The dynamics of health and labour market transitions at older ages: evidence from a multi-state model

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Abstract

Despite its clear relevance and policy significance, there is still sparse evidence on the effects of ill-health on the dynamics of labour state transitions among older individuals. We provide novel evidence by considering retirement as mobility among full-time work, part-time work, self-employment and inactivity, using a dynamic multinomial choice model that simultaneously accounts for state dependence, individual-level and state-specific unobserved heterogeneity, captivity and correlations between labour market states. We also simulate the dynamic paths for the four labour states from both transitory and permanent health shocks. We find strong state dependence for all four labour states even after accounting for individual effects. Both ill-health and health shocks are found to greatly increase the probability of leaving full-time employment into inactivity, and we find some evidence of part-time and self-employment paths. Significant evidence is found for "captivity" effects for the "inactive" state, and correlations across labour states. We also show that the degree of state dependence is over-estimated and, for men, the effects of ill-health under-estimated, if unobserved individual effects are not controlled for in dynamic models.

Keywords: health; dynamic labour transitions; captivity; unobserved heterogeneity

JEL classifications: C23, **I10**, **J24, J2**

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1. Introduction

An ageing population poses a fundamental burden to the sustainability of any social security system (Bloom *et al.*, 2010; Gruber and Wise, 2009). This demographic change, combined with the generosity of pension systems and disability benefit schemes in the majority of developed economies, also has profound consequences for the labour markets (Börsch-Supan, 2003; D'Addio *et al.*, 2010; ILO, 2016). According to the United Nations (2015), the average percentage of the population aged 60 years and over has grown from 9.9% in 2000 to 12.3% in 2015 worldwide, and is predicted to grow to 16.5% and 21.5% by 2013 and 2050, respectively. In Australia, a country with one of the longest life expectancies in the world (OECD, 2016), the number of working aged people between 15 and 64 years for every person aged 65 and over has fallen from 7.3 people in 1974-75 to an estimated 4.5 people in 2015. By 2054-55, this proportion is projected to be nearly halved again to 2.7 people (Commonwealth of Australia, 2015). To relieve the pressure, governments in many countries have increased the statutory retirement age to encourage people to stay in the labour force longer (United Nations, 2015). Early exits from the labour market and increased fragmentation of individuals' labour market trajectories also highlight the need for re-examining the determinants of individuals' labour market choices, particularly in the later part of the life-cycle. Identification of both determinants and trajectories of labour transitions at older ages would allow governments and policy makers to formulate policies to avoid the loss of contribution from a potentially active labour force.

Aside from age itself, health is a crucial factor that significantly affects the labour market transition or retirement decisions of older workers. Whilst advances in medical technology mean that people are living longer, we also observe increasing diagnosis and higher prevalence of chronic health conditions, especially among older people, such as cardiovascular diseases, diabetes, arthritis and mental health diseases.[2] Although the literature has established that ill-health is strongly associated with labour market decisions, especially in the retirement choices (see for example, Disney *et al.*, 2006; Lindeboom and Kerkhofs, 2009; Lindeboom, 2012), modelling the link between health and labour market transitions is a complex task.

One important aspect in modelling labour market transitions for older individuals is that retirement is often a multi-stage process. Empirical evidence consistently finds that retirement often involves multi-states, and that a considerable number of individuals only partially retire initially (for example, 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 pension before becoming permanently inactive (Kerkhofs *et al*., 1999; Bruce *et al*., 2000; Blundell *et al*., 2002). Indeed, in the majority of the OECD countries, a large proportion of the self-employed consists of middle-aged or older workers (Blanchflower, 2000; Gu, 2009). Moreover, even though research on the determinants of self-employment has received some attention (e.g. Parker, 2004, 2006; Li *et al.* 2016), very few empirical studies have explored the relationship between health and self-employment as a pathway to retirement (Fuchs, 1982; Zissimopoulos and Karoly, 2007; Parker and Rougier, 2007). There is also no clear consensus on the direction of the effect of health on the decision to choose self-employment as versus waged employment for older individuals. Finally, none of these studies have modelled simultaneously the multi-state choice of full-time, part-time, self-employment and inactivity in a panel data model context.

[2] See the Australian Institute for Health and Welfare, AIHW, 2014 report for statistics about Australia.

Another aspect of modelling the health and labour market relationship is the inherent dynamic and state dependent nature of labour market transitions. 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). However, observed state correlation may also be due to persistent time-invariant unobserved individual effects. Availability of panel data offers the potential for disentangling the effects of true state dependence and spurious dependence due to persistent unobserved individual heterogeneity. In addition, multi-state labour market choices may be correlated via both common observable and unobservable factors, and standard multinomial logit models do not allow for such correlation via the unobservable factors. Finally, individual health status is potentially endogenous and driven by unobservable factors that may also impact on labour market decisions.

The objective of the paper is to study the impact of health on older individuals' labour market decisions by employing a modelling strategy that accounts for the many aspects of this complex relationship. We use the subset of older individuals drawn from thirteen waves (2001-2013) of panel data from the Household, Income and Labour Dynamics in Australia Survey (HILDA; Watson and Wooden, 2012). We explicitly consider retirement as a multi-state process and examine the effect of ill-health and health shocks on the mobility between full-time employment, part-time employment, self-employment and inactivity, using a dynamic multinomial choice framework. Specifically, we employ a dynamic multi-state DOGIT (Gaudry and Dagenais, 1979) Ordered Generalized Extreme Value (DOGEV) model (Fry and Harris, 2005) which jointly accounts for state dependence, individual-level unobserved heterogeneity, correlation of neighboring alternative labour market choices, and captivity to particular labour market states due to choice heterogeneity. More specifically, we devote particular attention to the notion of true state dependence *versus* unobserved heterogeneity. We estimate a multinomial dynamic panel data model with random individual 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.

As the treatment of observed health is very important, following the literature (for example, Bound, 1991; Bound *et al.*, 1999; Brown *et al.*, 2010; Jones *et al.*, 2010), we account for potential measurement error in self-assessed health (SAH) status by building a latent health stock model. This involves 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 is available in the data and could help identifying the impact of health shocks on labour outcomes. We simulate the resulted immediate and equilibrium probability paths for the four labour market states from both transitory and permanent health shocks.

In doing so, this paper offers several important contributions to the literature. Firstly, the multi-state dynamic transition model allows for a closer examination of older workers' labour market transitions via part-time and self-employment trajectories. In particular, this paper extends the knowledge of the relationship between ill-health and labour transitions by modelling transitions to part-time, self-employment and inactivity in a dynamic multi-state setting. Secondly, we separately accommodate true labour market state dependence and persistence due to time-invariant unobservable individual heterogeneity, and estimate the effects of ill-health in this setting. We also illustrate the dynamic effects of health shocks by predicting the short-run and long-run probability paths for all four labour market states following health changes. Thirdly, previous studies have not reached consensus on the direction of the effect of health on the choice of self-employment versus paid employment due to different model specifications. As compared to previous works based on static models that do not explicitly account for individual-level unobserved heterogeneity or labour state dynamics, our estimates appear to suggest that both the impacts of health and health shocks on these transitions and the degree of labour market state dependence can be over-estimated. Furthermore, unlike earlier approaches, our DOGEV model simultaneously accounts for both correlations between close related labour market states via unobservable characteristics and potential captivity to particular labour market states. The DOGIT (due to Gaudry and Dagenais, 1979) part of the specification of choice probabilities allows for choice-specific loyalty or captivity due to unobservable choice characteristics that are not driven by individual characteristics. These overcome the restrictive feature of Independence of Irrelevant Alternatives (IIA) of a MNL model. Indeed, we do find significant correlation(s) and captivity effects and show that ignoring such effects could lead to seriously biased findings and policy recommendation. Finally, we incorporate a health stock model and accommodate potential measurement error(s) in self-assessed health status. In summary, 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 endogeneity of self-stated health status.

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. Our aim is to bring together elements from these three distinct strands of literature and propose a dynamic multi-state model of health and labour transitions at older ages that account for the dynamics of labour supply, unobserved heterogeneity and reporting bias of self-assessed measures of health.

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) (e.g. Magnac, 2000; 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. A number of studies on labour-market transitions have focused on the estimation of dynamic multinomial choice models with individual-level unobserved heterogeneity. However, none of them have analysed jointly transitions towards part-time and self-employment among older workers as well as both individual and labour state-specific unobserved heterogeneity. For example, Uhlendorff (2006) estimates a dynamic multinomial logit model 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 individual 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.[3]

A key element of the current research relates to how "ill-health" should be defined and entered into our labour supply models. 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, cancer or hospitalisations (e.g. Datta Gupta and Larsen, 2007; García-Gómez *et al.*, 2013; Trevisan and Zantomio, 2016; Jones *et al.*, 2016). Health shocks are also defined using differences in responses between consecutive waves on the five point self-assessed measure of health or identified as a sudden drop in a self-assessed measure of health satisfaction (for example, Riphahn, 1999). Potentially important elements in the definition of a health shock are the measurement of its severity and the

[3] Still within the broader literature concerned with dynamic employment behaviour among older individuals, Blau and Gilleskie (e.g. 2006; 2008) employ US data from the Health and Retirement Study (HRS) and dynamic discrete-choice structural models to focus mainly on the effects of health insurance on labour transitions. Among other findings, they conclude that health insurance appears to have a limited effect on both the labour force behaviour of older couples and older men with the largest effects on men in ill-health, respectively.

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*., (2006) 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 and, as a result, the probability of being out of work. Pertinent to the current study, studies on Australian data typically 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, 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 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.[4]

[4] Zissimopoulos and Karoly (2008) find that also in the U.S. liquidity constraints and prior job characteristics are further relevant predictors of transitions towards self-employment in the latter part of an individual's work career. Li *et al*., (2016) employs a 2006 Dutch pension policy reform and show that a drop in pension wealth may reduce movements into self-employment.

3. Econometric framework

3.1 A dynamic multi-state model for labour transitions

We focus our attention on the effect of health on mobility between j = 1 to J = 4 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 models (with unobserved effects). We assume a first order Markov process to capture state dependence and unobserved individual effect(s) to account for unobserved heterogeneity in order to distinguish between true and "spurious" state dependence. A useful starting point is the multinomial logit (MNL) model, which is consistent with the notion of the Random Utility Maximisation assumption of consumer behaviour (Green, 2003), where each labour market outcome is associated with a given level of utility. As is common, assume the utility for individual i from choosing labour state j in period t, V_{ijt}, is given by:

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

where X_{it} and P_{it-1} are (row) vectors containing individual observed characteristics in period t (we will use constant, age, education, geographical origin, living in an 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. Individual characteristics contained 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}. It is the joint inclusion of both the lagged state indicators and the unobserved effects that allow us to distinguish between state dependence *versus* unobserved heterogeneity (Arulampalam, 2000). ε_{ijt} is the idiosyncratic error term, assumed to be independent of the regressors and α_{ij}. Again, as is usual, we assume that 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:

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

On the assumption that the ε_{ijt} independently and identically follow a Type I extreme value distribution. 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. As is common in the literature, we also assume that the unobserved heterogeneity for the J-1 remaining choices follows a multivariate normal distribution with zero mean and a J-1 variance-covariance matrix.[5] 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 is:

[5] 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).

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

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

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

where R values are drawn from the assumed (multivariate normal) distribution of the unobserved heterogeneity. For each of these draws the likelihood is calculated and then averaged over the R draws.[6]

3.2 Initial conditions problem

As it is important to distinguishing between state dependence and unobserved heterogeneity requiring estimation of dynamic models, it is necessary to account for the so-called 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

[6] Models are estimated using user-written Gauss code; available on request from the authors. In particular, the dynamic random effects models presented in section 5 were estimated using 100 Halton draws. As a sensitivity test increased numbers of these were experimented with, and made no substantive difference to the results. For a description of the mechanics of Halton sequences in the present context, see Train (2000).

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:

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

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 $(J-1)$ 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 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).

3.3 Extending the framework to allow for correlations and captivity

As stated, the basic model as it stands is essentially a MNL one of the form:

$$P_{ijt}^{MNL} = \frac{\exp(V_{ijt})}{\sum_{k=1}^{J} \exp(V_{ikt})}.$$

A drawback of the MNL approach is that the idiosyncratic error terms are assumed to be independent. Especially with regard to an empirical model of labour supply, there are strong *a priori* reasons that these will be correlated across states: the unobservables driving an individual's utility gained from full-time employment must surely be related to those from part-time (and so on). To this extent, Small's (1987) OGEV (Ordered Generalised Extreme Value) model relaxes this independence assumption, imposing a correlation between alternatives that are near neighbours. The correlation is captured by an additional parameter ρ, that is (inversely) related to the actual correlation (which here has no closed form solution, Small, 1987). The standard OGEV probabilities are given by (Small, 1987)[7]:

$$P_{ij}^{OGEV} = \frac{\exp(\rho^{-1}V_{ij})}{\sum_{r=1}^{J+1}\left[\left\{\exp(\rho^{-1}V_{i,r-1}) + \exp(\rho^{-1}V_{ir})\right\}^{\rho}\right]} \times \left[\left\{\exp(\rho^{-1}V_{i,j-1}) + \exp(\rho^{-1}V_{ij})\right\}^{\rho-1} + \left\{\exp(\rho^{-1}V_{ij}) + \exp(\rho^{-1}V_{i,j+1})\right\}^{\rho-1}\right], \qquad (6)$$

with the convention that $\rho^{-1}V_{i0} = \rho^{-1}V_{i,J+1} = 0$ and where $0 < \rho \leq 1$. The actual correlation has no closed form solution, but is inversely related to ρ such that as $\rho \rightarrow 1$ $P^{OGEV} \rightarrow P^{MNL}$. In addition to such correlation of local alternatives, it is also probable that individuals will be "captive" (or "trapped"), to a certain extent, in various labour market states. That is, even once we have conditioned upon an individual's observed and unobserved heterogeneity, there will also likely be a residual amount of such appertaining to the labour market state itself. This can be accounted for by using a (labour) state-specific parameter to capture the unobserved heterogeneity of the labour state itself. Such an approach is in essence, the DOGIT model of Gaudry and Dagenais (1979), as it can

[7] Note we subsequently omit the *t* subscript to avoid cluttering the notation.

explicitly allow for both heterogeneity of the individual and the labour market choice itself. Indeed, such an approach has been applied before to labour market choices with regard to occupational choice (Brown *et al.*, 2008). In this regard, the DOGIT achieves this including additional choice-specific parameters, θ_j, which account for the heterogeneity of the labour market state itself. Fry and Harris (1996) suggest combining both the elements of the DOGIT and OGEV models into the DOGEV model, which in the current context, will have probabilities of the form:

$$P_{ij}^{DOGEV} = \frac{\theta_j}{1+\sum_{k=1}^{J}\theta_k} + \frac{1}{1+\sum_{k=1}^{J}\theta_k}\left(P_{ij}^{OGEV}\right). \tag{7}$$

The first term in equation (7) represents the extent that an individual is trapped in, or captive to, alternative *j*; the term before P_{ij}^{OGEV} is essentially the probability of "free-choice". The DOGEV model thus simultaneously allows for correlation of close neighbouring alternatives and for individuals to be trapped, to a certain extent, in particular labour market states: both of which appear to be very important to the application at hand.[8]

3.4 Models 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 (e.g. Anderson and Burkhauser, 1985; Bazzoli, 1985; Stern, 1989; Bound, 1991; Bound *et al*., 1999; Au *et al*., 2005). Firstly, 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

[8] We note here, that following Brown *et al.*, (2008) it would be possible to parameterise the inherent captivity parameters with observed personal covariates. However, there are no obvious candidates that would uniquely identify these effects whilst being orthogonal to the labour supply decision.

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 and/or mis-measurement of the health status covariate 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 (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 (see, for example, 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 key variables

This paper uses panel data drawn from the first 13 waves (2001-2013) 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). It is a rich source of health and labour variables and its design resembles the one of other important longitudinal surveys such as the British Household Panel Survey (BHPS) and the U.S. based Panel Study of Income Dynamics (PSID).

As our primary interest lies in the effects of health on labour market choices of older workers, we only make use of a sub-sample of individuals aged between 50 years of age to the year prior state retirement age. We thus obtain an estimation sample which consists of 2,455 individuals, 1,228 men and 1,227 women, all aged between 50 and 65. 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 the health stock model.

(*Tables 1 and 2 around here)*

Employment status

As stated, 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.[9] According to this categorisation, we define self-employed individuals as those who self-report being owner-managers of either incorporated or unincorporated enterprises.[10] Our broad definition of economic inactivity comprises individuals both voluntarily inactive (retired) and involuntarily inactive (unemployed).[11]

Health and health shocks

Following the literature noted above, we define ill-health using a latent health stock measure obtained by regressing a five class measure of self-assessed health (SAH) with a series of more specific health indicators using generalised ordered probit (GOP) 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). GOP models also allow for heterogeneous 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),

[9] Australian Labour Market Statistics, ABS, Issue 6105.0, July 2011.

[10] 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).

[11] 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.

ethnicity, education, employment status, income and other demographic characteristics (see lower part of Table 2).

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. 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 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), and moreover is definitionally, an exogenous shock.

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; gender (by estimating separate models for men and women); 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

As our interest lies in transition probabilities (and their relationship to health levels), we focus our discussion here on these (standard descriptive statistics for the explanatory variables broken down by gender are presented in Table 1). Thus Tables 3a and 3b contain the observed transition proportions 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 3a and 3b 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 health condition, such observed persistence appears to be lower for almost all labour market outcomes with the exception of inactivity. In particular, individuals previously in full-time employment experiencing a health shock seem to downshift mainly towards inactivity. Interestingly, while following a health shock the proportion of men in part-time employment appears to slightly increase, we observe a decrease in the ones of women in part-time work and no women in self-employment. Moreover, for men previously employed part-time, sudden health deteriorations increase the percentage of individuals still in part-time, substantially augment the one for inactivity and also present corresponding empty cells for full-time and self-employment. For women in part-time work at t - 1, health shocks also reduce observed proportions in full and part-time while increasing the ones for self-employment and inactivity. The remaining observed empty cells reflect the absence of individuals suffering from health shocks in those labour categories. The presence of long-term health conditions appears to affect observed percentages differently. For example, for those previously in full-time employment, long-term ill-health appears to increase percentages of individuals in all other three labour states. Overall, individuals with long-term health conditions also appear to present more frequent observed movements between part-time and self-employment.

5. Estimation results

Partial effects

Due to the complexities of the models employed, we report the effects of covariates as partial effects on the probability of being in each state (evaluated at the sample means of covariates, with standard errors being estimated using the Delta method). Key results for the labour transition models are displayed separately for men and women in Tables 4 and 5. 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.

(Tables 4 and 5 around here)

Each table contains partial effects for key variables, captivity parameters (θ), correlations between adjacent labour market states (ρ) as well as variance-covariance matrices for the random effects from our dynamic DOGEV models.[12] The variances and correlation coefficients for the individual random effects (see the variance covariance matrices at the bottom of Tables 4 and 5) show that there is a statistically non-zero variance for the individual unobserved effects in all models, justifying the random effect specification. This suggests that models ignoring these would be mis-specified. Furthermore, the results suggest that for women there are significant correlations via these terms between self-employment and inactivity choices (model I) as well as between all labour market choices (model II). However, for men there appears to be significant correlations across all labour choices only in one model (model I). The DOGEV models further find a highly statistically significant ρ in all specifications for women (significantly different from both 0 and 1). This implies that there are significant correlations in the idiosyncratic errors between local adjacent labour market states and that an OGEV specification would be more appropriate than a standard MNL model ignoring these.

We freely estimated all captivity parameters in all models. Without fail, there was strong evidence of captivity to the inactive labour market state, but not to any other (the respective

[12] Coefficient estimates are available upon request.

θ_j value was 0). That is, once we have conditioned on a whole host of factors (such as observed and unobserved heterogeneity, cross-equation correlations, past labour market experience, and so on), there is only a "residual" effect for this inactive state. This suggests that, to a certain extent, individuals are trapped in this particular labour market state. We evaluate and quantity these effects in greater detail below, but note here that the significance of the captivity effects, the correlation coefficient and the unobserved effects, clearly suggest that models ignoring these would be mis-specified.

We focus our attention on the partial effects of the health variables and the one-period lagged labour market states. For men (Table 4), all partial 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. More specifically, the presence of long-term conditions appears to decrease the probability of choosing full-time employment by around 17 percentage points (pp) while the occurrence of health shocks seems to decrease the same probability by between 11 to 14.6pp. Partial effects of all health variables are positive and statistically significant for being in inactivity. This appears to suggest that both sudden and gradual health deteriorations increase the probability of inactivity: the former increases the probability of becoming inactive by between 20 to 27pp while the latter by around 22.5pp. We also observe negative and significant partial effects of the health shocks variable for part-time employment (between around 4.7 to 7.5pp) and self-employment (5pp, model II). Our estimates also show a negative, although only weakly significant, partial effect of the long-term variable on self-employment. This might suggest that for older men suffering from either long-term conditions or health shocks decrease the probability of choosing part-time and, to a lesser extent, self-employment.

According to both models for men, genuine labour market persistence appears to exist in all 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 period. These results also present some evidence of cross-mobility among labour market states, suggesting that older male individuals might fluctuate between different labour states, especially among part-time and inactivity.

For women, partial 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 decrease the probability of choosing full-time employment while they increase the probability of opting for inactivity. However, the partial effects for health shocks appear to be larger and consistently more significant if compared to the ones of the long-term care variable. 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.

With regard to the effect of other covariates, we find that 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 marital status.[13] 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 partial effects

[13] Tables with the full set of partial effects for models II for both men and women can be found in the Appendix. Partial effects for model I are similar and available upon request.

quantitatively smaller as age increases) and a positive function of income. The probability of part-time employment seems to depend negatively on marital status (although only at 10% significance level) while being in self-employment is positively associated mainly with age. The likelihood of choosing inactivity appears to decrease with age (even though partial effects seem to become smaller as age increases), for higher levels of income and in the absence of home ownership.

As for the models estimated for women, the larger and most consistently significant partial effects are the ones for the age dummies (positive for all labour states, although with smaller partial effects for older age categories and for transitions into self-employment); household income (positive for transitions to full-time and part-time employment, negative to inactivity); and marital status (this time negative for full-time and part-time employment but positive for inactivity). Also, higher levels of education are positively associated with transitions to self-employment (although only weakly) and negatively associated with inactivity. Relative to being a manager, holding a highly ranked white collar job appears to decrease the likelihood of choosing full-time employment and to increase the ones of opting for part-time and inactivity.

Model evaluation and comparison of partial effects across models

Table 6 evaluates our DOGEV models by reporting sample proportions (Sample) and average probabilities (AP) of models I and II for both men and women. In terms of these, the models appear to replicate very closely the observed sample proportions across all specifications. The Table also reports captive probabilities (and corresponding standard errors) derived from the previously estimated captivity parameters for inactivity. These quantify the captivity effects and imply a 2 percent probability of being “captive” to inactivity for men and a similar effect for women (although 1 for model I). The size of these effects is not negligible as these probabilities are irrespective of individual preferences. Indeed, although dwarfed by the effects of past labour market status, these captivity effects of around 2pp, are of the same order of magnitude as the effects of ill-health on labour market status. Indeed, such significant captivity effects, also appear to validate the use of such a model capable of accounting for labour market state heterogeneity.

(Table 6 around here)

Table 7 and 8 compare partial effects obtained from pooled and random effects dynamic multinomial logit models (MNL and RE MNL), pooled DOGEV specifications and our dynamic random effects DOGEV models (RE DOGEV). These are computed for model II (the one which includes long-term health conditions and health shocks) for both genders. For men (Table 7), these appear to show that the size of the partial effects for our key variables substantially vary across models. For example, all other three models seem to underestimate the partial effects of both long-term health and health shocks on transitions out of full-employment and into inactivity if compared to our preferred specification. As expected, standard dynamic pooled models (whether MNL or DOGEV) without random effects also appear to overestimate the effects of state dependence for each labour state. For women (Table 8), partial effects estimated for the long-term health variable appears to generally overestimate the effects found with the RE DOGEV with particularly large differences, also in terms of statistical significance, between standard MNL and RE DOGEV. Partial effects for health shocks appear also to be different and present varying level of statistical significance across specifications. State dependence is also systematically overestimated for all but RE models.

(Tables 7 and 8 around here)

Simulating the dynamic employment responses to ill-health and health shocks

In order to further illustrate the effects of health and health shocks on labour market transitions, we use the estimated parameters to evaluate the effect of both a health shock and the presence of a long-term health condition on the subsequent labour market transitions over time. That is, following Knights *et al.*, (2002) explicitly we firstly consider the estimated probability of each labour market state (evaluated at observed and unobserved heterogeneity means). However, to evaluate the effect of both a health shock and a long-term health condition, we consider the probability in time t_0 of such an event by turning this respective dummy "on", whilst holding all other variables at sample means. To analyse the temporal effects of this, as estimated by the model, in period t_1 we again evaluate the probability of each labour market state, but with the lagged labour market state indicators replaced by their probabilistic values evaluated at t -1 (i.e., t_0). We then roll this temporal succession forward for several time periods until the long run effects have been reached.

We consider two variants of this exercise: permanent and transitory "shocks"; the former is where the relevant dummy variables is turned "on" and kept on; the latter is where it is only kept turned on for one period. The results for this exercise (for males and females, permanent and transitory shocks, and for the health variables "health shock" and "long-term health") are reported in Figures 1 and 2.

[Figures 1 and 2 about here]

Firstly considering males and a permanent health shock, we can see that both the short-run and long-run effects on the trajectory of increased likelihood of transiting into inactivity are very pronounced. After the shock has happened, males are some 17pp more likely to be in this state 1 year later; and in total, the long-run effect amounts to some 25pp increase. Most of the effect of these dynamics seem to have been played out after about 2-3 years. The effects of this on the other labour states appear dwarfed relative to the magnitude of the inactivity effects, but are nonetheless far from negligible, although once more most of the action appears to take place in the year following the initiation of the shock. The short- and long-run effect are all negative for transitions into full-time, part-time and self-employment, and most (least) pronounced for full-time (part-time). The short run effects are -0.09pp and -0.03pp respectively, and the long run ones -0.12pp and -0.05pp.

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 older workers by employing a dynamic multi-state framework. Our analysis was motivated by the scarcity of knowledge around the relationship between health deterioration and dynamic labour market transitions 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. As compared to previous studies, our empirical analysis proposes a *dynamic* multi-state DOGEV model that accounts simultaneously for state dependence, individual-level unobserved heterogeneity, captivity to specific labour market states and correlations between adjacent states, together with potential reporting bias of the self-assessed measures of health.

The findings indicate the presence of strong true state dependence in all labour marker states even after time-invariant individual unobserved effects are controlled for. We find that both men and women experiencing a health shock have a substantially higher propensity of shifting out of full-time employment: if previously employed full-time, health shocks significantly increase the probability of opting for economic inactivity. Although we find some evidence of part-time and self-employment paths, our estimates suggest smaller impacts of health and health shocks on transitions to part-time and self-employment than those from previous research based on static models not accounting for unobserved heterogeneity. This may be the result of the use of a dynamic model and the possibility of drawing more precise trajectories of labour market transitions between different periods while also accounting for wide range of unobservable factors.

Our preferred model shows that, although health effects are sizeable, for the probability of each of the labour market states, the magnitudes of these effects is substantially smaller than that of the state dependence effect for staying in the same state for both men and women. The simulated dynamic response paths for the two types of health change scenarios show that it takes about 2-3 years for the labour state probabilities to reach equilibrium, with the impact of permanent health change much higher than that from a one off health change. The impact of health deteriorations on the probability for inactivity is the most profound.

Comparison of our preferred model with three other alternative models shows that it is crucial to control for time-persistent individual effects in a dynamic model and, to a lesser extent, to allow for the additional DOGEV features of cross-state correlation and captivity. We show that for each of all four labour states, the magnitude of state dependence will be significantly over-estimated if time-invariant individual heterogeneity is not controlled in the dynamic model for both men and women. However, the degree of state dependence for the probability of staying in the existing state would be slightly under-estimated if a dynamic random effect MNL model rather than a DOGEV is used. Finally, the effects of health changes would be under-estimated for men if using the other three alternative models, although the difference in the effects for women would be less significant.

Overall, our dynamic model offers new and more comprehensive evidence on both the role of genuine state dependence in dynamic labour market transitions and the identification of specific health-driven retirement pathways among older workers. It also identifies the presence of significant captivity effects for inactivity and underlines the need for a dynamic specification capable of capturing state dependence and labour state heterogeneity when modelling the effects of health on labour market transitions at older ages.

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References

AIHW (2014), *Australia's Health 2014*, Australian Institute of Health and Welfare, Australia's Health Series No.14, Cat. No. AUS 178, Canberra.

Anderson, K. H. and Burkhauser, R. V. (1985). 'The retirement-health nexus: a new measure

of an old puzzle', *Journal of Human Resources,* 20**,** 315-330.
Arulampalam, S. W. (2000). 'Unemployment Persistence', *Oxford Economic Papers,* 52**,** 24-50.
Au, D. W. H., Crossley, T. F. and Schellhorn, M. (2005). 'The effect of health changes and long-term health on the work activity of older Canadians', *Health Economics,* 14 (10)**,** 999-1018.
Bazzoli, G. (1985). 'The early retirement decision: New empirical evidence on the influence of health', *Journal of Human Resources,* 20, 214-234.
Börsch-Supan, A. (2003). 'Labor market effects of population aging', *Labour*, 17(s1), 5-44.
Bjørner, T. B. and Søren, L.-P. (2007). 'A Dynamic Random Effects Multinomial Logit Model of Household Car Ownership', *Nationaløkonomisk Tidsskrift,* 145**,** 83-100.
Blau, D. M., and Gilleskie, D. B. (2006). 'Health insurance and retirement of married couples', *Journal of Applied Econometrics*, 21(7), 935-953.
Blau, D. M., and Gilleskie, D. B. (2008). 'The role of retiree health insurance in the employment behavior of older men', *International Economic Review*, 49(2), 475-514.
Bloom, D.E., Canning, D. and Fink, G. (2010). 'Implications of population ageing for economic growth', *Oxford Review of Economic Policy,* 26(4), 583-612.
Blundell, R., Meghir, C. and Smith, S. (2002). 'Pension incentives and the pattern of early retirement', *Economic Journal,* 112 (478)**,** c153-c170.
Bound, J. (1991). 'Self-reported versus objective measures of health in retirement models', *Journal of Human Resources,* 26**,** 106-138.
Bound, J., Schoenbaum, M., Stinebrickner, T. R. and Waidmann, T. (1999). 'The dynamic effects of health on the labour force transitions of older workers', *Labour Economics,* 6 (2)**,** 179-202.
Brown, S., Fry, T.R.L. and Harris, M.N. (2008). 'Untangling Supply and Demand in Occupational Choice', *Economics Letters,* 99, 414 – 417.
Brown, S., Roberts, J. and Taylor, K. (2010). 'Reservation wages, labour market participation and health', *Journal of the Royal Statistical Society: Series A (Statistics in Society),* 173 (3)**,** 501-529.
Bruce, D., Quinn, D. H.-E. and Quinn, J. (2000). 'Self-Employment and Labor Market Transitions at Older Ages', *Boston College Center for Retirement Research Working Paper No. 2000-13.*
Buddelmeyer, H. and Wooden, M. (2008). 'Transitions from Casual Employment in Australia', *Melbourne Institute Working Paper Series,* Melbourne Institute of Applied Economic and Social Research, The University of Melbourne, wp2008n07.
Cai, L. and Kalb, G. (2006). 'Health status and labour force participation: evidence from Australia', *Health Economics,* 15 (3)**,** 241-261.
Caliendo, M. and Uhlendorff, A. (2008). 'Self-Employment Dynamics, State Dependence and Cross-Mobility Patterns', *IZA Discussion Papers,* Institute for the Study of Labor (IZA), 3900.
Chamberlain, G. (1984) 'Panel data', In Griliches, Z. and Intriligator, M., D. (Eds.) *Handbook of Econometrics.* Amsterdam, Elsevier.
Commonwealth of Australia (2015), *2015 Intergenerational Report - Australia in 2055,* the Treasury, Commonwealth of Australia.
D'Addio, A.C., Keese, M. and Whitehouse, E. (2010). 'Population ageing and labour markets', *Oxford Review of Economic Policy,* 26(4), 613-635.
Datta-Gupta, N. and Larsen, M. (2007). 'Health shocks and retirement: the role of welfare state institutions ', *European Journal of Ageing,* 4 (3), 183-190.
Disney, R., Emmerson, C. and Wakefield, M. (2006). 'Ill-health and retirement in Britain: a panel data-based analysis', *Journal of Health Economics,* 25, 621-649.

Doeringer, P. (1995). *Bridges to Retirement: Older Workers in a Changing Labor Market,* Ithaca, NY, ILR Press.
Erdem, T. and Sun, B. (2001). 'Testing for Choice Dynamics in Panel Data', *Journal of Business & Economic Statistics,* 19 (2)**,** 142-152.
Fry, T.R.L. and Harris, M.N. (1996). 'A Monte Carlo Study of Tests for the Independence of Irrelevant Alternatives Property', *Transportation Research B*, 30 (1), 19-30.
Fry, T.R.L., and Harris, M.N. (2005). 'The dogit ordered generalized extreme value model', *Australian & New Zealand Journal of Statistics*, 47(4), 531-542.
Fuchs, V. R. (1982). 'Self-employment and labour force participation of older males', *Journal of Human Resources* 17 (3)**,** 339-357.
Garcia-Gomez, P., Jones, A. M. and Rice, N. (2010). 'Health effects on labour market exits and entries', *Labour Economics,* 17 (1)**,** 62-76.
García-Gómez, P., Van Kippersluis, H., O'Donnell, O. and Van Doorslaer, E. (2013). 'Long-term and spillover effects of health shocks on employment and income', *Journal of Human Resources*, 48(4), 873-909.
Gaudry, M. and M. Dagenais (1979) 'The Dogit Model.' *Transportation Research - Part B,* 13B, 105-112.
Green, W. H. (2003). *Econometric Analysis,* Prentice Hall.
Griliches, Z. (1974). 'Errors in Variables and Other Unobservables', *Econometrica,* 42 (6)**,** 971-998.
Gruber, J., and Wise D. A., eds. *Social security programs and retirement around the world*. University of Chicago Press, 2009.
Gu, Q. (2009). 'Self-Employment among Older Workers: Assistance Programs, Liquidity Constraints and Employment Patterns', RAND Corporation.
Haan, P. (2010). 'A Multi-state model of state dependence in labor supply: Intertemporal labor supply effects of a shift from joint to individual taxation', *Labour Economics,* 17 (2)**,** 323-335.
Haan, P. and Uhlendorff, A. (2007). 'Intertemporal Labor Supply and Involuntary Unemployment', *IZA Discussion Papers,* Institute for the Study of Labor (IZA), 2888.
Heckman, J. J. (1981) 'The incidental parameter problem and the Problem of Initial conditions in estimating a discrete-time discrete data stochastic process', In Manski, C. and McFadden, D. (Eds.) *Structural analysis of discrete Data with Econometric Applications.* London, MIT Press.
Hyslop, D. R. (1999). 'State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women', *Econometrica,* 67 (6)**,** 1255-1294.
International Labour Organization, (ILO). *World Employment Social Outlook – Trends 2016*.
Jimenez-Martin, S., Labeaga, J.-M. and Vilaplana-Prieto, C. (2006). 'A sequential model of older workers' labor force transitions after a health shock', *Health Economics,* 15 (9)**,** 35-66.
Jones, A. M., Rice, N. and Roberts, J. (2010). 'Sick of work or too sick to work? Evidence on self-reported health shocks and early retirement from the BHPS', *Economic Modelling,* 27 (4)**,** 866-880.
Jones, A.M., Rice, N. and Zantomio, F. 2016. 'Acute health shocks and labour market outcomes', *University Ca'Foscari of Venice, Dept. of Economics Research Paper Series*, (9).
Kerkhofs, M. and Lindeboom, M. (1995). 'Subjective health measures and state dependent reporting errors', *Health Economics,* 4 (221-235).
Kerkhofs, M., Lindeboom, M. and Theeuwes, J. (1999). 'Retirement, financial incentives and health', *Labour Economics,* 6 (2), 203-227.

Knights, S., Harris, M. N. and Loundes, J. (2002). 'Dynamic Relationships in the Australian Labour Market: Heterogeneity and State Dependence', *Economic Record,* 78 (242)**,** 284-298.
Li, Y., Mastrogiacomo, M., Hochguertel, S., and Bloemen, H. (2016). 'The Role of Wealth in the Start-up Decision of New Self-employed: Evidence from a Pension Policy Reform', *Labour Economics*, *forthcoming*.
Lindeboom, M. (2012) 'Health and work among older workers', In Jones, A. M. (Ed.) *Elgar Companion to Health Economics* Edward Elgar: Aldershot.
Lindeboom, M. and Kerkhofs, M. (2009). 'Health and work of the elderly: subjective health measures, reporting errors and endogeneity in the relationship between health and work', *Journal of Applied Econometrics*, 24(6), 1024-1046.
Lindeboom, M., Llena-Nozal, A. and Klaauw, B. V. D. (2006). 'Disability and Work: The Role of Health Shocks and Childhood Circumstances', *IZA Discussion Papers,* Institute for the Study of Labor (IZA), 2096.
Lindeboom, M. and Van Doorslaer, E. (2004). 'Cut-point shift and index shift in self-reported health', *Journal of Health Economics,* 23 (6), 1083-1099.
Magnac, T. (2000). 'Subsidised training and youth employment: distinguishing unobserved heterogeneity from state dependence in labour market histories', *Economic Journal,* 110(466), 805-837.
Malchow-Møller, N. and Svarer, M. (2003). 'Estimation of the multinomial logit model with random effects', *Applied Economics Letters,* 10 (7)**,** 389-392.
Mundlak, Y. (1978). 'On the Pooling of Time Series and Cross Section Data', *Econometrica,* 46 (1)**,** 69-85.
Organisation for Economic Co-operation and Development (OECD) 2016. OECD Health Statistics 2015. Paris: OECD.
Oguzoglu, U. (2011). 'Severity of Work Disability and Work', *Economic Record,* 87 (278)**,** 370-383.
Parker, S. C. (2004). *The Economics of Self-employment and Entrepreneurship,* Cambridge, Cambridge University Press.
Parker, S. C. (2006). *The Economics Of Entrepreneurship* Edward Elgar.
Parker, S. C. and Rougier, J. C. (2007). 'The Retirement Behaviour of Self-Employed in Britain', *Applied Economics,* 39**,** 697-713.
Peracchi, F. and Welch, F. (1994). 'Trends in Labor Force Transitions of Older Men and Women', *Journal of Labour Economics,* 12 (2), 210-242.
Pudney, S. and Shields, M. (2000). 'Gender, race, pay and promotion in the British nursing profession: estimation of a generalized ordered probit model', *Journal of Applied Econometrics,* 15 (4)**,** 367-399.
Revelt, D. and Train, K. (1998). 'Mixed Logit With Repeated Choices: Households' Choices Of Appliance Efficiency Level', *The Review of Economics and Statistics,* 80 (4)**,** 647-657.
Riphahn, R. T. (1999). 'Income and employment effects of health shocks. A test case for the German welfare state.', *Journal of Population Economics,* 12**,** 363-389.
Ruhm, C. (1990). 'Bridge jobs and partial retirement', *Journal of Labor Economics,* 8 482-501.
Ruhm, C. (1992). 'Secular changes in the work and retirement patterns of older men', *Journal of Human Resources,* 30.
Small, K. (1987). 'A discrete choice model for ordered alternatives', *Econometrica*, 55, 409-424.
Stern, S. (1989). 'Measuring the effect of disability on labour force participation', *Journal of Human Resources,* 24**,** 361-395.

Train, K. (2000). 'Halton Sequences for Mixed Logit', *Department of Economics, Working Paper No. 1035* Department of Economics, Institute for Business and Economic Research, UC Berkeley.

Train, K. (2003). *Discrete Choice Methods with Simulation*, Cambridge University Press.

Trevisan, E. and Zantomio, F. (2016). 'The impact of acute health shocks on the labour supply of older workers: evidence from sixteen European countries', *Labour Economics, forthcoming*.

Uhlendorff, A. (2006). 'From No Pay to Low Pay and Back Again? : A Multi-State Model of Low Pay Dynamics', *Discussion Papers of DIW Berlin,* DIW Berlin, German Institute for Economic Research, 648.

United Nations (2015), *World Population Ageing 2015*, Department of Economic and Social Affairs Population Division, New York.

Watson, N. and Wooden, M.P. (2012). The HILDA Survey: a case study in the design and development of a successful household panel survey. *Longitudinal and Life Course Studies*, 3(3), 369-381.

Wooldridge, J. M. (2005). 'Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity', *Journal of Applied Econometrics,* 20 (1)**,** 39-54.

Zhang, X., Zhao, X. and Harris, A. (2009). Chronic Diseases and Labour Force Participation in Australia. *Journal of Health Economics,* 28(1): 91-108.

Zissimopoulos, J.M. and Karoly, L. (2007). 'Transitions to Self-employment at Older Ages: the Role of wealth, Health, Health insurance and other factors ', *Labour Economics,* 14, 269-295.

Zissimopoulos, J.M. and Karoly, L.A. (2008). 'Labor-force dynamics at older ages: Movements into self-employment for workers and nonworkers', *Research on Aging*.

Zucchelli, E., Jones, A. M., Harris, A. and Rice, N. (2010). 'The effects of health shocks on labour market exits: evidence from the HILDA Survey', *Australian Journal of Labour Economics* 13 (2)**,** 191-218.

Tables

Table 1: Variables - main model

		Men		Women	
Labour outcomes		Mean	S.D.	Mean	S.D.
Employed full-time	1 if employed as an employee either full-time, 0 otherwise	0.3054	0.46	0.184	0.388
Employed part-time	1 if employed as an employee part-time, 0 otherwise	0.0857	0.28	0.183	0.387
Self-employed	1 if own account worker, 0 otherwise	0.2252	0.42	0.093	0.29
Inactive	1 if economically inactive, 0 otherwise	0.3837	0.49	0.54	0.498
Health variables					
Health shocks	1 if suffered a serious injury or illness in the past 12 months, 0 otherwise	0.0919	0.29	0.077	0.266
Long-term health	1 if having a long-term health condition, 0 otherwise	0.2753	0.45	0.265	0.441
Health stock	Latent self-assessed health measure obtain from the health stock model	1.4718	1.11	1.333	1.013
Other covariates					
Age 50-54	1 if individual is aged between 50-54, 0 otherwise	0.1526	0.36	0.149	0.356
Age 55-59	1 if individual is aged between 55-59, 0 otherwise	0.3375	0.47	0.339	0.474
Age 60-65	1 if individual is aged between 60-65, 0 otherwise (baseline category)	0.4391	0.5	0.438	0.496
Education/degrees	1 if individual holds a first degree/post degree qualifications, 0 otherwise	0.2016	0.4	0.177	0.382
Education/certificate	1 if advanced diploma or certificate, 0 otherwise	0.3753	0.48	0.199	0.399
Education 12	1 if highest education completed is year 12, 0 otherwise (baseline category)	0.4231	0.49	0.624	0.484
White collar 1	1 if last/current job as manager, administrator or professional, 0 otherwise	0.2769	0.45	0.18	0.384
White collar 2	1 if clerical, sales or service worker, 0 otherwise (baseline category)	0.0952	0.29	0.208	0.406
Blue collar	1 if tradesperson, labourer, production or transport worker, 0 otherwise	0.208	0.41	0.065	0.246
Log household income	Log of individual-specific total household income from all sources	10.976	0.9	10.78	0.885
Renting home	1 if living in a rented house, 0 otherwise	0.1265	0.33	0.14	0.347
Own-mortgage	1 if living in a owned house, 0 otherwise (baseline category)	0.8498	0.36	0.84	0.367
Single	1 if individual is single, 0 otherwise (baseline category)	0.2439	0.43	0.316	0.465
Marital status	1 if married or living with a partner, 0 otherwise	0.7561	0.43	0.684	0.465
Own dependent children	1 if having own dependent children, 0 otherwise	0.3034	0.46	0.219	0.414
Born Australia	1 if born in Australia, 0 otherwise (baseline category)	0.7076	0.45	0.721	0.449
Born overseas	1 if born overseas, 0 otherwise	0.2924	0.45	0.279	0.449
Major city area	1 if living in a major city area, 0 otherwise (baseline category)	0.5776	0.49	0.586	0.493
Regional/remote area	1 if living in a inner or remote area, 0 otherwise	0.4224	0.49	0.414	0.493

Table 2: Variables - health stock model

Dependent variable	
Self-assessed health (SAH)	1: Excellent, 2: Very good, 3: Good, 4: Fair, 5: Poor
Covariates - latent health index	
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	
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
Age 2	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 an inner or remote area, 0 otherwise

Table 3a: Observed labour market transition probabilities – 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	84.66	4.89	3.2	7.26	100	83.09	8.45	1.58	6.87	100
PT, t-1	12.03	64.41	6.61	16.95	100	6.73	75.48	2.27	15.52	100
SE, t-1	5.35	3.32	84.03	7.30	100	2.32	5.21	79.02	13.46	100
INA, t-1	1.93	3.95	3.19	90.93	100	0.68	3.43	1.55	94.34	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	77.19	5.26	1.75	15.79	100	74.07	3.7	-	22.22	100
PT, t-1	-	69.23	-	30.77	100	4.76	52.38	9.52	33.33	100
SE, t-1	2.27	2.27	79.55	15.91	100	7.14	-	50.0	42.86	100
INA, t-1	3.13	3.13	1.56	92.19	100	-	3.94	2.36	93.7	100

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

Table 3b: Observed labour market transition probabilities - 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	86.02	4.46	3.08	6.44	100	84.31	8.58	1.17	5.94	100
PT, t-1	14.08	63.98	5.8	16.15	100	7.08	76.48	2.12	14.32	100
SE, t-1	5.43	3.24	85.61	5.73	100	2.11	5.04	80.49	12.36	100
INA, t-1	3.6	5.72	4.16	86.52	100	0.82	4.11	2.08	92.98	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	55.38	10.77	6.92	26.92	100	66.67	14.91	3.51	14.91	100
PT, t-1	2.48	63.64	6.61	27.27	100	6.67	67.22	1.11	25.0	100
SE, t-1	3.64	3.64	76.52	16.19	100	2.35	7.06	65.88	24.71	100
INA, t-1	0.62	2.47	2.01	94.9	100	0.7	3.02	0.85	95.43	100

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

Table 4: Partial effects on the probabilities of four labour states - Dynamic RE DOGEV for men

	PE - Model (I)				**PE - Model (II)**			
Health Variables	**FT**	**PT**	**SE**	**INA**	**FT**	**PT**	**SE**	**INA**
Health stock (t-1)	-0.1019***	-0.0097	-0.0227*	0.1344***	-	-	-	-
	(0.017)	(0.010)	(0.013)	(0.021)				
Long-term health (t-1)	-	-	-	-	-0.1698***	-0.018	-0.0366*	0.2246***
					(0.032)	(0.018)	(0.021)	(0.039)
Health shocks	-0.1118***	-0.0476**	-0.0387	0.1983***	-0.146***	-0.0756***	-0.0509**	0.2726***
	(0.037)	(0.023)	(0.030)	(0.047)	(0.034)	(0.023)	(0.025)	(0.045)
Occupation at t-1								
Part-time(t-1)	-0.3760***	0.1605***	0.0663*	0.1491***	-0.3696***	0.131***	0.0544	0.1841***
	(0.053)	(0.032)	(0.040)	(0.073)	(0.054)	(0.029)	(0.034)	(0.071)
Self-employed(t-1)	-0.4053***	0.0327	0.3567***	0.0158	-0.3986***	0.0247	0.2756***	0.0982
	(0.063)	(0.031)	(0.062)	(0.081)	(0.057)	(0.026)	(0.048)	(0.083)
Inactive (t-1)	-0.7075***	-0.0339	-0.0636*	0.8050***	-0.6851***	-0.0378	-0.0595*	0.7825***
	(0.060)	(0.025)	(0.036)	(0.058)	(0.066)	(0.023)	(0.032)	(0.062)
θ	-	-	-	0.0228***	-	-	-	0.0209***
				(0.006)				(0.005)
ρ	-				-			
	Variance covariance matrix				*Variance covariance matrix*			
	1.780***	0.5517*	0.7899**		1.775***	0.2182	0.5991	
	0.5517*	1.924***	0.9932**		0.2182	2.29***	0.7836	
	0.7899**	0.9932**	2.531***		0.5991	0.7836	2.66***	
Log-likelihood:	-3500				-3925			
N	6887				7742			

This table reports partial effects of dynamic random effects DOGEV. All models include the full set of covariates. 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. θ are captivity parameters and ρ are correlations between adjacent labour market states.

Table 5: Partial effects on the probabilities of four labour states - Dynamic RE DOGEV for women

	PE - Model (I)				**PE - Model (II)**			
Health Variables	**FT**	**PT**	**SE**	**INA**	**FT**	**PT**	**SE**	**INA**
Health stock (t-1)	-0.0118***	-0.0390***	-0.0005	0.05138*	-	-	-	-
	(0.004)	(0.013)	(0.002)	(0.027)				
Long-term health (t-1)	-	-	-	-	-0.0104*	-0.0278	-0.0041	0.0424
					(0.006)	(0.019)	(0.004)	(0.038)
Health shocks	-0.0292**	-0.0480	-0.0054	0.0826***	-0.0178**	-0.0523**	-0.0033	0.0735***
	(0.011)	(0.031)	(0.030)	(0.007)	(0.007)	(0.026)	(0.005)	(0.028)
Occupation at t-1								
Part-time(t-1)	-0.1094***	0.1107***	-0.0055	0.0042	-0.0505**	0.1123***	-0.0012	-0.0606*
	(0.027)	(0.036)	(0.007)	(0.049)	(0.017)	(0.027)	(0.005)	(0.033)
Self-employed(t-1)	-0.1226***	-0.1033*	0.0356**	0.1902***	-0.0659***	-0.0928**	0.0300**	0.1288***
	(0.032)	(0.054)	(0.014)	(0.063)	(0.022)	(0.042)	(0.012)	(0.049)
Inactive (t-1)	-0.1851***	-0.3248***	-0.0141	0.5240***	-0.0921***	-0.2737***	-0.0061	0.3719***
	(0.040)	(0.060)	(0.015)	(0.059)	(0.026)	(0.038)	(0.009)	(0.043)
θ	-	-	-	0.0181***	-	-	-	-
				(0.006)				
ρ	0.5428***				0.5147***			
	(0.147)				(0.109)			
	Variance covariance matrix				*Variance covariance matrix*			
	0.6007***	0.5556	0.2211		1.009***	1.125**	1.049***	
	0.5556	2.707***	1.452***		1.125**	3.527***	2.497***	
	0.2211	1.452***	2.303***		1.049***	2.497***	3.266***	
Log-likelihood:	-3254				-3633			
N	7368				8366			

This table reports partial effects of dynamic random effects DOGEV. All models include the full set of covariates. 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. θ are captivity parameters and ρ are correlations between adjacent labour market states.

Table: 6 - Sample and average predicted probabilities for labour states

	Men				Women			
	Sample (I)	AP (I)	Sample (II)	AP (II)	Sample (I)	AP (I)	Sample (II)	AP (II)
FT	0.3055	0.3142	0.3003	0.3105	0.1847	0.1830	0.1811	0.1692
PT	0.0937	0.0727	0.0907	0.0670	0.1882	0.2021	0.1853	0.2092
SE	0.2158	0.2158	0.2136	0.2114	0.0899	0.0889	0.0859	0.0884
INA	0.3851	0.3974	0.3954	0.4111	0.5372	0.5259	0.5477	0.5332
Captive probability (INA)								
		0.02236		0.02049		0.0178		2.83E-08
		(0.006)		(0.005)		(0.006)		(0.001)

This table reports sample proportions and average predicted probabilities of dynamic random effects DOGEV models I and II for all labour market states for both men and women; FT = employed full-time; PT = employed part-time; SE = self-employed; INA = inactive. It also presents captive probabilities and corresponding standard errors for the estimated captivity parameters for inactivity.

Table 7: Partial effects: comparison across models - Men

	MNL	RE MNL	DOGEV	RE DOGEV
Health Variables				
Long-term health (t-1)				
FT	-0.1335***	-0.1454***	-0.1489***	-0.1698***
PT	-0.0037	-0.0153	-1.49E-05	-0.018
SE	-0.0177	-0.0272	-0.0220	-0.0366*
INA	0.1548***	0.1878***	0.1709***	0.2246***
Health shocks				
FT	-0.0936***	-0.126***	-0.1019***	-0.146***
PT	-0.0619***	-0.0604***	-0.0698***	-0.0756***
SE	-0.0276	-0.0332*	-0.0500*	-0.0509**
INA	0.1832***	0.2196***	0.2218***	0.2726***
Occupation at t-1				
Part-time(t-1)				
FT	-0.3957***	-0.3424***	-0.4128***	-0.3696***
PT	0.2484***	0.1200**	0.3031***	0.131***
SE	0.05252**	0.0578**	0.0524	0.0544
INA	0.0947**	0.1646**	0.0573	0.1841***
Self-employed(t-1)				
FT	-0.4686***	-0.3818***	-0.52***	-0.3986***
PT	-0.0066	0.0252	-0.0417	0.0247
SE	0.4221***	0.2406***	0.5482***	0.2756***
INA	0.0532	0.1160	0.0135	0.0982
Inactive (t-1)				
FT	-0.705***	-0.6382***	-0.7221***	-0.6851***
PT	-0.0579***	-0.0280	-0.069**	-0.0378
SE	-0.0596**	-0.0389	-0.0982***	-0.0595*
INA	0.8226***	0.7051***	0.8894***	0.7825***

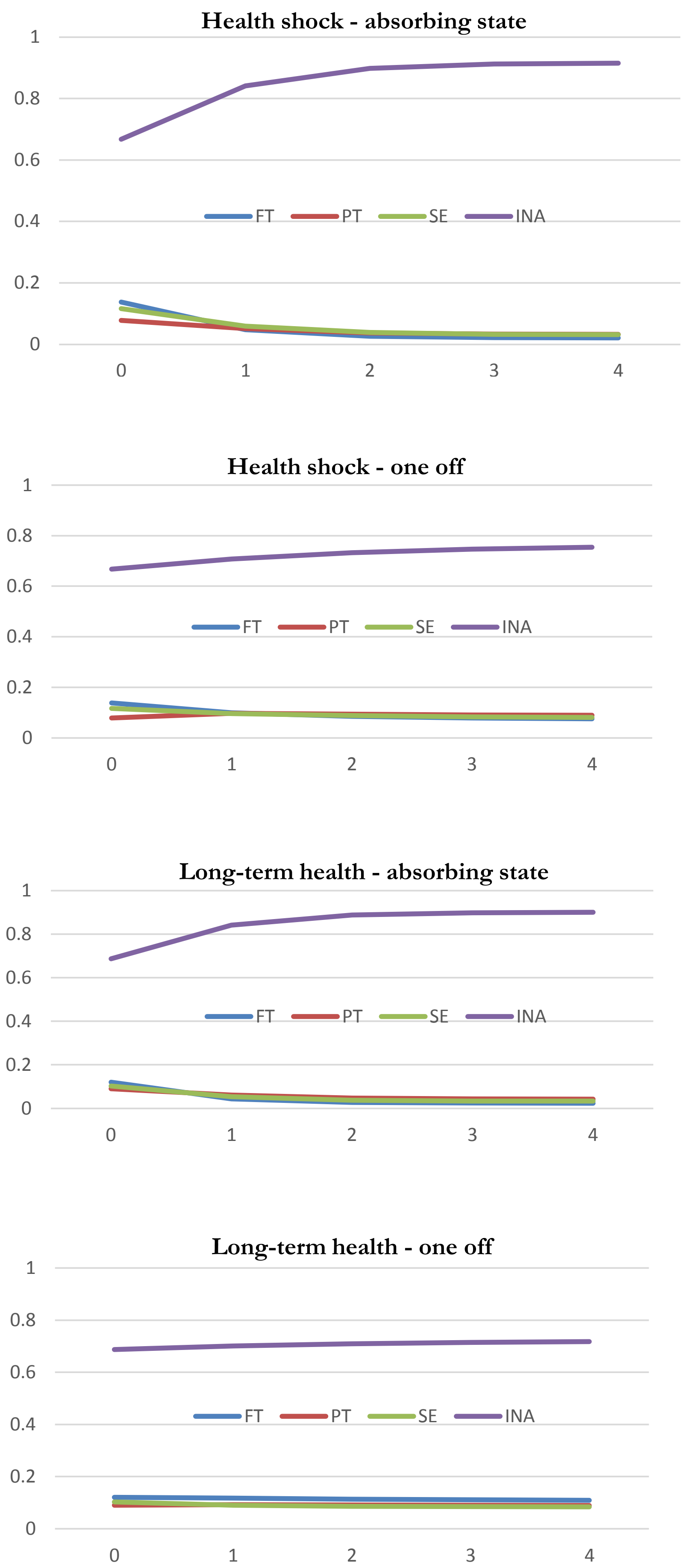
Notes: this table compares partial effects across models. MNL = pooled dynamic Multinomial Logit; RE MNL = dynamic random effects Multinomial Logit; DOGEV = pooled dynamic DOGEV; RE DOGEV = dynamic random effects DOGEV.
FT = employed full-time; PT = employed part-time; SE = Self-employment; INA = inactivity.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Table 8: Partial effects: comparison across models - Women

	MNL	RE MNL	DOGEV	RE DOGEV
Health Variables				
Long-term health (t-1)				
FT	-0.01847**	-0.0117**	-0.0173**	-0.0104*
PT	-0.01156*	-0.0264	-0.0108	-0.0278
SE	-0.0138	-0.0062	-0.0130	-0.0041
INA	0.04385**	0.0444**	0.041**	0.0424
Health shocks				
FT	-0.0309***	-0.0189***	-0.0309***	-0.0178**
PT	-0.0405*	-0.0488**	-0.0410	-0.0523**
SE	-0.0199**	-0.0066	-0.0182	-0.0033
INA	0.0914***	0.0744***	0.0901***	0.0735***
Occupation at t-1				
Part-time(t-1)				
FT	-0.1433***	-0.0523***	-0.1445***	-0.0505**
PT	0.2108***	0.1424***	0.1977***	0.1123***
SE	-0.0007	0.0010	-0.0025	-0.0012
INA	-0.0668**	-0.0910***	-0.0507*	-0.0606*
Self-employed(t-1)				
FT	-0.1762***	-0.0636***	-0.1856***	-0.0659***
PT	-0.0916***	-0.0442	-0.1423***	-0.0928**
SE	0.1288***	0.0282**	0.1375***	0.0300**
INA	0.1391***	0.0796	0.1904***	0.1288***
Inactive (t-1)				
FT	-0.2604***	-0.0956***	-0.2535***	-0.0921***
PT	-0.316***	-0.2148***	-0.3711***	-0.2737***
SE	-0.04405***	-0.0158**	-0.0329**	-0.0061
INA	0.6205***	0.3263***	0.6576***	0.3719***

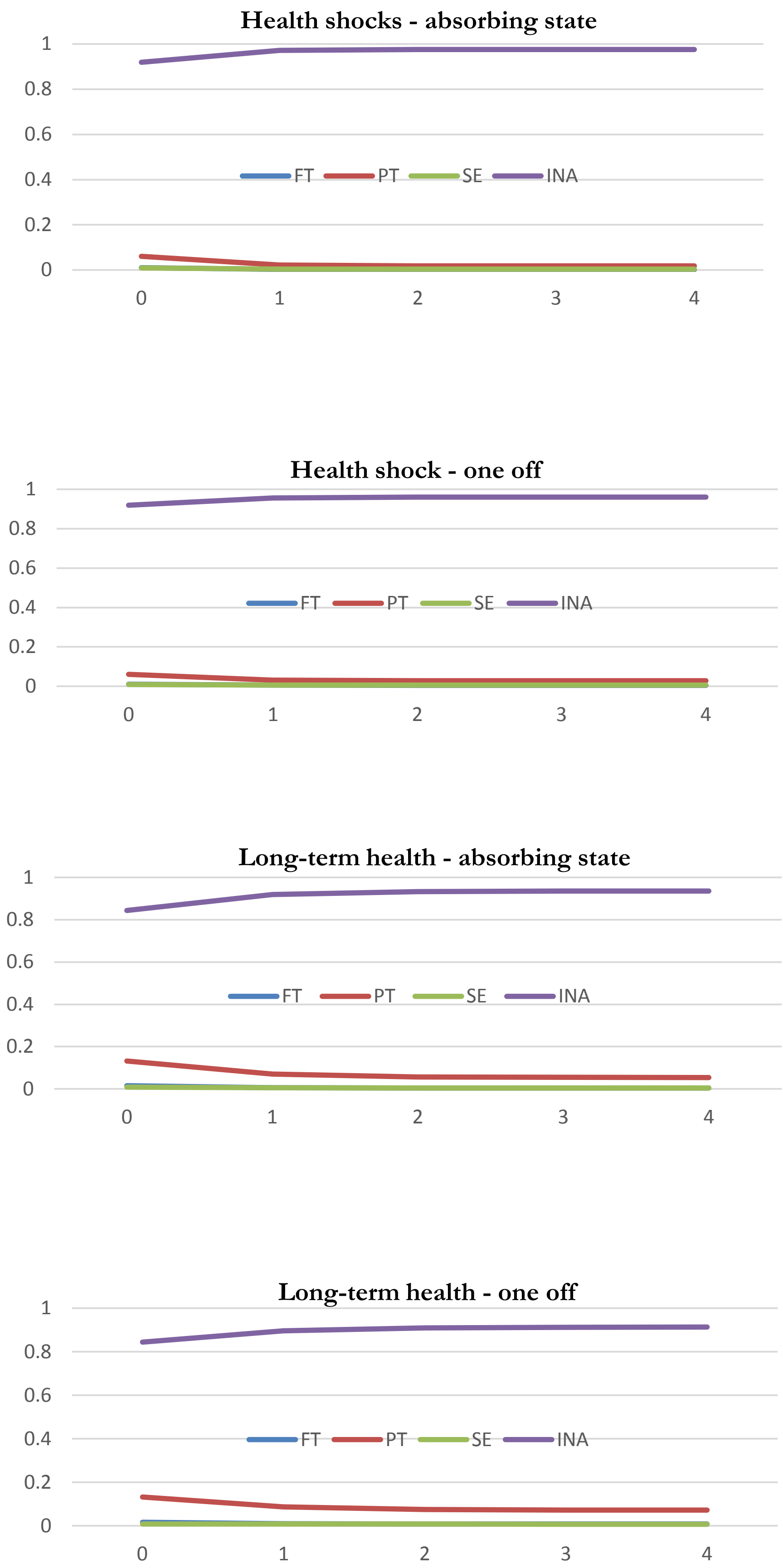
Notes: this table compares partial effects across models. MNL = pooled dynamic Multinomial Logit; RE MNL = dynamic random effects Multinomial Logit; DOGEV = pooled dynamic DOGEV; RE DOGEV = dynamic random effects DOGEV.
FT = employed full-time; PT = employed part-time; SE = Self-employment; INA = inactivity.
* p < 0.10, ** p < 0.05, *** p < 0.01.

Figure 1: Simulated dynamic employment responses – Men



Notes: simulated dynamic employment responses in the presence of health shocks and long-term conditions as alternatively absorbing states or one off conditions. FT = employed full-time; PT = employed part-time; SE = self-employed; INA = inactive.

Figure 2: Simulated dynamic employment responses – Women



Notes: simulated dynamic employment responses in the presence of health shocks and long-term conditions as alternatively absorbing states or one off conditions. FT = employed full-time; PT = employed part-time; SE = self-employed; INA = inactive.

Appendix

Partial effects for Dynamic RE DOGEV - Men and Women

	Men - Model (II)				Women - Model (II)			
Health Variables	**FT**	**PT**	**SE**	**INA**	**FT**	**PT**	**SE**	**INA**
Long-term health (t-1)	-0.1698***	-0.018	-0.0366*	0.2246***	-0.0104*	-0.0278	-0.0041	0.0424
	(0.032)	(0.018)	(0.021)	(0.039)	(0.006)	(0.019)	(0.004)	(0.038)
Health shocks	-0.146***	-0.0756***	-0.0509**	0.2726***	-0.0178**	-0.0523**	-0.0033	0.0735***
	(0.034)	(0.023)	(0.025)	(0.045)	(0.007)	(0.026)	(0.005)	(0.028)
Occupation at t-1								
Part-time(t-1)	-0.3696***	0.131***	0.0544	0.1841***	-0.0505**	0.1123***	-0.0012	-0.0606*
	(0.054)	(0.029)	(0.034)	(0.071)	(0.017)	(0.027)	(0.005)	(0.033)
Self-employed(t-1)	-0.3986***	0.0247	0.2756***	0.0982	-0.0659***	-0.0928**	0.0300**	0.1288***
	(0.057)	(0.026)	(0.048)	(0.083)	(0.022)	(0.042)	(0.012)	(0.049)
Inactive (t-1)	-0.6851***	-0.0378	-0.0595*	0.7825***	-0.0921***	-0.2737***	-0.0061	0.3719***
	(0.066)	(0.023)	(0.032)	(0.062)	(0.026)	(0.038)	(0.009)	(0.043)
Other variables								
Age between 50-54	0.3769***	-0.0044	0.1708***	-0.5433***	0.05412***	0.1907***	0.0159*	-0.2608***
	(0.047)	(0.025)	(0.035)	(0.066)	(0.014)	(0.033)	(0.009)	(0.093)
Age between 55-59	0.2076***	-0.0143	0.1133***	-0.3066***	0.0338***	0.1281***	0.0090	-0.1709***
	(0.027)	(0.014)	(0.021)	(0.036)	(0.009)	(0.020)	(0.006)	(0.022)
Education/certificate	0.0239	-0.0293	-0.0078	0.0133	0.0089	-0.0023	0.0055	-0.0121
	(0.031)	(0.019)	(0.023)	(0.045)	(0.006)	(0.028)	(0.005)	(0.030)
Education/degree	-0.0163	0.0302	-0.0150	0.0010	0.0119	0.0429	0.0109*	-0.0657**
	(0.040)	(0.024)	(0.030)	(0.061)	(0.007)	(0.027)	(0.006)	(0.031)
White collar 1(0)	-0.0398	0.0436	0.0074	-0.0112	-0.0173**	-0.0591**	0.0034	0.0730**
	(0.042)	(0.028)	(0.034)	(0.069)	(0.007)	(0.029)	(0.005)	(0.032)
Blue collar(0)	0.0257	0.0114	-0.0401	0.0029	-0.0109	-0.0234	-0.0072	0.0416
	(0.041)	(0.027)	(0.036)	(0.067)	(0.008)	(0.037)	(0.008)	(0.042)
Log household income(t-1)	0.0919***	-0.0010	0.0149	-0.1058***	0.0196***	0.0613***	-0.0022	-0.0787***
	(0.026)	(0.013)	(0.014)	(0.030)	(0.006)	(0.017)	(0.003)	(0.017)
Rented house(t-1)	0.0860**	0.0119	0.0361	-0.134**	-0.0007	-0.0198	-0.0020	0.0226
	(0.041)	(0.025)	(0.031)	(0.060)	(0.006)	(0.026)	(0.006)	(0.027)
Marital status(t-1)	-0.0110	-0.0418*	0.0458	0.0070	-0.0356***	-0.0902***	0.0058	0.1201***
	(0.038)	(0.022)	(0.028)	(0.053)	(0.010)	(0.026)	(0.005)	(0.029)
Own children(t-1)	0.0106	0.0199	0.0085	-0.0390	-0.0073	-0.0294	-0.0022	0.0389
	(0.029)	(0.018)	(0.023)	(0.045)	(0.006)	(0.026)	(0.005)	(0.029)
Born overseas	-0.0271	-0.0181	-0.0012	0.0463	0.0028	0.0015	-0.0034	-0.0010
	(0.029)	(0.019)	(0.023)	(0.044)	(0.005)	(0.025)	(0.004)	(0.027)
Remote region	-0.0412	-0.0042	0.0150	0.0304	0.0075	0.0104	0.0033	-0.0212
	(0.027)	(0.017)	(0.021)	(0.041)	(0.005)	(0.020)	(0.004)	(0.030)
Average household income	0.0948***	0.0262	0.0556**	-0.1767***	0.0046	0.0083	0.0045	-0.0174
	(0.034)	(0.019)	(0.022)	(0.045)	(0.005)	(0.022)	(0.004)	(0.024)
Part-time(0)	-0.1803***	0.1439***	-0.0203	0.0567	-0.0329***	0.0900***	-0.0108	-0.0463
	(0.059)	(0.031)	(0.054)	(0.087)	(0.010)	(0.032)	(0.007)	(0.035)
Self-employed(0)	-0.1734***	-0.0591**	0.4099***	-0.1773**	-0.0391***	-0.0806**	0.0521***	0.0676
	(0.054)	(0.031)	(0.042)	(0.071)	(0.013)	(0.042)	(0.017)	(0.090)