-3.22	0.05	4.92
INA, t-1	-1.76	-4.66	-0.14	6.57

No long-term health	FT, t	PT, t	SE, t	INA, t	Total
FT, t-1	75.83	13.23	3.16	7.75	100
PT, t-1	15.05	63.81	4.56	16.56	100
SE, t-1	8.81	10.55	62.91	17.71	100
INA, t-1	5.19	11.33	4.08	79.4	100

Long-term health	FT, t	PT, t	SE, t	INA, t	Total
FT, t-1	64.43	15.66	3.81	16.08	100
PT, t-1	9.31	59.25	3.54	27.89	100
SE, t-1	7.23	10.94	53.61	28.22	100
INA, t-1	2.46	7.64	2.54	87.36	100

Differences	FT, t	PT, t	SE, t	INA, t
FT, t-1	-11.4	2.43	0.65	8.33
PT, t-1	-5.74	-4.56	-1.02	11.33
SE, t-1	-1.58	0.39	-9.3	10.51
INA, t-1	-2.73	-3.69	-1.54	7.96

Notes: all values are in percentages; FT = employed-full-time; PT = employed part-time; SE = self-employed and INA = inactive

Full sets of results (AME)

Full results for models in Table 5 - Men								
		AME - Model (I)				AME - Model (II)		
Health Variables	**FT**	**PT**	**SE**	**INA**	**FT**	**PT**	**SE**	**INA**
Health stock (t-1)	-0.0206***	-0.0000	-0.0021	0.0227***	-	-	-	-
	(0.004)	(0.003)	(0.003)	(0.004)				
Long-term health (t-1)		-	-	-	-0.0500***	0.0113*	-0.0012	0.0398***
					(0.009)	(0.007)	-0.0082	(0.007)
Health shocks	-0.0169	-0.0208*	-0.0034	0.0413***	-0.0500***	-0.0284***	(0.007)	0.0574***
	(0.010)	(0.011)	(0.008)	(0.010)	(0.009)	(0.011)	(0.008)	(0.010)
Occupation at t-1								
Part-time(t-1)	-0.1941***	0.1195***	0.0407***	0.0339***	-0.1929***	0.1174***	0.0416***	0.0338***
	(0.010)	(0.007)	(0.010)	(0.009)	(0.010)	(0.007)	(0.010)	(0.009)
Self-employed(t-1)	-0.2152***	0.0261***	0.1696***	0.0194**	-0.2111***	0.0202**	0.1725***	0.0183**
	(0.009)	(0.008)	(0.007)	(0.010)	(0.009)	(0.008)	(0.007)	(0.009)
Inactive (t-1)	-0.2465***	0.0229***	0.0166*	0.2069***	-0.2403***	0.0160**	0.0178**	0.2064***
	(0.010)	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.008)	(0.007)
Other variables								
Age between 45-49	0.0795***	-0.0339**	0.0191*	-0.0648***	0.0786***	-0.0276**	0.0164	-0.0674***
	(0.014)	(0.015)	(0.011)	(0.014)	(0.013)	(0.013)	(0.011)	(0.013)
Age between 50-54	0.0785***	-0.0117	0.0197***	-0.0865***	0.0770***	-0.0147*	0.0215***	-0.0837***
	(0.009)	(0.008)	(0.007)	(0.009)	(0.009)	(0.008)	(0.007)	(0.009)
Age between 55-59	0.0374***	-0.0075	0.0152**	-0.0451***	0.0408***	-0.0113*	0.0154**	-0.0449***
	(0.008)	(0.006)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)
Education/certificate	0.0072	-0.0088	-0.0033	0.0048	0.0076	-0.0058	-0.0005	-0.0013
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.006)	(0.007)
Education/degree	-0.0070	0.0138	-0.0005	-0.0063	-0.0071	0.0175**	-0.0003	-0.0101
	(0.011)	(0.009)	(0.009)	(0.010)	(0.010)	(0.008)	(0.009)	(0.009)
White collar 1(0)	-0.0301***	0.0189*	0.0016	0.0094	-0.0216**	0.0138	0.0020	0.0058
	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.009)	(0.010)	(0.010)
Blue collar(0)	-0.0037	0.0014	0.0014	0.0009	0.0030	-0.0029	-0.0009	0.0007
	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Log household income(t-1)	-0.0344***	0.0057	-0.0064	0.0351***	-0.0336***	0.0071	-0.0065	0.0329***
	(0.007)	(0.007)	(0.005)	(0.007)	(0.006)	(0.007)	(0.005)	(0.006)
Rented house(t-1)	0.0124	-0.0012	0.0082	-0.0194**	0.0096	0.0040	0.0069	-0.0205**
	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)	(0.007)	(0.009)	(0.009)
Marital status(t-1)	-0.0008	0.0075	0.0169**	-0.0236***	-0.0075	0.0031	0.0158*	-0.0114
	(0.010)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)
Own children(t-1)	0.0122	0.0014	0.0007	-0.0145*	-0.0075	0.0005	0.0019	-0.0142*
	(0.008)	(0.007)	(0.006)	(0.008)	(0.009)	(0.007)	(0.007)	(0.008)
Born overseas	-0.0101	-0.0165**	0.0107	0.0158**	-0.0079	-0.0173**	0.0098	0.0154**
	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Remote region	-0.0170**	0.0041	0.0105*	0.0023	-0.0187***	0.0026	0.0114*	0.0046
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Average log household income	0.0697***	-0.0209**	0.0147**	-0.0635***	0.0728***	-0.0208***	0.0149**	-0.0668***
	(0.010)	(0.009)	(0.007)	(0.009)	(0.009)	(0.009)	(0.007)	(0.009)
Part-time(0)	-0.0321**	0.0459***	-0.0163	0.0024	-0.0280**	0.0427***	-0.0194	0.0047
	(0.015)	(0.010)	(0.015)	(0.012)	(0.014)	(0.009)	(0.015)	(0.012)
Self-employed(0)	-0.0537***	-0.0200**	0.0901***	-0.0163	-0.0551***	-0.0144	0.0856***	-0.0159
	(0.011)	(0.010)	(0.009)	(0.011)	(0.010)	(0.010)	(0.009)	(0.010)
Inactive(0)	-0.0696***	0.0012	0.0238*	0.0445***	-0.0551***	-0.0067	0.0185	0.0451***
	(0.016)	(0.012)	(0.014)	(0.012)	(0.010)	(0.011)	(0.013)	(0.012)
AIC	6676.4				7387.5			
BIC	7294.1				8012.9			
Log-likelihood:	-3263.2				-3618.8			
N	6974				7721			
LR test (p value)	160.1(0.000)				206.6(0.000)			
Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01								

Full results for models in Table 6 - Women								
	AME - Model (I)				AME - Model (II)			
Health Variables	**FT**	**PT**	**SE**	**INA**	**FT**	**PT**	**SE**	**INA**
Health stock (t-1)	-0.0061	-0.0050	-0.0033	0.0145***	-	-	-	-
	(0.004)	(0.004)	(0.003)	(0.004)				
Long-term health (t-1)		-	-	-	-0.0282***	0.0045	-0.0085	0.0322***
					(0.009)	(0.010)	(0.006)	(0.008)
Health shocks	-0.0236*	-0.0243*	0.0017	0.0462***	-0.0198*	-0.0315**	0.0018	0.0496***
	(0.012)	(0.014)	(0.008)	(0.012)	(0.011)	(0.013)	(0.008)	(0.011)
Occupation at t-1								
Part-time(t-1)	-0.2029***	0.2056***	0.0062	-0.00887	-0.2017***	0.2013***	0.0055	-0.0050
	(0.006)	(0.008)	(0.006)	(0.010)	(0.006)	(0.008)	(0.006)	(0.009)
Self-employed(t-1)	-0.1994***	0.0240	0.1093***	0.0659***	-0.1954***	0.0141	0.1063***	0.0750***
	(0.016)	(0.019)	(0.006)	(0.014)	(0.015)	(0.018)	(0.006)	(0.013)
Inactive (t-1)	-0.2243***	-0.0065	0.0004	0.2304***	-0.2205***	-0.0159	-0.0002	0.2366***
	(0.010)	(0.011)	(0.006)	(0.009)	(0.009)	(0.011)	(0.006)	(0.009)
Other variables								
Age between 45-49	0.0370***	0.0286**	0.0106	-0.0764***	0.0457***	0.0285**	0.0101	-0.0843***
	(0.013)	(0.014)	(0.010)	(0.014)	(0.012)	(0.014)	(0.009)	(0.013)
Age between 50-54	0.0437***	0.0261**	0.0008	-0.0706***	0.0459***	0.0277**	0.0010	-0.0746***
	(0.010)	(0.011)	(0.007)	(0.010)	(0.009)	(0.011)	(0.006)	(0.009)
Age between 55-59	0.0222***	0.0113	0.0044	-0.0380***	0.0241***	0.0137	0.0038	-0.0416***
	(0.009)	(0.011)	(0.006)	(0.008)	(0.008)	(0.010)	(0.006)	(0.007)
Education/certificate	0.0174**	0.0015	0.0072	-0.0262***	0.0188**	-0.0030	0.0094*	-0.0253***
	(0.009)	(0.010)	(0.005)	(0.009)	(0.008)	(0.009)	(0.005)	(0.008)
Education/degree	0.0137	0.0108	0.0015	-0.0260**	0.0161*	0.0044	0.0049	-0.0254**
	(0.010)	(0.012)	(0.007)	(0.011)	(0.009)	(0.011)	(0.007)	(0.011)
White collar 1(0)	-0.0164	-0.0091	0.0022	0.0233**	-0.0166*	-0.0026	0.0021	0.0172*
	(0.009)	(0.011)	(0.007)	(0.011)	(0.009)	(0.011)	(0.006)	(0.010)
Blue collar(0)	-0.0065	-0.0026	-0.0118	0.0209*	-0.0052	0.0002	-0.0082	0.0133
	(0.011)	(0.013)	(0.009)	(0.012)	(0.011)	(0.012)	(0.008)	(0.012)
Log household income(t-1)	-0.0165***	-0.0103*	0.0034	0.0234***	-0.0135**	-0.0142**	0.0018	0.0260***
	(0.006)	(0.006)	(0.004)	(0.006)	(0.006)	(0.006)	(0.003)	(0.006)
Rented house(t-1)	-0.0032	-0.0057	0.0080	0.0009	-0.0013	-0.0106	0.0080	0.0040
	(0.010)	(0.012)	(0.009)	(0.012)	(0.010)	(0.011)	(0.008)	(0.011)
Marital status(t-1)	-0.0570***	0.0121	0.0097	0.0352***	-0.0601***	0.0155	0.0121**	0.0325
	(0.009)	(0.011)	(0.006)	(0.010)	(0.009)	(0.010)	(0.006)	(0.009)
Own children(t-1)	0.0034	0.0029	0.0010	-0.0073	-0.0002	0.0021	0.0007	-0.0027
	(0.007)	(0.009)	(0.006)	(0.009)	(0.007)	(0.009)	(0.005)	(0.008)
Born overseas	-0.0009	-0.0059	-0.0008	0.0076	-0.0023	-0.0075	0.0004	0.0094
	(0.008)	(0.009)	(0.006)	(0.009)	(0.007)	(0.009)	(0.005)	(0.008)
Remote region	0.0004	-0.0068	0.0079	-0.0016	0.0011	-0.0090	0.0077	0.0001
	(0.007)	(0.008)	(0.005)	(0.008)	(0.007)	(0.008)	(0.005)	(0.008)
Average log household income	0.0523***	0.0023	0.0029	-0.0575***	0.0504***	0.0049	0.0022	-0.0576***
	(0.009)	(0.010)	(0.006)	(0.010)	(0.009)	(0.010)	(0.005)	(0.010)
Part-time(0)	-0.0534***	0.0710***	-0.0281***	0.0105	-0.0496***	0.0716***	-0.0295***	0.0076
	(0.009)	(0.011)	(0.008)	(0.011)	(0.009)	(0.011)	(0.008)	(0.010)
Self-employed(0)	-0.0522***	0.0013	0.0435***	0.0074	-0.0528***	0.0077	0.0422***	0.0028
	(0.018)	(0.019)	(0.007)	(0.016)	(0.017)	(0.018)	(0.007)	(0.015)
Inactive(0)	-0.0758***	0.0056	-0.0177*	0.0879***	-0.0746***	0.0114	-0.0193**	0.0825***
	(0.016)	(0.016)	(0.009)	(0.013)	(0.014)	(0.015)	(0.009)	(0.012)
AIC	7401.4				8271.6			
BIC	8020.1				8899.3			
Log-likelihood:	-3625.7				-4060.8			
N	7066				7971			
LR test (p value)	190.7(0.000)				279.3(0.000)			
Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01								