Ageing workforces, ill-health, and multi-state labour market transitions

30/04/2020

Mark N. Harris, Curtin University, Perth, Australia

Xueyan Zhao, Monash University, Melbourne, Australia

Eugenio Zucchelli[1], Lancaster University, Lancaster, UK;

Madrid Institute for Advanced Study (MIAS), Universidad Autónoma de Madrid, Spain

Abstract

We provide novel evidence on the effects of ill-health on the dynamics of labour state transitions by considering retirement as mobility between full-time work, part-time work, self-employment and inactivity. We employ a dynamic multi-state model which accounts for state-dependence and different types of unobservables. Our model allows for both individual heterogeneity and labour-state gravity, as well as correlations between labour market states. We estimate this model on rich longitudinal data from the Household, Income and Labour Dynamics in Australia survey. We find that both ill-health and health shocks greatly increase the probability of leaving full-time employment and moving into inactivity. Simulated dynamic trajectories suggest larger impacts of long-term health conditions than those of a one-off health shock as well as some evidence of health-driven retirement pathways via part-time work and self-employment. Our findings also indicate that the effects of health changes could be under-estimated and the magnitude of true labour market state dependence over-estimated if individual effects or labour dynamic transitions are not accounted for in the model.

Keywords: ill-health; dynamic panel models, labour market transitions; retirement

JEL classifications: C23, I10, J24, J2

Acknowledgements: we would like to thank Manuel Arellano, Alan Duncan, Andrew Jones, Martin Karlsson, David Madden, Pedro Mira, Karen Mumford, Aurora Ortiz-Nunez, Nigel Rice, Arne Risa-Hole, Karl Taylor, Ian Walker, Jeffrey Wooldridge, Maurizio Zanardi and attendants to seminars at Universidad Autónoma (Madrid), CEMFI, City (London), Duisburg-Essen and York (UK) as well as participants to the 2017 International Health Economics Association (iHEA) World Congress and the 2017 joint European Economic Association/European Meeting of the Econometric Society (EEA/ESEM) for valuable comments. We would also like to thank the editor and two anonymous referees for their useful suggestions. This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Community Services and Indigenous Affairs (FaCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (MIAESR). The findings and views reported in this paper, however, are those of the author and should not be attributed to either FaHCSIA or the MIAESR. Eugenio Zucchelli gratefully acknowledges support from the Tomás y Valiente Fellowship funded by the Madrid Institute for Advanced Study (MIAS), Universidad Autónoma de Madrid, and grants SI1/PJI/2019-00326 and H2019/HUM-5793 funded by the Comunidad de Madrid. We also acknowledge support from the Australian Research Council (ARC).

[1] Corresponding author. Primary address: Department of Economic Analysis: Economic Theory and Economic History, Universidad Autónoma de Madrid (UAM), C/Francisco Tomás y Valiente 5, 28049 Madrid, Spain. Email: eugenio.zucchelli@uam.es. Tel: +34 91 947 3065. Lancaster University, Furness Building, LA1 4YG, UK. Email: e.zucchelli@lancaster.ac.uk.

1. Introduction

An ageing population poses a threat and 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 (2017), the global population aged 60 years or over in 2017 more than doubled since 1980 and is predicted to double again by 2050. In Australia, a country with one of the longest life expectancies in the world (OECD, 2016), the number of working age people between 15 and 64 years for every person aged 65 or over has fallen from 7.3 people in 1974-75 to 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). 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. Thus, 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. Importantly, although the literature has established that ill-health is strongly associated with labour market decisions, including retirement choices (e.g. Disney *et al.*, 2006; Lindeboom and Kerkhofs, 2009; Lindeboom, 2012; Blundell *et al.*, 2016), multiple health-driven pathways into retirement need to be considered to fully capture the complexity of the labour market transitions of older workers.

The main objective of this paper is to explore the effects of ill-health and health shocks on individuals' labour market transitions of older workers by employing a highly flexible dynamic multi-state panel data model with several novel features. More specifically, we consider retirement as a multi-state process and examine the effects of health and health shocks on the mobility between full-time employment, part-time employment, self-employment and inactivity, using a dynamic DOGIT (Gaudry and Dagenais, 1979) Ordered Generalized Extreme Value (DOGEV) model (Fry and Harris, 2005). This model extends the conventional Multinomial Logit (MNL) model to further allow for the error terms of the utilities of some of the choices to be correlated, relaxing the undesirable Independence of Irrelevant Alternatives (IIA) restrictions, whilst still being computationally much simpler than alternative models such as the Multinomial Probit (MNP). Our specification also jointly accounts for labour market state-dependence, individual-level unobserved heterogeneity, gravity to particular labour states due to choice heterogeneity, as well as potential endogeneity of self-reported health. In this way, we can more precisely distinguish between the effects of past employment experience, health and other key observable characteristics as well as further unobservable individual and choice-specific effects on employment behaviour. We estimate this model using a sample of older individuals drawn from the first thirteen waves (2001-2013) of the Household, Income and Labour Dynamics in Australia Survey (HILDA; Watson and Wooden, 2012). Given its wealth of both health and work-related variables, HILDA is uniquely suited to study the relationship between health and labour supply.

Our analysis is motivated by the fact that retirement often involves multi-states, and many older workers only partially retire initially (for example, Ruhm, 1990, 1992; 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 (for example, Kerkhofs *et al*., 1999; Bruce *et al*., 2000; Blundell *et al*., 2002). In addition, 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). With the onset of ill-health, self-employment may provide a more flexible and accommodating work environment for older workers as a route leading to permanent retirement. However, empirical evidence on the direction of the effect of health on self-employment is limited and inconclusive and it has been difficult to establish whether ill-health is a "push" or "pull" factor in the decision to enter self-employment.[2] Finally, studies on Australian data conclude that ill-health and health shocks are important determinants of labour market exits (e.g. Cai and Kalb, 2006; Zhang *et al*., 2009) and that work disability and its severity can also explain changes in labour force decisions inside the Australian labour market (Oguzoglu, 2011). However, earlier studies including those using Australian data, did not consider all possible health-driven paths such as full-time, part-time, self-employment and inactivity in a panel data context.[3]

[2] Using longitudinal data from the US Retirement History Study, Fuchs (1982) found no impact of health on transitions to self-employment. Estimates produced by employing data from the British Retirement Study indicate a negative effect of ill-health on participation to self-employment (Parker and Rougier, 2007). Furthermore, using panel data from the US 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.

[3] Furthermore, trends of rising self-employment among older workers are especially marked in Australia, where the median age of all business owner managers (48 years) is ten years more than that of employees. And between

Another important aspect of labour market decision is its dynamic nature. Whilst most studies on the relationship between health and labour market decisions involve only cross-sectional data, the availability of panel data allows for separate identification of true state dependence and labour market persistence due to time-invariant individual heterogeneity (Heckman, 1981; Hsiao, 2014). Examples of dynamic panel models for binary as well as multiple labour market outcomes include Hyslop (1999); Knights *et al.* (2002); Haan (2010); Buddelmeyer and Wooden (2011); and Damrongplasit, et al (2019). Invariably, they all find true state dependence. However, none of these studies focused on older workers and their multi-state labour market transitions, allowing for both true state dependence and individual heterogeneity as well as labour state-specific effects. Clearly, correct dynamic specification with two separate sources of labour market persistence allows for health shocks to have a long-lasting effect via habit formation as well as for comparison of the impact of health with that of state dependence.

Finally, while there are common characteristics in individuals' retirement decisions across developed countries, differences in healthcare payment systems and health insurance settings imply that the relationship between health and labour market decisions may differ across countries. For example, in the United States, an individual's labour market decisions can have a significant impact on his/her healthcare costs, especially in the presence of an adverse health shock, as health insurance is linked with one's employment. On the other hand, whilst Australia has a universal public healthcare cover for all (Medicare), 50% of the population purchased private health insurance to have dental and aligned healthcare cover as well as more timely elective care. Neither cover is associated with work status, so Australia is observed as among the highest rates of disability pensions for the 60-64 year group among developed countries even though it does not have a mandatory retirement age (Blundell, *et al*. 2016).[4]

This paper offers several important contributions to the literature. Firstly, the proposed *dynamic* model allows for the examination of older workers' routes into inactivity via part-

---

2006-2016, the proportion of owner managers of businesses aged 65 and over nearly doubled, reaching around 10 percent (Australian Bureau of Statistics, 2016). Data also indicate that in recent years there has been an increase in the proportion of individuals working part-time, especially among those aged 55 years old or plus (Cassidy and Parsons, 2017). These figures suggest the presence of part-time and self-employment routes into retirement.

[4] Australia has a publicly funded universal healthcare system for all Australian citizens and permanent residents called Medicare. For further information on Medicare and private health insurance in Australia, see https://www.humanservices.gov.au/individuals/medicare [last accessed on 29/01/2020].

time and self-employment trajectories, specifically within a labour market currently experiencing increasing trends of part-time and self-employment among older individuals (Australian Bureau of Statistics, 2016). This contributes directly to the limited literature concerning health and older workers' multi-state labour market transitions, which still presents mixed findings and does not often account for dynamic transitions. Secondly, unlike earlier approaches, our model simultaneously allows for time-invariant (via individual random effects) and time-variant (via idiosyncratic errors) unobservable correlations across labour market states for the same individuals. Indeed, we do find statistical significance for both correlations, and show that ignoring these could lead to very different findings and policy recommendations. Thirdly, our dynamic model separately estimates true state dependence and individual effects for all labour states. We show that the health effect can be under-estimated and the state dependence can be over-estimated without accounting for labour dynamic effects or individual effects. Fourthly, we further illustrate our dynamic panel models by simulating the effects of health change scenarios and predicting the dynamic probability pathways for all four labour market states. These simulations illustrate the long lasting health-driven labour market trajectory. Additionally, a key element of our research is the handling of the health variables. We distinguish between gradual (health stock and long-term conditions) and sudden health deterioration (health shocks), as information on the incidence of unexpected health shock is available in the data and could help easing potential endogeneity concerns. Following the literature (e.g., Bound, 1991; Brown *et al.*, 2010; Jones *et al.*, 2010), we also account for potential measurement error in self-assessed health (SAH) status by building a latent health stock model.

2. Econometric framework

We propose a dynamic multi-state model to explore the relationship between health and labour state transitions among older individuals. This is a reduced-form dynamic model specifically aimed at examining health-driven part-time and self-employment pathways into economic inactivity. While structural modelling could be a valuable alternative approach, it would require more data than available for a credible identification. Importantly, structural models of labour supply would typically only allow for a limited number of pathways into retirement/inactivity (Blundell *et al.*, 2016).[5] Since our main objective is to precisely explore

[5] For a recent and comprehensive review of structural models of retirement, see Blundell *et al.* (2016).

a multiplicity of health-driven paths into inactivity, we choose to estimate a more flexible reduced-form model.

2.1 A dynamic multi-state model for labour transitions

We focus our attention on the effect of health on choice 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 (Greene, 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:

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

where X_{it} and H_{it-1} are (row) vectors containing individual observed characteristics in period t and $t-1$ respectively, with unknown weights, β_j and χ_j. Current period regressors X_{it} contain constant, age, education, geographical origin, and a dummy variable for living in an inner or remote region, and these are assumed to affect the labour state in the same time period. Individual characteristics in H_{it-1} include health, marital status, household income, housing tenure, and having own dependent children. These are assumed to affect labour market decisions in lagged form, which also help easing any potential problems of endogeneity. More specifically, these characteristics are lagged one period to reduce concerns around the potential simultaneity between health and employment (Lindeboom, 2012); to help disentangling the interdependence between marital status, the presence of dependent children and labour supply decisions, especially among women (Blundell *et al.*, 20016; van der Klaauw, 1996); and to better account for the well-established roles of income and wealth in determining retirement behaviour (French, 2005). Furthermore, lagged values of the individual characteristics mentioned above are potentially more informative than current values in a model of labour supply, as it is reasonable to assume that individuals may take time to adjust to changes to these conditions, e.g. between good health and a work-limiting health condition. $L_{it-1} = (L_{2it-1}, L_{3it-1}, \dots, L_{Jit-1})$ is a vector of (J-1) binary dummy variables indicating lagged labour market states with parameter vector ϕ_j, with $L_{jit-1} = 1$ if individual i at time (t-1) chooses labour state j, and $L_{jit-1} = 0$ otherwise.[6] Individual-specific time-invariant unobserved heterogeneity is represented by α_{ij} and is allowed to vary by labour state j. It is the joint inclusion of both the lagged labour state indicators and the unobserved effects that allows 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, $L_{jit} = 1$ if $V_{ijt} \geq V_{ikt}$ for all $j \neq k$ $(j, k = 1, \dots, J)$. Finally, λ_t represents year fixed effects and contains T-1 year dummies to capture any macroeconomic demand-side factors for individual years. All variables used are defined and summarised in Tables 1 and 2.

We consider a random effect model, but rather than assuming independence between individual effects and all exogenous covariates, we follow Mundlak (1978), Chamberlain (1985) and Wooldridge (2005) to link the individual effect α_{ij} to the initial labour condition and its random component as:

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

where L_{i1} is a vector for the J-1 values of the employment status variables in the initial period (t =1), $\overline{PX}_i$ is the average of any time-varying exogenous variables (including both X_{it} and H_{it-1}), and μ_{ij} is the unobservable component of the individual random effects. Note that this simply translates into including among our regressors dummy variables for the initial values of the dependent variables and the average over the sample period of the observations for the

[6] The inclusion of one lagged labour states should not be too restrictive in this case for two main reasons. First, previous employment history should affect current labour states via one-lagged labour states. Secondly, labour state interdependencies are often stronger within short-term horizons (e.g. Prowse, 2012). Additionally, earlier versions of our models included a variable based on the number of years of tenure with the current employer – this variable did not appear to be statistically significant; estimates are available upon request.

exogenous variables. Note also that this approach addresses 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). Here our approach does not assume that the initial labour states L_{i1} is non-random or uncorrelated with individual effects; in fact, both of them are allowed to be arbitrarily correlated with the observed regressors.

Note also that with this specification, choice fixed effects common for all individuals (or individual-specific choice effects) are modelled with the intercepts β_{0j} in β_j and choice-specific individual effects are modelled by α_{ij}. On the assumption that the ε_{ijt} independently and identically follow a Type I Extreme Value distribution, and conditional on μ_{ij} individual random effects, the probability of an individual i choosing alternative j in period t is given by:

$$P_{ijt} = P\left(L_{jit} = 1 \middle| X_{it}, H_{it-1}, Z_{it-1}, \mu_{i1}, \dots, \mu_{iJ}\right) = \frac{\exp(X_{it}\beta_j + H_{it-1}\chi_j + L_{it-1}\phi_j + \lambda_t + L_{1i}\vartheta_j + \overline{PX}_i\eta_j + \mu_{ij})}{\sum_{k=1}^{J}\exp(X_{it}\beta_k + H_{it-1}\chi_k + L_{it-1}\phi_k + \lambda_t + L_{1i}\vartheta_k + \overline{PX}_i\eta_k + \mu_{ik})}. \quad (3)$$

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 (3) are set to zero. As is common in the literature, a distributional form can be assigned to μ_{ij} in order to integrate out the unobserved heterogeneity. Here we assume that the unobserved heterogeneity μ_{ij} for the *J*-1 remaining choices follows a multivariate normal distribution with zero mean and a *J*-1 dimension variance-covariance matrix, and independent of all the covariates, the initial conditions and the idiosyncratic error term (ε_{ijt}).[7] The sample likelihood for the multinomial logit with random effects is:

[7] 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).

$$L = \prod_{i=1}^{N} \int_{-\infty}^{\infty} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp\left(X_{it}\beta_j + H_{it-1}\chi_j + L_{it-1}\phi_j + \lambda_t + L_{1i}\vartheta_j + \overline{PX}_i\eta_j + \mu_{ij}\right)}{\sum_{k=1}^{4} \exp\left(X_{it}\beta_k + H_{it-1}\chi_k + L_{it-1}\phi_k + \lambda_t + L_{1i}\vartheta_k + \overline{PX}_i\eta_k + \mu_{ik}\right)} \right)^{L_{ijt}} f(\mu)d(\mu) \quad (4)$$

Expression (4) cannot be solved analytically (due to the presence of the unobserved effects) and is approximated using simulated maximum likelihood methods (Train, 2003). The simulated sample likelihood is given by:

$$L^{sim} = \prod_{i=1}^{N} \frac{1}{R} \prod_{r=1}^{R} \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{\exp\left(X_{it}\beta_j + H_{it-1}\chi_j + L_{it-1}\phi_j + \lambda_t + L_{1i}\vartheta_j + \overline{PX}_i\eta_j + \mu_{ij}{}^{(r)}\right)}{\sum_{k=1}^{4} \exp\left(X_{it}\beta_k + H_{it-1}\chi_k + L_{it-1}\phi_k + \lambda_t + L_{1i}\vartheta_k + \overline{PX}_i\eta_k + \mu_{ik}{}^{(r)}\right)} \right)^{L_{ijt}}, (5)$$

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.[8]

2.2 Extending the framework to allow for correlations and gravity

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

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

Standard MNL models are computationally tractable and easy to estimate. However, they also impose a series of undesirable restrictions, which translate into strong behavioural assumptions. Ideally, researchers would want to model the effects of ill-health on labour states transitions by employing a more flexible random utility-consistent discrete-choice model. For this reason, we build on recent advances concerning the family of McFadden's Generalized Extreme Value (GEV) models (McFadden, 1978) and propose a dynamic panel data specification of the infrequently used DOGEV model.

A major 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

[8] 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).

strong *a priori* reasons that these will be correlated across states. That is, 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 and allows for the unobservable factors to be correlated for some closer related choices, specifically by 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)[9]:

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

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 $\rho \rightarrow 1$ $P^{OGEV} \rightarrow P^{MNL}$. This is a more flexible specification compared to a Nested Logit model as it allows exploring "proximate covariance" between close alternative labour states without imposing zero correlation between specific pairs of choices and a more rigid nested (tree like) structure (Small, 1987).[10] For an application of the OGEV model, see Harris *et al*. (2006).

In addition to such correlation of local alternatives, it is also probable that individuals will be "gravitated" to a certain extent towards various labour market states regardless of individual characteristics. This can be accounted for by using an additional (labour) state-specific unobserved heterogeneity parameter. Such an approach is in essence the DOGIT model of Gaudry and Dagenais (1979) as it can explicitly allow for both individual-level and labour state-specific heterogeneity. Indeed, this approach has been applied before to labour market choices with regard to occupational choice (Brown *et al.*, 2008).

[9] Note we subsequently omit in both equations (6) and (7) the *t* subscript to avoid cluttering the notation.

[10] Note that in this case the order of the different outcomes only dictates which labour states are correlated by including correlations between adjacent choices. That is, in our application we do not focus on nor claim the presence of a natural order between the labour states defining our dependent variable. This is because we are mostly interested in testing the presence of correlations between close alternatives via unobservables afforded by the OGEV model.

Essentially, the DOGIT model extends the standard MNL by including additional choice-specific parameters, θ_j. These additional components have been previously labelled as "loyalty", "gravity" or "captivity" parameters (Fry and Harris, 1996). A useful interpretation for our purposes is the so-called "two-stage" choice process described in Fry and Harris (1996). In the "first stage" the individual faces a choice set comprised of $J+1$ alternatives, $\{1,\ldots,J+1\}=\{1,\ldots,J,C\}$, where C denotes the full choice set. If a singleton alternative is selected in stage 1, then there is no "stage 2 choice" and the corresponding alternative is the one selected. However, if the $J+1$ alternative is selected in stage 1, then in the second stage of the choice process the individual will make selections according to the random utility model underlying the usual MNL approach. 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 heterogenous choice-specific effect that measures the extent that an individual is gravitated to alternative j, and this is augmented to the individual specific part of the probability P_{ij}^{OGEV} for all individuals. The DOGEV model thus simultaneously allows for correlation of close neighbouring alternatives and for individuals to be gravitated to particular labour market states, both of which appear to be very important to the application at hand. Indeed, DOGIT, OGEV and MNL are all sub-models nested within the DOGEV model.

The DOGIT choice-specific parameter, usually termed captivity but also "loyalty" or "gravity" (Fry and Harris, 2005), allows individuals to be drawn to particular choices, irrespective of their personal characteristics. This is in addition to any state-dependence and in this case could be interpreted as a combination of demand-side effects and omitted variables constant across employment states. An estimated "large" gravity parameter would imply that the choice probability for a specific labour state is mainly driven by unobservables related to the states themselves, irrespective of observed *individual* heterogeneity. These could be related to labour market supply-side factors, including characteristics of the employers and contractual conditions which may make a particular labour state more attractive or perceived as higher quality but that could not be directly observed. Conversely, an estimated nil value for captivity would suggest that choice probabilities are mainly driven by observable heterogeneity. Here, we aim at exploring whether choice probabilities are a combination of the two, i.e. labour state-specific captivity and observed heterogeneity.[11] In short, we propose a very flexible and rich multinomial model, incorporating correlated random effects along with components borrowed from both the OGEV and DOGIT models.

2.3 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 (Anderson and Burkhauser, 1985; Bazzoli, 1985; Stern, 1989; Bound, 1991; 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 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). 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; Black *et al*., 2017). 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

[11] We also note 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. Moreover, we deem our models already sufficiently heavily parameterised.

simply mirrors standard methods of dealing with errors-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). While this approach does not deal directly with the potential reverse causality between health and employment outcomes (e.g. Adam *et al.*, 2007; Lindeboom, 2012; Rohwedder and Willis, 2010), it allows accounting for systematic reporting bias which may distort the estimates of the effect of self-reported measures of ill-health on labour supply. Furthermore, since our health stock index exploits information from a wide range of specific health measures (including activities of daily living; work-limiting conditions; and bodily pain), it is likely to be a more reliable measure of general health compared to standard single SAH measures. 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. Finally, we include in all models a variable defining health shocks. This variable should also help to further disentangling the relationship between health and work by exploiting unexpected events and their timings. Details for all the above mentioned health variables are reported in the following section.

3. Data

3.1 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). Its design resembles other important longitudinal surveys such as the British Household Panel Survey (BHPS); the German Socioeconomic Panel (SOEP); and the U.S. based Panel Study of Income Dynamics (PSID), but it has more extensive information on health and labour variables. Because of its wealth of variables, including health shocks and length, and the possibility to observe labour market transitions between consecutive years, HILDA is well suited for our analysis. Furthermore, the employment variables included in HILDA are more in line with the International Labour Organization guidelines if compared to the ones of BHPS and SOEP (Watson and Wooden, 2011).

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 of 65 for the whole 13-wave panel. 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 in an unbalanced panel. The variables used in our analysis are summarised in Tables 1 and 2. Table A1 contains definitions and sample statistics of the dependent and explanatory variables used in the labour transitions model, while Table A2 presents the variables used in the health stock model (see Online Appendix).

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.[12] According to this categorisation, we define self-employed individuals as those who self-report being owner-managers of either incorporated or unincorporated enterprises.[13] Our broad definition of economic inactivity comprises individuals both voluntarily inactive (retired) and involuntarily inactive (unemployed). More precisely, we define as voluntarily inactive individuals who self-report being retired, disabled, unpaid volunteer and looking after an ill-person. However, it should be noted that only 1.2% of middle-age and older individuals in our sample are involuntarily inactive/unemployed.

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 A2). 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

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

[13] 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).

(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), 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".[14] 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.

[14] Although this is arguably a more accurate measure of health than the general SAH variable, a recent paper by Black *et al*. (2017) finds evidence of justification bias among HILDA respondents answering questions on disability and long-term health conditions. More specifically, non-employed respondents and disability recipients, especially among male individuals, appear to overstate their level of disability. The authors suggest this might be due to financial incentives but also the social desire to justify non-employment. Given our definition of inactivity, this is likely to affect a relatively small proportion of individuals included in the inactive category, i.e. those who self-report disability and the unemployed, which represent 14.7% and 1.2% of the individuals in the category, respectively. Still, we should be cautious when interpreting the effects of this variable on labour transitions.

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 A1). 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 and simultaneity issues. Following the approach of Mundlak (1978) and Wooldridge (2005) to deal with initial conditions and potential correlations between individual effects and observed regressors, we add into our specifications initial (wave 1) values of the labour state dummies and the average of the sample period of individual-specific household income. Importantly, the inclusion of the latter explicitly allows our income variable (which includes potentially endogenous labour income) to be correlated with the individual effects. Finally, year-specific shocks are accounted for using annual (wave) dummies.

3.2 Observed labour state transitions

As our interest lies in transition probabilities and their relationship to health levels, we first look at the observed transition probabilities. Tables 1a and 1b 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 1a and 1b 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.

4. Discussion of model results

Due to the complexities of the models and the large amount of model results, we only report and discuss the marginal effects of covariates on the probability of being in each labour state, evaluated at the sample means of covariates, with standard errors being estimated using the Delta method.[15] Note that to account for the fact that our health stock measure is obtained using the predicted values from the first-stage generalised ordered probit models, the standard errors for the estimates in the second-stage DOGEV models are adjusted for the additional variance from the first-stage using the approach of Murphy and Topel (1985). Table A3 in the online appendix presents the estimated marginal effects of all socioeconomic covariates for Model II.[16]

Key results including the marginal effects for the lagged labour state and health variables are presented for both models and displayed separately for men and women in Tables 2 and 3. As noted earlier, we consider both health state and health shocks. Health state is considered with

[15] We also evaluated partial effects at specific health states. Results are similar and available upon request. Coefficient estimates and the associated standard errors are not reported due to space limit but are also available upon request.
[16] Estimates of the marginal effects for the full set of year/wave dummies and all other marginal effect results for Model I are available upon request.

two alternative definitions: a latent health stock variable purged of reporting bias instrumented from the first stage and a dummy 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 as a dummy variable based on information on the occurrence of a serious injury or illness. Each of Tables 2 and 3 contains partial effects for key variables, gravity parameters (θ), correlation between adjacent labour market states (ρ), as well as variance-covariance matrices for the random effects μ_{ij} from our dynamic DOGEV models.

(Tables 2 and 3 here)

Labour state correlation and gravity

We freely estimated all gravity parameters in all models. Without fail, there was strong evidence of a gravity effect for the inactive labour market state, but not to any other states (the respective θ_j value was essentially 0). That is, once we have conditioned on a whole host of factors (such as observed and unobserved individual 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 gravitated to the inactivity state regardless of differences in individual characteristics.

The DOGEV models further find a highly statistically significant ρ (i.e. significantly different from 0) in all specifications for women and one for men. This implies that there are significant correlations in the time-varying idiosyncratic errors between local adjacent labour market states and that an OGEV specification would be more appropriate than the nested standard MNL model ignoring these. We evaluate and quantify these effects in greater details below but note here that the significance of the gravity effects and the correlation coefficient clearly suggests that models ignoring these could be mis-specified. The significance of estimate for ρ would also serve as a rejection of the independence of irrelevant alternatives (IIA) property for the nested Multinomial Logit model.

State dependence and individual heterogeneity

One key advantage of our dynamic panel data model is its ability to separately identify true labour market state dependence and state dependence due to individual heterogeneity. Our results show that both sources are significant in contributing to the observed labour market state dependence, so mis-specifying the model with only one of the two channels would confuse the two effects. The estimated variances for the individual random effects at the bottom of Tables 2 and 3 show that there is a statistically non-zero variance for the individual unobserved effects μ_{ij} in all models, justifying the existence of significant time-invariant individual effects. Furthermore, the estimated covariances for individual unobserved effects μ_{ij} are significant at 1%-10% levels for both men and women for both models, except for the case of men for Model I for the pair of SE and INA. These suggest that the correlation across states/choices for the same individual exists for both time-invariant random effects (via the significant estimates for the off-diagonal covariances for effects μ_{ij}'s) and for time-variant errors ε_{ijt} (via the significant estimate of ρ) for the same individual i. This particularly highlighted the strength of our complex model that allows for both such correlations. In summary, there is strong evidence for significant individual time-invariant unobserved effects for all choices and these effects are also mostly correlated across labour market states.

Next, we turn to the true labour market state dependence as captured by ϕ_j. According to both models for both men and women, genuine labour market persistence exists in all states considered. Being employed part-time, self-employed or inactive in year t-1 greatly increases the probability of staying in the same labour market state in year t. However, being in any of these labour market states in the previous period greatly decreases the probability of choosing full-time employment in the subsequent period for both men and women, relative to those being employed full-time in the previous period. The results also present some interesting evidence of cross-mobility among labour market states, and other pathways to retirement (INA) in addition to the pathway of FT to INA. For example, for men PT work is shown to be a pathway to both SE and INA, with higher probability of PT transiting to either SE or INA relative to previous FT workers, controlling for all other observable factors. No evidence is found for higher chance of previous SE (relative to previous FT workers) transiting to INA. This is different for women. An interesting finding for women is that SE is a greater pathway to INA than part-time (both models in Table 3). This is different from the observed transition probabilities, where both PT and SE are equally greater pathways to INA relative to FT work when other factors are not controlled. Another interesting difference is that a previously INA man is more likely to go back to PT work than a previously FT-working man transiting to PT work. For women, a previously INA woman is much less likely to move to PT work than a previously FT-working women. In other words, men may fluctuate between different states whilst women follow more clearly the downward transition paths to INA.

Partial effects of health

We next focus our attention on the partial effects of the health variables. For men (Table 2), partial effects of the health and health shocks variables are negative and statistically significant on the probability for full-time employment, especially in model II. 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 16 percentage points (pp) while the occurrence of health shocks seems to decrease the same probability by around 13.6pp. 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 13.1 to 26.5pp while the latter by around 21.1pp. We also observe a negative and significant partial effect of the health shocks variable for part-time employment (around 8.1pp, model II). Our estimates also show a negative, although only weakly significant, partial effect of health shocks on self-employment (4.8pp, model II). This suggest that for older men, health shocks decrease the probabilities of choosing all of FT, PT or SE, and only increase the chance for INA.

For women, partial effects obtained from both models I and II (Table 3) indicate a similar role of ill-health and health shocks in determining labour market states, although health shocks appear to play a larger role if compared to ill-health and long-term health conditions. More specifically, health shocks decrease the probability of choosing full-time employment while increasing the probability of opting for inactivity (model II). Also, ill-health and the incidence of health shocks both appear to decrease the probability of being in part-time employment.

Partial effects of other covariates

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 are also influenced by age, education, income, type of jobs and marital status.[17] 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 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 negatively associated with age. The likelihood of choosing inactivity appears to increase with age.

As for the models estimated for women, the larger and most consistently significant partial effects are the ones for the age dummies (positive for transitions to full- and part-time and negative to inactivity, although with smaller partial effects for older age categories); household income (also 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 full-time and 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 inactivity and to a lesser extent part-time.

Model selection and results from alternative models

Table 4 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/gravity probabilities (and corresponding standard errors) derived from the previously estimated gravity parameters for inactivity. These quantify the gravity effects and imply a probability around 1.5-1.9 percent of being "gravitated" to inactivity for both genders. 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 gravity effects of nearly 2pp, are of the same order of magnitude as the effects of ill-health on labour market status. Indeed, such significant gravity effects, also appear to validate the use of a model capable of accounting for labour market state heterogeneity.

[17] 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.

From the model selection point of view, the statistical significance of the estimates for ρ, θ and variances and covariances for μ_{ij}'s serves as the rejection of the null hypotheses regarding each of these parameters and suggests that our random effect (RE) DOGEV model is the preferred model over the simpler models. In order to highlight the impact of estimating our more general model, we next estimate three alternative rejected models in order to compare how the key results would differ if these simpler models were used.

In Tables 5 and 6 we compare the key results from our RE DOGEV model from those from: a pooled dynamic MNL (MNL), a RE dynamic MNL (RE MNL), and a pooled dynamic DOGEV (DOGEV) models. These are computed for model II (where long-term health conditions and health shocks are included) for both genders. Comparing the impacts of health first, overall the effects of both health variables seem to be *under-estimated* for the probabilities of FT and INA for both men and women if using any of the three simpler models (except for one case of health shocks effect on INA state from the DOGEV model). In particular, for men (Table 5), these differences can be substantial, ranging from 2pp to 8pp in probability values (or 15% to 44% as relative differences). For women, the differences are much smaller. As for the effects of state dependence, the results for both own-state dependence and cross-state transition can be significantly different if using the 3 simpler models. As expected, own-state persistence can be over-estimated without RE controlling for individual heterogeneity for both men and women, and the differences for men are more substantial. The results for RE MNL model are different for men versus women. Without allowing for cross state correlations, the RE MNL slightly underestimate own-state dependence for men, whilst for women, it can be over or under estimate such dependence. In summary, there can be significant differences in our key results if any of the rejected and simpler models are used.

(Tables 4, 5 and 6 here)

5. Simulating the dynamic employment paths due to ill-health

In order to further illustrate the dynamic effects of health on labour market decisions, especially including the long-lasting indirect health effect via labour market dynamic state dependence, we use the estimated models to simulate the labour state probability paths from various scenarios of ill-health. We extend the simulation approach taken in Damrongplasit *et al*. (2019) for a binary outcome dynamic model to the multinomial case. To fully illustrate all situations for any given health change scenario, we would need to consider 16 probability paths for all of the 4 initial labour states (4 paths per 4 different initial conditions). To contain the scale of the simulation, we focus on the case of initial FT employment, which is more relevant to our retirement focus. For each health change scenario, we consider a stylised simulation by using a sub-sample of all the 60-year-old men/women in the estimating sample, and we simulate paths from age 60 to 65. We keep all their exogenous variables (other than the health variable being simulated), fixed at their observed levels at age 60 throughout the simulation. This is so as to isolate the effects of *only* one exogenous health change in each scenario of the simulation and to illustrate its trajectory. We evaluate simulated individual probabilities for each state, using exactly the same random effects as used in estimation based on the estimated error components variance-covariance matrix. Final stylised probability profiles for each of all four states are then obtained as the average of these simulated ones, over all of the individuals considered in the simulation sub-sample. Note that we choose all 60-year-old men/women in the sample, not just those who were working at the age of 60. This is done in order to conduct the counterfactual simulation of the health impact on *all* 60-year-old males/females (not the impact on the sub-group of individuals who are working).

Specifically, we consider three health change scenarios under Model II: a one-off '*health shock'* at the initial period only, with no health shock for subsequent periods; a permanent '*long-term health condition'* switched on for all simulation years; and a change of *'health stock'* across three different health stock quantiles (Q1, Q2 and Q3). We simulate the four labour market probability paths for 60-year-old individuals, assuming they are all working FT at the start of the simulated period.[18] Following the algorithms proposed in Damrongplasit *et al*. (2019), a health change in period *t* will initially change the probability of all four labour states for the current period *t* (or the next period t+1 in the case of lagged health regressor) in the first instance. However, through the dynamic model via the lagged labour state variables, the impact will roll over to all future periods for all four labour state/choice probabilities. So, the probability profiles are simulated over time, by considering all labour market states in all future time periods, and all possible pathways the individual could have taken to have arrived at the probability for a particular state in that particular time period (Damrongplasit *et al.*, 2019). For any particular path, joint probabilities over time are simply the product of marginal ones where joint dependence is allowed for by the common unobserved effect.[19] The simulation results for males and females are reported in Figures 1 and 2, respectively.

(Figures 1 and 2 here)

We first focus on the first two health change scenarios for men in Figure 1. The first graph in Figure 1 for the one-off health shock scenario suggests a significant reduction of the probability for FT employment from about 0.39 to 0.22. Interestingly, this appears to translate into higher probabilities for INA (from 0.44 to 0.47) as well as for PT (0.07 to 0.12) and SE (0.11 to 0.19). Since higher probabilities to PT and SE also include the possibility of downward transitions from PT/SE to INA, overall these simulations seem to suggest evidence of PT and SE pathways into INA following a one-off health shock. Notably, the immediate impacts on all four labour states settle quickly within 2 or 3 years before reaching a new equilibrium.

[18] We have also simulated labour state probability paths using observed lagged labour states and without imposing working full-time as initial state. Corresponding graphs are available upon request.
[19] It should be borne in mind that all estimates from our models, including simulated labour trajectories are based on and valid for the current pension system. The age pension age remained 65 for the entire estimating sample.

The impact of a long-lasting long-term condition is somewhat different (second graph in Figure 1). The probability of FT work decreases more significantly from 0.37 to 0.11, and that of INA increases from 0.42 to 0.60. While the probabilities for PT and SE change from 0.10 and 0.11 to 0.11 and 0.18 respectively, the significant increase in the INA probability also indicate a high possibility for a more direct transition from FT to INA. In comparison, it seems that the impact of a persistent long-term health condition for all periods of the simulation is worse than a one-off health shock at the start of the simulation, and there is also a stronger evidence of PT/SE pathways for the case of a one-off health shock at the beginning of the period, for a random selected 60-year-old man in the sample. Corresponding top two graphs in Figure 2 for women appear to show similar patterns with the same evidence of PT/SE as pathways of labour market transition, although the probabilities settle at different values.

It is also interesting to compare the difference a person's location on the health stock distribution can make to his/her employment states when faced with a new health change. We do this for the case of a one-off health shock, and the lower three graphs in Figure 1 show the impacts for men on the first to third quantiles (Q1-Q3) of the health stock distribution, with Q1 representing the healthy end of the health stock. Whereas we find similar inactivity pathways, the impacts for the less healthy on the Q3 health distribution are more severe, with the projected probability for FT employment changes from around 0.39 to a long-term 0.14, and that for INA from 0.40 to 0.60 for an otherwise randomly selected 60-year-old man. Similar results apply to women. In all simulated paths, the initial effect settles into an equilibrium probability after 2-3 years for all four labour states.

6. Conclusions and discussion

This study proposes a new and more flexible model to examine labour market transitions between full-time employment, part-time employment, self-employment and inactivity among older workers. As retirement age increases across the world, understanding the various pathways of transitioning from full-time employment to permanent inactivity is crucial for designing government policies aimed at encouraging individuals to work longer. Our analysis was motivated by both the scarcity of knowledge and mixed findings around the relationship between ill-health and different paths into inactivity for workers in the later stage of their work lives. Our dynamic multi-state panel model specification includes more flexible features such as captivity/gravity to specific labour market states, correlation across all states for time-invariant individual random effects, as well as correlations between neighbouring labour states via time-varying idiosyncratic errors. These allow to more flexibly and realistically representing an individual's behaviour and accounting for demand-side factors. Our results show that our model is the preferred model by the data. We find significant individual heterogeneity and evidence of correlations across labour states via both time-invariant and time-variant unobservable individual factors. We have also estimated three alternative simpler models, and our results show that estimates for key results of interest can vary substantially if these realistic model features are not accounted for.

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. More specifically, it aims at unveiling whether, and for how long, ill-health and health shocks might drive individuals of both genders towards reducing the amount of hours worked (part-time work) or to choose a type of employment which they perceive as more flexible (self-employment) before becoming economically inactive. Importantly, our model does so by also accounting for demand-side and labour-state specific unobservables, which may "gravitate" individuals to specific labour states, irrespective of individual characteristics. Robust evidence around the role of health, as well other important determinants of frequently observed labour transitions, may help governments to devise more targeted incentives for older workers to remain active in the labour market.

As expected, our 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 show that the magnitudes of true labour market state dependence for all four states could be *over-estimated* for both men and women if individual effects are not controlled, with the differences for men being particularly substantial. The overestimation of state dependence would be especially marked for self-employment (men) and inactivity (women), with differences of around 30pp and 35pp if compared to the estimated partial effects of our preferred specification, respectively. We also find that the effects of both health variables could be *under-estimated* for the probabilities of full-time work and inactivity for both men and women if individual effects and cross-state correlations are not accounted for.

We find that for both genders experiencing a health shock or having a long-term health condition leads to a substantially lower propensity for full-time employment and a higher probability for inactivity. This is in line with earlier evidence on the effects of ill-health on labour force participation (e.g. Blundell et al., 2016), including the one produced using Australian data (e.g. Cai and Kalb, 2006; Zhang et al., 2009). However, in contrast with previous research based on static models not accounting for different types of unobserved heterogeneity, our estimates obtained using a DOGEV model suggest overall smaller impacts of health and health shocks on the probabilities of part-time and self-employment. For instance, Zissimopoulos and Karoly (2007) employ a more standard multinomial logit model and find that in the US work-limiting health conditions have a large positive effect on the probability of choosing self-employment among older workers. Results obtained by Gannon and Roberts (2011) using a multinomial probit model with individual effects and a Mundlack-type estimator (Mundlack, 1978), suggest that in the UK individuals aged 50 or over with health problems have a higher probability of working part-time. Differences between our findings and earlier evidence may be the result of the use of a dynamic model and the possibility of drawing more precise trajectories of labour market transitions while accounting for several types of unobservable factors. Interestingly, our model also suggests 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. In other words, true state dependence is stronger for workers in their later stage of work lives.

Our simulated dynamic response paths illustrate how even a one-off health change can have a long-lasting impact on the labour market state trajectory. The simulations provide support for large decreases in full-time employment and increases in inactivity together with evidence of health-driven retirement pathways via part-time work and self-employment for both men and women. Yet, the latter appear to be more pronounced following a one-off shock than a lasting long-term condition. Overall, we show that the effect of a permanent health change is larger than that of a one-off health shock.

It should be noted that our labour trajectories do not control directly for some potentially important institutional factors, such as the structure of the social security system and the tax system, which might inform some of movements within and outside the labour market. However, our models account for a number of important elements such as employment dynamics, health dynamics, the roles of individual and labour-state specific unobserved heterogeneity and a broad range of demographic and socioeconomic variables. As such, our highly flexible approach builds on results from previous studies on health and labour transitions and provide new evidence on the existence of heath-driven inactivity paths, using a more comprehensive empirical model.

References

Adam, S., Bonsang, E., Germain, S., and Perelman, S. (2007). 'Retirement and cognitive reserve: a stochastic frontier approach applied to survey data', *No. DP 2007/04, CREPP.*

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.

Australian Labour Market Statistics, (2011). Australian Labour Market Statistics, Issue 6105.0

Australian Bureau of Statistics, (2016). Census of Population and Housing: Reflecting Australia - Stories from the Census – Business owner managers across Australia, Issue 2071.0

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.

Blanchflower, D.G. (2000). 'Self-employment in OECD countries', *Labour Economics*, *7*(5), 471-505.

Black, N., Johnston, D. W. and Suziedelyte, A. (2017). 'Justification bias in self-reported disability: new evidence from panel data', *Journal of Health Economics*, 54, 124-134.

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.

Blundell, R., Costa Dias, M., Meghir, C., and Shaw, J. (2016). 'Female labor supply, human capital, and welfare reform'. *Econometrica*, 84(5), 1705-1753.

Blundell, R., French, E. and Tetlow, G. (2016). Retirement incentives and labor supply. In *Handbook of the Economics of Population Aging* (Vol. 1, pp. 457-566). North-Holland.

Bound, J. (1991). 'Self-reported versus objective measures of health in retirement models', *Journal of Human Resources,* 26**,** 106-138.

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. (2011). Transitions Out of Casual Employment: The Australian Experience. *Industrial Relations: A Journal of Economy and Society*, 50, 109–130.

Cai, L. and Kalb, G. (2006). 'Health status and labour force participation: evidence from Australia', *Health Economics,* 15 (3)**,** 241-261.

Cassidy, N. and Parsons, S. (2017). 'The Rising Share of Part-time Employment', *Reserve Bank of Australia (RBA) Bulletin, September*, pp.19-26.

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.

Damrongplasit, K., Hsiao, C. and Zhao, X. (2019). 'Health status and labour market outcome: Empirical evidence from Australia', *Pacific Economic Review*, 24(2), pp.269-292.

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.

French, E. (2005). 'The effects of health, wealth, and wages on labour supply and retirement behaviour'. *The Review of Economic Studies*, 72(2), 395-427.

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.

Gannon, B., and Roberts, J. (2011). 'Part-time work and health among older workers in Ireland and Britain'. *Applied Economics*, 43(30), 4749-4757.

García-Gómez, P., and López Nicolás, Á. (2006). ' Health shocks, employment and income in the Spanish labour market', *Health Economics*, 15(9), 997-1009.

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.

Harris, M., P. Ramful, and X. Zhao (2006), "An Ordered Generalised Extreme Value Model with Application to Alcohol Consumption in Australia", *Journal of Health Economics*, 25(4): 782-801.

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.

Hsiao, C. (2014). *Analysis of panel data* (No. 54). Cambridge University 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.

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.

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. and Van Doorslaer, E. (2004). 'Cut-point shift and index shift in self-reported health', *Journal of Health Economics,* 23 (6), 1083-1099.

McFadden, D. (1978). Modeling the choice of residential location. In Spatial Interaction Theory and Planning Models, eds A. Karlqvist, L. Lundqvist & J. Weibull, pp.75–96.Amsterdam: North Holland Publishing Company.

Mundlak, Y. (1978). 'On the Pooling of Time Series and Cross Section Data', *Econometrica,* 46 (1)**,** 69-85.

Murphy, K. M., and Topel, R. H. (2002). 'Estimation and inference in two-step econometric models', *Journal of Business & Economic Statistics*, 20(1), 88-97.

OECD, (2017). *OECD Employment Outlook 2017*, OECD Publishing, Paris.

Oguzoglu, U. (2011). 'Severity of Work Disability and Work', *Economic Record,* 87 (278)**,** 370-383.

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.

Prowse, V. (2012). 'Modeling employment dynamics with state dependence and unobserved heterogeneity', *Journal of Business & Economic Statistics*, 30(3), pp.411-431.

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.

Rohwedder, S., and Willis, R. J. (2010). 'Mental retirement', *Journal of Economic Perspectives*, *24*(1), 119-38.

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.

United Nations (2017). *World Population Ageing 2017*, Department of Economic and Social Affairs Population Division, New York.

Van der Klaauw, W. (1996). 'Female labour supply and marital status decisions: A life-cycle model'. *The Review of Economic Studies*, 63(2), 199-235.

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.

Tables

Table 1a: 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 1b: 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 2: 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)	-0.0900***	0.0000	-0.0283	0.1183***	-	-	-	-
	(0.023)	(0.013)	(0.021)	(0.017)				
Long-term health (t-1)	-	-	-	-	-0.1575***	-0.0210	-0.0334	0.2118***
					(0.032)	(0.018)	(0.021)	(0.041)
Health shocks	-0.0666	-0.0362	-0.0282	0.1310**	-0.1364***	-0.0814***	-0.0479*	0.2657***
	(0.050)	(0.035)	(0.053)	(0.051)	(0.033)	(0.023)	(0.024)	(0.045)
Occupation at t-1								
Part-time(t-1)	-0.5311***	0.2440***	0.1836**	0.1035	-0.3367***	0.1410***	0.0626*	0.1332*
	(0.068)	(0.061)	(0.074)	(0.076)	(0.053)	(0.028)	(0.033)	(0.067)
Self-employed(t-1)	-0.6705***	0.0108	0.7272***	-0.0675	-0.3679***	0.0241	0.2575***	0.0000
	(0.080)	(0.044)	(0.144)	(0.102)	(0.054)	(0.027)	(0.051)	(0.084)
Inactive (t-1)	-0.9041***	0.0807*	0.0985	0.7249***	-0.6358***	-0.0383	-0.0472	0.7213***
	(0.067)	(0.044)	(0.073)	(0.084)	(0.060)	(0.024)	(0.031)	(0.061)
Wave dummies	yes	yes	yes	yes	yes	yes	yes	yes
θ	-	-	-	0.0201***	0.0024			0.0192***
				(0.007)	(0.002)			(0.005)
ρ	0.4526***				1.000			
	(0.087)				(70.710)			
	Variance covariance matrix				*Variance covariance matrix*			
	1.044***	0.5961**	0.4057		1.912***	0.3997	0.9962**	
	0.5961**	1.343***	1.177***		0.3997	2.673***	1.037*	
	0.4057	1.177***	2.374***		0.9962**	1.037*	3.685***	
Log-likelihood:	-3239				-3901			
N	6315				7742			

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

Table 3: 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)	-0.0142*	-0.0540**	-0.0053	0.0734***	-	-	-	-
	(0.008)	(0.021)	(0.005)	(0.024)				
Long-term health (t-1)	-	-	-	-	-0.0085	-0.0282	-0.0056	0.0424*
					(0.005)	(0.022)	(0.004)	(0.024)
Health shocks	-0.0264*	-0.0549	-0.0073	0.0886*	-0.0173***	-0.0604**	-0.0039	0.0816***
	(0.015)	(0.045)	(0.009)	(0.052)	(0.006)	(0.027)	(0.005)	(0.030)
Occupation at t-1								
Part-time(t-1)	-0.1371***	0.2085***	-0.0093	-0.0620	-0.0480***	0.0973***	-0.0023	-0.0470
	(0.042)	(0.059)	(0.014)	(0.074)	(0.015)	(0.033)	(0.005)	(0.038)
Self-employed(t-1)	-0.1485***	-0.0937	0.0438**	0.1984*	-0.0598***	-0.1165***	0.0252***	0.1510***
	(0.051)	(0.088)	(0.022)	(0.103)	(0.017)	(0.049)	(0.011)	(0.054)
Inactive (t-1)	-0.2224***	-0.3847***	-0.0232	0.6304***	-0.0862***	-0.2858***	-0.0065	0.3785***
	(0.062)	(0.083)	(0.021)	(0.093)	(0.022)	(0.049)	(0.009)	(0.052)
Wave dummies	yes				yes			
θ	-	-	-	0.0194***	-	-	-	0.0160***
				(0.007)				(0.005)
ρ	0.7063***				0.5363***			
	(0.247)				(0.151)			
	Variance covariance matrix				*Variance covariance matrix*			
	0.7737**	1.083**	0.6838*		1.050***	1.447***	1.199***	
	1.083**	3.869**	1.893***		1.447***	4.327***	3.071***	
	0.6838*	1.893***	3.132***		1.199***	3.071***	4.399***	
Log-likelihood:	-2923				-3592			
N	6711				8366			

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

Table: 4 - Summary probabilities

	Men				Women			
	Sample (I)	AP (I)	Sample (II)	AP (II)	Sample (I)	AP (I)	Sample (II)	AP (II)
FT	0.3086	0.2837	0.3003	0.3075	0.1849	0.1787	0.1811	0.1669
PT	0.0982	0.1309	0.09067	0.0694	0.1915	0.1989	0.1853	0.2045
SE	0.2165	0.2134	0.2136	0.2096	0.0914	0.0810	0.0859	0.0849
INA	0.3786	0.3719	0.3954	0.4134	0.5321	0.5414	0.5477	0.5410
Gravity probability (INA)								
		0.01969		0.0187		0.0190		0.0157
		(0.006)		(0.004)		(0.006)		(0.005)

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 gravity probabilities and corresponding standard errors for the estimated gravity parameters for inactivity.

Table 5: Partial effects: comparison across models - Men

	MNL	RE MNL	DOGEV	RE DOGEV
Health Variables				
Long-term health (t-1)				
FT	-0.1338***	-0.1358***	-0.1513***	-0.1575***
PT	-0.0047	-0.0178	-0.0015	-0.0210
SE	-0.0171	-0.0243	-0.0183	-0.0334
INA	0.1556***	0.1778***	0.1710***	0.2118***
Health shocks				
FT	-0.0923***	-0.1189***	-0.0101***	-0.1364***
PT	-0.0624***	-0.0658***	-0.0699	-0.0814***
SE	-0.0264	-0.0315	-0.0532*	-0.0479**
INA	0.1811***	0.2163***	0.2237***	0.2657***
Occupation at t-1				
Part-time(t-1)				
FT	-0.3989***	-0.3114***	-0.4307***	-0.3367***
PT	0.2457***	0.1300***	0.3140***	0.1410***
SE	0.0563*	0.0630**	0.0643*	0.0626*
INA	0.0969*	0.1184**	0.0525	0.1332**
Self-employed(t-1)				
FT	-0.4711***	-0.3505***	-0.5394***	-0.3679***
PT	-0.0077	0.0254	-0.0491	0.0241
SE	0.4245***	0.2285***	0.5765***	0.2575***
INA	0.0542	0.0966	0.0120	0.0863
Inactive (t-1)				
FT	-0.7108***	-0.5862***	-0.7397***	-0.6358***
PT	-0.0576***	-0.0294	-0.0594**	-0.0383
SE	-0.0593**	-0.0287	-0.1119***	-0.0472
INA	0.8277***	0.6443***	0.9109***	0.7213***

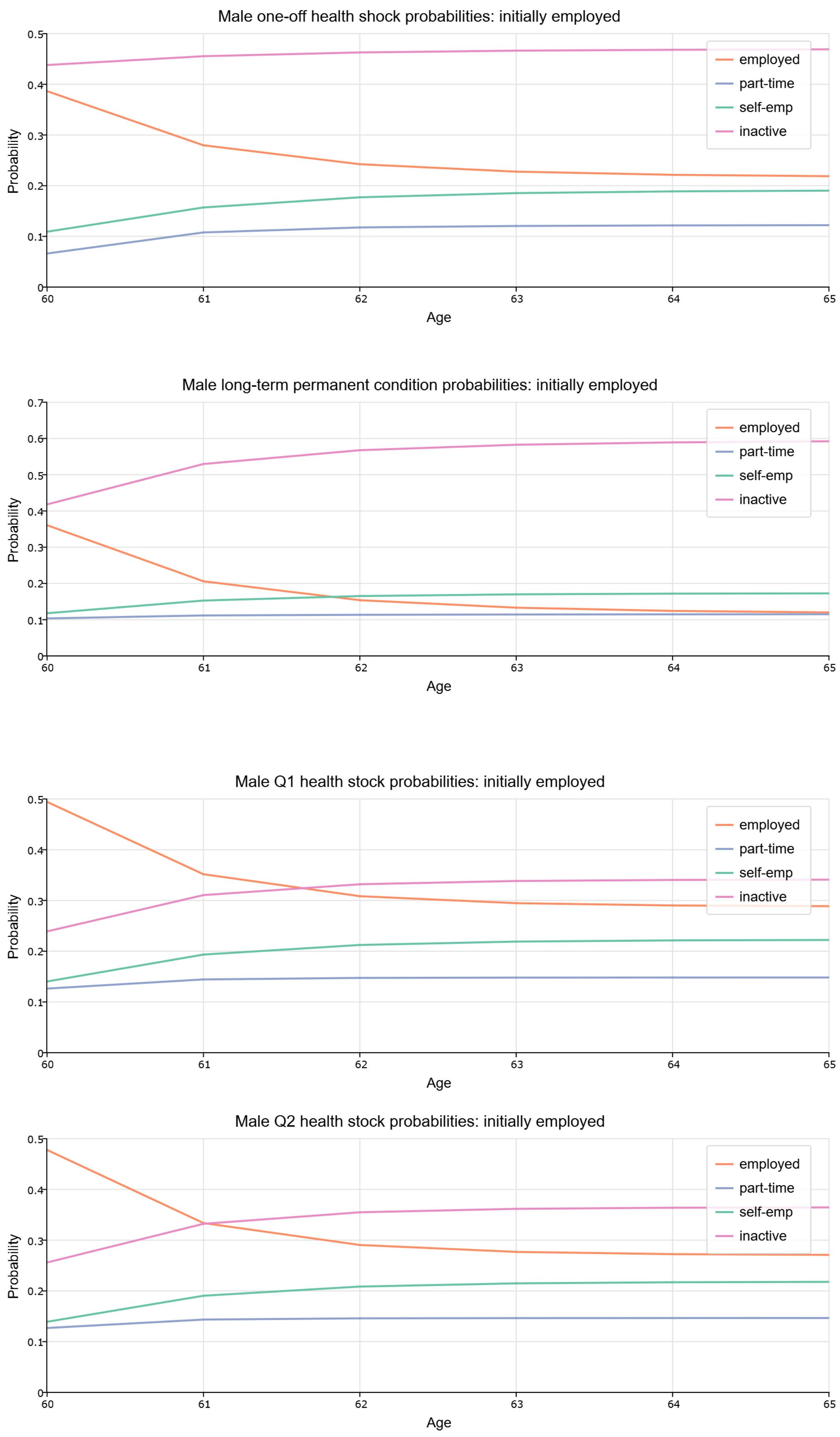
Notes: this table compares partial effects across models. MNL = pooled dynamic Multinomial Logit; RE MNL = dynamic random effects Multinomial Logit; DOGEV = pooled dynamic DOGEV; RE DOGEV = dynamic random effects DOGEV.
FT = employed full-time; PT = employed part-time; SE = Self-employment; INA = inactivity.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

Table 6: Partial effects: comparison across models - Women

	MNL	RE MNL	DOGEV	RE DOGEV
Health Variables				
Long-term health (t-1)				
FT	-0.0189**	-0.0181**	-0.0175*	-0.0172*
PT	-0.0113	-0.0206	-0.0124	-0.0247
SE	-0.0138*	-0.0051	-0.0142	-0.0057
INA	0.0440**	0.0438**	0.0440*	0.0475*
Health shocks				
FT	-0.0290***	-0.0281***	-0.0353***	-0.0305***
PT	-0.0395	-0.0426**	-0.0566*	-0.0479*
SE	-0.0185*	-0.0062	-0.0229	-0.0067
INA	0.0870***	0.0769***	0.1148***	0.0852**
Occupation at t-1				
Part-time(t-1)				
FT	-0.142***	-0.1066***	-0.1633***	-0.1157***
PT	0.2095***	0.1203***	0.1764***	0.0900***
SE	-0.0007	0.0008	-0.0093	-0.0025
INA	-0.0669**	-0.0145	-0.0038	0.0281
Self-employed(t-1)				
FT	-0.1755***	-0.1353***	-0.2012***	-0.1414***
PT	-0.0961***	-0.0625*	-0.2026***	-0.0957*
SE	0.1277***	0.0235**	0.1481***	0.0199**
INA	0.1439***	0.1742***	0.2556***	0.2172***
Inactive (t-1)				
FT	-0.2589***	-0.1842***	-0.2806***	-0.1957***
PT	-0.3189***	-0.185***	-0.4853***	-0.2397***
SE	-0.0442***	-0.0106**	-0.0415**	-0.0146*
INA	0.622***	0.3797***	0.8074***	0.4499***

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 – Model II, Men



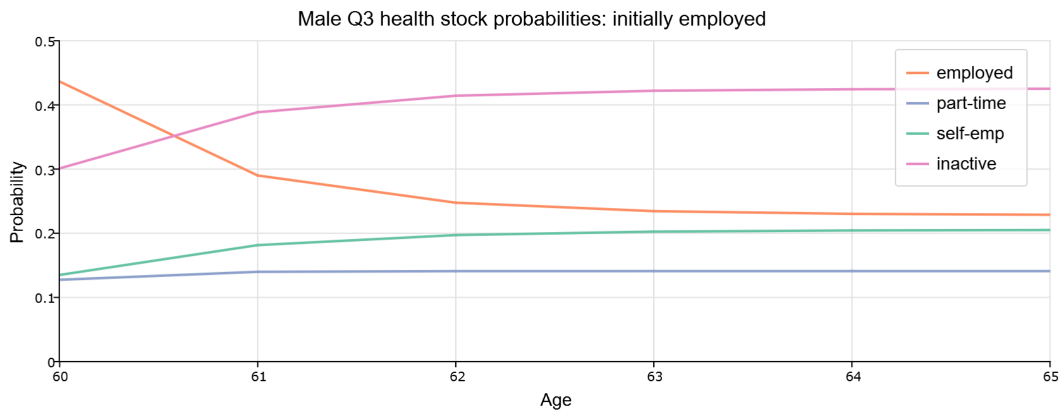
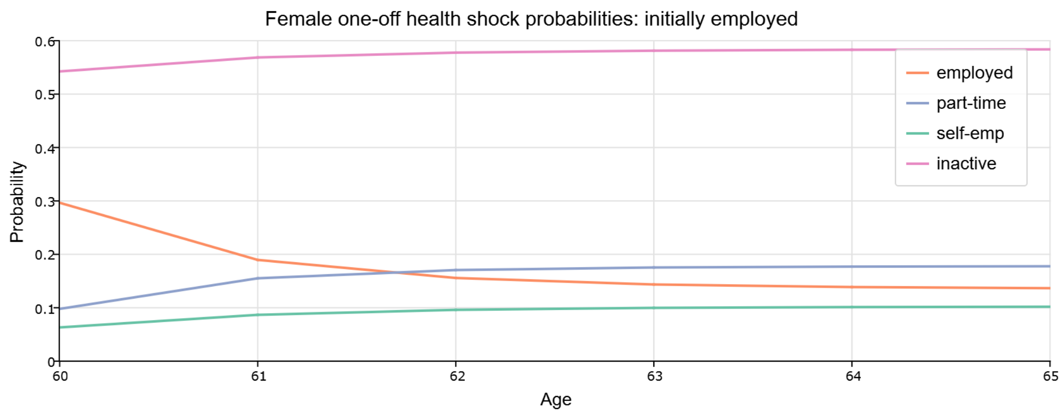
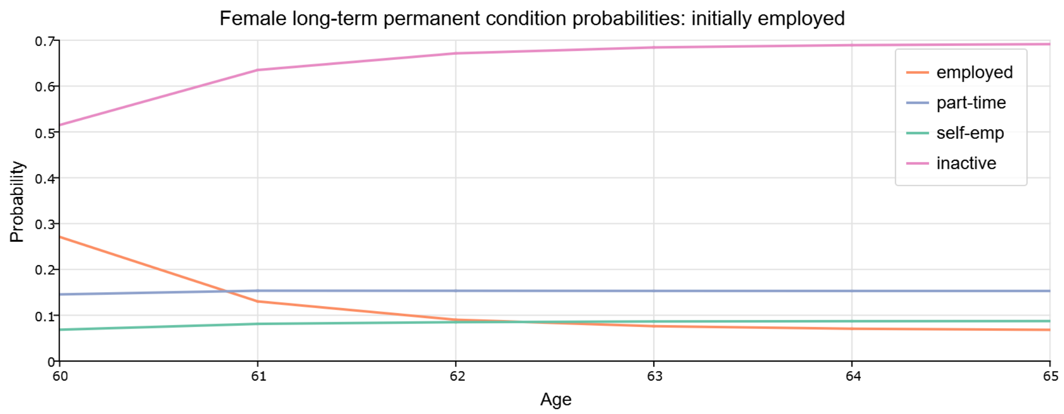
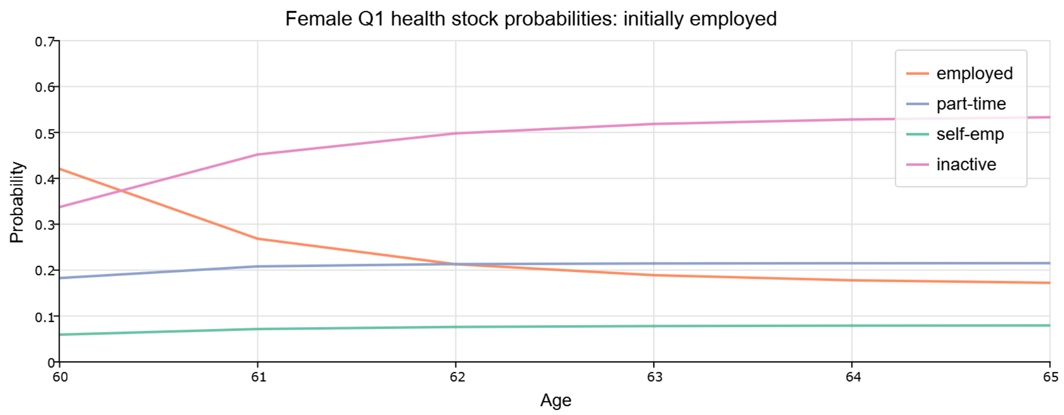
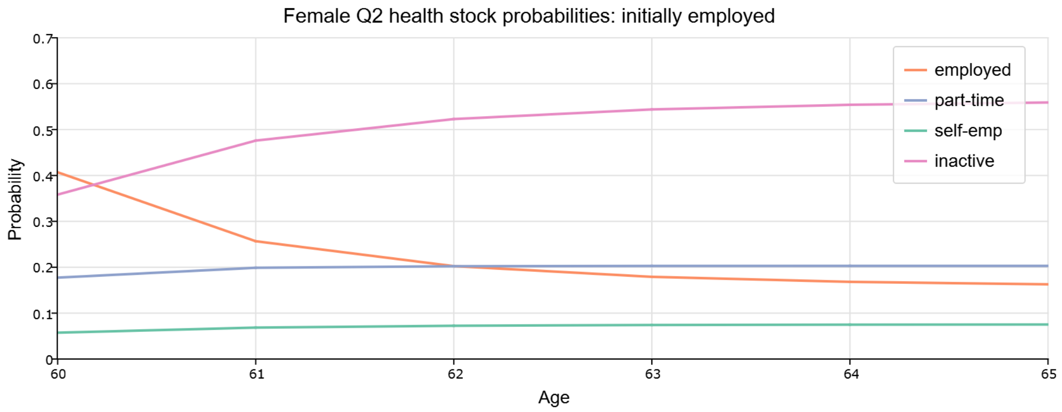


Figure 2: Simulated dynamic employment responses – Model II, Women

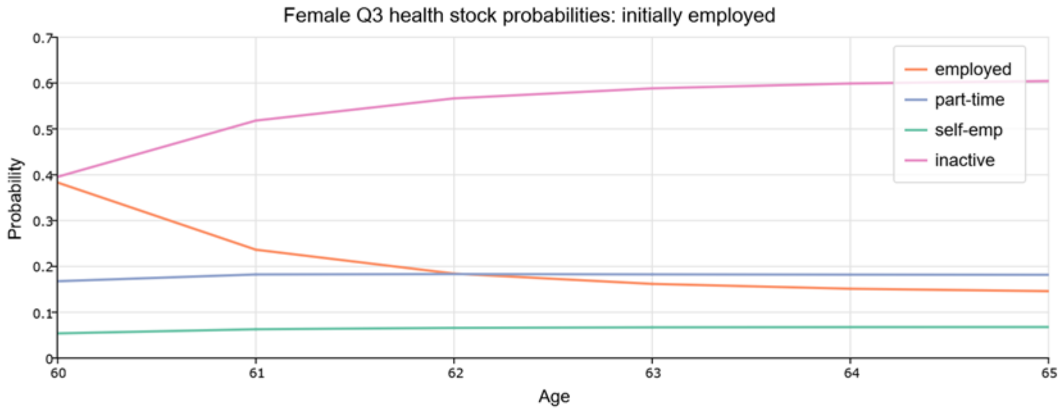








Female Q2 health stock probabilities: initially employed
Probability
Age
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
60
61
62
63
64
65
employed
part-time
self-emp
inactive



Female Q3 health stock probabilities: initially employed
Probability
Age
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
60
61
62
63
64
65
employed
part-time
self-emp
inactive

Online appendix

Table A1: 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 obtained 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 A2: 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 household 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 A3: 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)	-0.1575***	-0.0210	-0.0334	0.2118***	-0.0085	-0.0282	-0.0056	0.0424*
	(0.032)	(0.018)	(0.021)	(0.041)	(0.005)	(0.022)	(0.004)	(0.024)
Health shocks	-0.1364***	-0.0814***	-0.0479*	0.2657***	-0.0173***	-0.0604**	-0.0039	0.0816***
	(0.033)	(0.023)	(0.024)	(0.045)	(0.006)	(0.027)	(0.005)	(0.030)
Occupation at t-1								
Part-time(t-1)	-0.3367***	0.1410***	0.0626*	0.1332**	-0.0480***	0.0973***	-0.0023	-0.0470
	(0.053)	(0.028)	(0.033)	(0.067)	(0.015)	(0.033)	(0.005)	(0.038)
Self-employed(t-1)	-0.3679***	0.0241	0.2575***	0.0863	-0.0598***	-0.1165***	0.0252***	0.1510***
	(0.054)	(0.027)	(0.051)	(0.084)	(0.017)	(0.049)	(0.011)	(0.054)
Inactive (t-1)	-0.6358***	-0.0383	-0.0472	0.7213***	-0.0862***	-0.2858***	-0.0065	0.3785***
	(0.060)	(0.024)	(0.031)	(0.061)	(0.022)	(0.049)	(0.009)	(0.052)
Other variables								
Age between 50-54	0.3036***	0.0059	0.1123***	-0.4218***	0.0406***	0.1512***	0.0095	-0.2021***
	(0.051)	(0.030)	(0.383)	(0.074)	(0.011)	(0.038)	(0.007)	(0.043)
Age between 55-59	0.1746***	-0.0109	0.0839***	-0.2476***	0.0243***	0.1060***	0.0045	-0.1348***
	(0.030)	(0.017)	(0.023)	(0.041)	(0.007)	(0.023)	(0.005)	(0.025)
Education/certificate	0.0294	-0.0306	-0.0082	0.0093	0.0099*	0.0085	0.0035	-0.0219
	(0.032)	(0.020)	(0.023)	(0.048)	(0.006)	(0.028)	(0.004)	(0.031)
Education/degree	-0.0136	0.0310	-0.0171	-0.0004	0.0126*	0.0511	0.0098*	-0.0735*
	(0.044)	(0.026)	(0.031)	(0.067)	(0.007)	(0.034)	(0.005)	(0.038)
White collar 1	-0.0414	0.0460	0.0058	-0.0103	-0.0181***	-0.0649*	0.0032	0.0798**
	(0.045)	(0.031)	(0.034)	(0.076)	(0.007)	(0.034)	(0.004)	(0.038)
Blue collar	0.0218	0.0129	-0.0399	0.0052	-0.0123	-0.0444	-0.0051	0.0618
	(0.045)	(0.031)	(0.036)	(0.073)	(0.008)	(0.039)	(0.006)	(0.044)
Log household income(t-1)	0.1028***	0.0001	0.0181	-0.1209***	0.0210***	0.0743***	-0.0012	-0.0941***
	(0.028)	(0.013)	(0.014)	(0.031)	(0.005)	(0.017)	(0.003)	(0.018)
Rented house(t-1)	0.08957**	0.0149	0.0394	-0.1439**	0.0013	-0.0161	-0.0012	0.0159
	(0.041)	(0.025)	(0.030)	(0.062)	(0.006)	(0.029)	(0.004)	(0.032)
Marital status(t-1)	-0.0157	-0.0443*	0.3895	0.0210	-0.0364***	-0.1139***	0.0026	0.1477***
	(0.039)	(0.023)	(0.028)	(0.056)	(0.009)	(0.028)	(0.005)	(0.031)
Own children(t-1)	0.0013	0.0216	-0.0009	-0.0219	-0.0078	-0.0371	-0.0032	0.0482*
	(0.031)	(0.019)	(0.025)	(0.046)	(0.005)	(0.025)	(0.004)	(0.028)
Born overseas	-0.0324	-0.0204	-0.0010	0.0538	0.0055	0.0135	-0.0029	-0.0160
	(0.032)	(0.021)	(0.230)	(0.048)	(0.005)	(0.025)	(0.004)	(0.029)
Remote region	-0.0422	-0.0043	0.0160	0.0305	0.0070	0.0084	0.0028	-0.0182
	(0.029)	(0.018)	(0.021)	(0.043)	(0.005)	(0.022)	(0.003)	(0.025)
Average household income	0.1073***	0.3279	0.0667***	-0.2068***	0.0052	0.0223	0.0065*	-0.0340
	(0.038)	(0.020)	(0.025)	(0.049)	(0.005)	(0.025)	(0.004)	(0.028)
Part-time	-0.2147***	0.1474***	-0.0421	0.1094	-0.0318***	0.0750**	-0.0088	-0.0343
	(0.063)	(0.034)	(0.052)	(0.093)	(0.009)	(0.035)	(0.006)	(0.038)
Self-employed	-0.1771***	-0.0502	0.3981***	-0.1708**	-0.0407***	-0.0856*	0.0471***	0.0792
	(0.053)	(0.033)	(0.044)	(0.073)	(0.012)	(0.052)	(0.015)	(0.056)
Inactive	-0.4146***	-0.0611	-0.0408	0.5165***	-0.0929***	-0.3744***	-0.0056	0.4730***
	(0.067)	(0.039)	(0.048)	(0.098)	(0.018)	(0.055)	(0.011)	(0.057)

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$