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Health status and labour market outcome: Empirical evidence from Australia

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This paper uses eight waves of Australia Household, Income and Labour Dynamics data to study the issues of state dependence and the short-run and long-run response to health shocks on the labour market. We consider six alternative panel data binary dependent variable models with different ways of modelling labour market dynamics and individual heterogeneity. We find that the key results with regard to labour market dependence and the impacts of health shocks are sensitive to model specification and pooling of male and female samples with differences as large as sixfold. Specification analysis is conducted and favours the dynamic fixed effects logit model for separate male and female samples. Methods for evaluating dynamic response paths to a one-time health shock for binary outcomes are also suggested and results are presented.

1 | INTRODUCTION

The present paper estimates a dynamic fixed effects (FE) binary outcome variable model using a rich panel data set, and demonstrates how important policy effects can be overestimated using a dynamic random effect (RE) and other model specifications. The impacts of individuals' health on their labour market decisions have increasingly been of interest to governments around the world. Both population ageing and increasing prevalence of chronic conditions in the developed countries have major economic implications for the labour markets. Chronic conditions such as diabetes, cardiovascular diseases and mental health diseases continue to affect increasing proportions of the populations (Zhang, Zhao, & Harris, 2009). This trend, combined with the trend of population ageing and increasing availability of disability welfare in many countries, not only places an increasing burden on the health-care systems around the world, but also poses a significant challenge to the labour markets due to early exits. Conversely, any medical research or public health strategies aimed at reducing chronic diseases will also have a positive flow-on effect on the labour market. Therefore, understanding the link between individuals' health conditions and their labour market outcomes is crucial for government policy design and for a comprehensive calculation of the burden of diseases.

It is well established both in theory and in empirical studies that health plays an important role in an individual's labour participation decision. Becker (1964), Grossman (1972) and Currie and Madrian (1999) regard health as a type of human capital endowment akin to education that is linked to the labour market performance. Chirikos (1993) and Dwyer and Mitchell (1999) postulate that poor health makes work more difficult and less fulfilling, thus increasing the utility of leisure relative to the utility derived from work. On the other hand, Dwyer and Mitchell (1999) and Cai and Kalb (2006) argue that the income effect from lower earnings associated with poor health could dominate the substitution effect between work and leisure.

However, quantifying the impact of a health shock or the onset of chronic conditions on an individual's labour market decision is a challenging task. There are many empirical studies measuring the impact of health on labour participation decisions (Bazzoli, 1985; Bound, Schoenbaum, Stinebrickner, & Waidmann, 1999; Cai, 2010; Cai & Kalb, 2006; Disney, Emmerson, & Wakefield, 2006; Dwyer & Mitchell, 1999; Garcia-Gomez, Jones, & Rice, 2010; Siddiqui, 1997; Zhang et al., 2009; Zissimopoulos & Karoly, 2007). Most of these use cross-sectional data. Econometric methodologies using cross-sectional data rely on the generalized law of large numbers to hold; that is, individual outcomes are random draws from a population that has a constant mean conditional on some observable factors. Furthermore, the estimated impact of a change in an observable factor is considered instant and stays there forever. However, inertia in human behaviour and institutional and technological rigidities have led many to believe that :"all interesting economic behaviour is inherently dynamic, dynamic models are the only relevant models; what might superficially appear to be a static model only conceals underlying dynamics, since any state variable presumed to influence present behaviour is likely to depend in some way on past behaviour; and cross-sectional data may effectively be precluded from studying the dynamics, but in which dynamics affects what is observed" Nerlove (2002, p. 46).

There are already some studies using panel data to estimate dynamic labour participation models (e.g. Knights, Harris, & Loundes, 2002; Oguzoglu, 2007, 2010; Zucchelli, Harris, & Zhao, 2012), but they use RE dynamic discrete choice models to capture individual effects. Factors affecting individual outcomes are numerous. Observable explanatory variables often only capture part of the factors affecting individual outcomes. If the observed outcome is also a function of individual-specific effects that are persistent across time, then the observed dynamic response could be spurious in the sense that it also captures the time-persistent individual-specific effect. Although panel data allow the impacts of unobserved individual-specific effects to be controlled, the RE specification assumes that the individual-specific effects are random draws from a common distribution and are uncorrelated with the included observable explanatory variables for the same individuals. If the individual effects are, indeed, correlated with the included explanatory variables (e.g. Chamberlain, 1980), which is most likely the case in empirical studies, the estimates of the coefficients of observable factors based on a RE specification could be misleading.

Labour market status is a clear example where strong state persistence is observed and an FE model is more suitable to control for time-invariant individual effects. The labour participation decision could depend on an individual's unobserved innate ability. For instance, a career-oriented individual could still opt to work despite poor health, while a hedonic-oriented individual might prefer to enjoy the leisure despite good health. These unobserved individual-specific effects are more likely to be correlated with the observed confounding covariates, favouring an FE specification. Labour market outcomes are also inherently dynamic and possess true state dependence where current outcomes depend on past outcomes regardless of individual heterogeneity. Separation of the individual-specific effects and true state dependence (Heckman, 1981a,b; Hsiao, 2014) is critical in providing a correct assessment of the magnitude of health impacts on labour market outcomes. With policymakers seeking answers to "what if" type of questions, quantitative understanding of how individuals react to the onset of health conditions and their dynamic responses will help to understand the time horizon of the effects of a policy plan. Better control for time-persistent individual effects allows for better estimation of the effects of government programs helping people to find jobs. Finally, panel data also provide information for distinguishing the impacts of persistent health conditions and health shocks.

However, unlike the case of a dynamic FE model for a continuous dependent variable, for a nonlinear dynamic model with a binary dependent variable, controlling for unobserved individual FE that are also correlated with the observed individual characteristics is a lot more difficult. It imposes strict restrictions on the usable data. To overcome the shortage of degrees of freedom, a rich panel data set is required.

The present paper uses eight waves of data from the Household, Income and Labour Dynamics in Australia (HILDA; see https://www.melbourneinstitute.com/hilda/) to evaluate the impact of health on individuals' labour force participation decisions. We consider six different models with alternative static/dynamic and fixed/random individual effect specifications, and we compare key results for state dependence and the effect of health. Our main contributions to the literature consist of the following. First, we compare estimates from six alternative model specifications in dealing with dynamic state dependence and individual heterogeneity, and show how key results can be misestimated with restrictive model specifications. Second, we pay special attention to separating the impact of unobserved time-persistent individual characteristics and the impact of state dependence. Labour participation decisions could be strongly influenced by the unobserved individual characteristics. Ignoring the presence of time-persistent individual-specific effects could lead to spurious dependence or exaggerate the impact of state dependence (Hsiao, 2014). Third, we conduct specification analysis to select the model that appears to be most compatible with the data. Fourth, after taking account of state dependence and heterogeneity, we assess the impact of health status on labour market outcome by considering two different measures of health including health shock and activity limiting conditions. We also estimate our models separately for male and female subsamples, which allows us to assess the varying impact of each factor on labour market outcomes across gender. Fifth, while standard method for considering dynamic response is with a continuous variable, we suggest a method for calculating the short-run and long-run impact path of a one-off health shock for binary outcome variable (with or without estimating the individual-specific effects). Finally, our data spans the period of 8 years, which is exceedingly longer than other existing studies on the topic, although it complicates the FE estimation. However, it is essential to have a larger number of data points to yield reliable estimates for the dynamic FE model, as the conditions for the Honore and Kyriazidou (2000) conditional method are very stringent. These conditions include for each four periods under consideration that: (i) individuals in the two intermediate periods must switch positions; (ii) individuals must have identical covariates (x) values for the third and fourth period; (iii) there must be significant variation for covariates (x) values for the second and third period to obtain good estimates of β; and (iv) to obtain reliable estimates of the coefficient for the lagged state variable, individuals must also switch positions in the first and the last period. These conditions severely limit the useful sample observations.

This paper is organized as follows. Section 2 introduces the six econometric models. Section 3 provides a description of our data and some empirical observations from the data. Section 4 reports estimation results and discusses the relative marginal effects of covariates. Section 5 presents the dynamic labour market response paths from three health shock scenarios for the three dynamic models. Specification analysis is provided in Section 6, and conclusions and discussions are presented in Section 7.

2 | ECONOMETRIC MODELS

We consider two alternative labour market states: participating in the labour force ($y_{it} = 1$) and being out of the labour force ($y_{it} = 0$). Each individual is presumed to choose between these two mutually exclusive labour market states during each time period. We assume that y_{it} depends on a continuous latent response variable, y_{it}^*, passing the threshold where

$$y_{it} = \begin{cases} 1 & \text{if } y_{it}^* > 0, \text{and} \\ 0 & \text{if } y_{it}^* \leq 0. \end{cases} \tag{2.1}$$

We consider six different specifications for y_{it}^*:

Model 1:

$$y_{it}^* = \beta' x_{it} + \varepsilon_{it}. \tag{2.2}$$

Models 2 and 3:

$$y_{it}^* = \beta' x_{it} + \alpha_i + \varepsilon_{it}. \tag{2.3}$$

Model 4:

$$y_{it}^* = \gamma y_{it-1} + \beta' x_{it} + \varepsilon_{it}. \tag{2.4}$$

Models 5 and 6:

$$y_{it}^* = \gamma y_{it-1} + \beta' x_{it} + \alpha_i + \varepsilon_{it}, \tag{2.5}$$

where x_{it} denotes the observable factors that affect the outcomes; ε_{it} denotes the impact of unobservable factors that vary across i and over t with mean 0 and are independent of x_{it}. Models 2, 3, 5 and 6 assume that the outcomes are also functions of some unobservable time-invariant individual-specific factors α_i. Models 2 and 5 assume that such α_i are independent of observable factors x_{it} and are independently and identically distributed. Models 3 and 6 allow α_i to be correlated with x_{it}. To avoid misspecifying the correlation patterns between the unobservable α_i and observable x_{it}, we shall treat α_i as fixed constants (Hsiao, 2014). Models 1–3 are static models, assuming that any changes in x_{it} lead to instant changes in y_{it}. Models 4–6 are dynamic models where the current outcome is dependent on the outcome of the previous period; they capture the impact of state dependence as well as the impact of covariates of all previous periods, so that changes in covariates have lasting accumulative effects on future outcomes. Models 5 and 6 separate the impact of time-persistent individual specific effects α_i and true state dependence effects on y_{it-1}, while Model 4 makes no such distinction. In other words, the estimated coefficient for the lagged dependent variable y_{it-1} for Model 4 could reflect both state dependence in the labour market and time-persistent individual specific effects. Model 5 assumes that individual specific effects α_i are independent of observed covariates, while Model 6 allows the correlation between the two.

For Models 1 and 4, we use the maximum likelihood method to estimate a binary logit model treating x_{it} and/or lagged choice as uncorrelated with ε_{it}. For Models 2 and 5, we use RE binary logit regression to obtain the coefficient estimates where in the latter model the initial value is treated as a fixed constant. For Model 3, we use Chamberlain (1982) conditional maximum likelihood estimates (MLE). Finally, for Model 6, we use Honore and Kyriazidou (2000) conditional MLE (designated as HK). Because the HK method is not widely implemented in empirical studies and the implementation of the HK conditional MLE involves 15 possible types of switching with 8 years of data, we spell out the detail in Appendix.

3 | DATA

This paper employs the eight waves (2002–2009) of the Household, Income and Labour Dynamics in Australia (HILDA) survey.[1] HILDA is an annual household-based panel survey that was started in 2001. People aged 15 and older are eligible for interviews. Both personal interviews and self-completed questionnaires are used to obtain personal information including health variables. After deleting missing observations, the resulting samples comprise 42,375 observations for males and 48,056 observations for females, although the estimating sample size varies by the model being estimated.

Definitions of all variables and summary statistics for males and females for the full sample are provided in Table 1. The dependent variable is a binary indicator variable for working or looking for work in the past 7 days. We include as covariates socio-demographic variables such as age, gender, marital status, whether an individual has children, education and household income. We also include the unemployment rate for a respondent's region of residence to reflect the macroeconomic conditions for a particular region and at a particular time period. Finally, we consider two different health variables: a binary variable *Health shock* based on an individual's answer to the question of whether there is personal injury or illness over the past 12 months, and an *Activity limiting condition* binary variable based on whether the individual has any long-term health condition, impairment or disability that restricts his or her everyday activities that has lasted or is likely to last for 6 months or more. In this study, both health variables are treated as exogenous. Because *Health shock* reports injury or illness that has occurred in the *past* year prior to the survey, one may also regard it as an indication for significant change in one's health condition in the previous year. We hope using these two variables can avoid the potential endogeneity issue using self-assessed health status variables that has bothered health economists.

Table 2 presents transition probabilities between successive periods between 2002 and 2009. The row totals show that at any given time t, approximately 75% of males and 62% of females participate in the labour force (LF). The rows show that among those males in the labour force in $t-1$, 95% remain in the LF in time t, while this probability is 91% for females. In contrast, for those not in the LF in $t-1$, 85% of them are still not in the LF at time t for both males and females. Therefore, strong "persistence" and "scarring" effects are detected without controlling for other explanatory variables. Once multivariate analysis is conducted, we will be able to further identify whether this strong persistence/scarring is due to true or spurious state dependence.

4 | RESULTS AND IMPACT ANALYSIS

4.1 | Estimated coefficients and relative marginal effects

Tables 3 and 4 report coefficient estimates for Models 1–4 and Models 5–6, respectively. Note that Models 1–3 are static, and Models 4–6 are dynamic. For each model, we estimate three different regressions for male, female and pooled samples. Although the magnitudes of the estimated coefficients are not directly interpretable for single index models, all model estimates have the expected

[1]The 2001 HILDA, which is the first wave of the data, is not included in the econometrics estimation because it does not contain a variable, *Activity limiting condition*, one of our main regressors. Only 2002–2009 data are used in the model estimation. However, the 2001 data is employed when studying the dynamic response path to health shocks in Section 5. In particular, we use the 2001 data as an initial period in separating individuals into four cohorts of males and females who were initially in and out of the labour force, in which we later apply Deaton's (1985) cohort approach.

TABLE 1 Summary statistics

Variables		Model 1 and 2			
		Male		Female	
		Mean	Standard deviation	Mean	Standard deviation
Labour force participation (y)	1 if a person is in the labour force during the past 7 days, otherwise 0	0.746	0.435	0.619	0.486
Age1554 (reference)	1 if age 15–54 years old, otherwise 0	0.709	0.454	0.709	0.454
Age5559	1 if age 55–59 years old, otherwise 0	0.075	0.263	0.073	0.260
Age6064	1 if age 60 to 64 years old, otherwise 0	0.064	0.245	0.060	0.238
Age65above	1 if age 65 years old or above, otherwise 0	0.152	0.359	0.157	0.364
Married	1 if married, otherwise 0	0.653	0.476	0.611	0.487
Less than year 12 (reference)	1 if less than 12 years of education, otherwise 0	0.298	0.458	0.391	0.488
Year 12	1 if complete 12 years of education, otherwise 0	0.138	0.345	0.157	0.364
Post school	1 if more than 12 years of education but less than bachelor degree, otherwise 0	0.366	0.482	0.234	0.423
Degree	1 if bachelor degree or above, otherwise 0	0.198	0.398	0.218	0.413
No child (reference)	1 for no dependent children, otherwise 0	0.697	0.460	0.654	0.476
Younger child	1 for having at least one child aged 0–4 years old, otherwise 0	0.119	0.324	0.133	0.339
Older child	1 for having at least one child aged 5 to 24 years old, otherwise 0	0.237	0.426	0.273	0.446
Unemployment rate	Unemployment rate in major statistical region	4.928	1.098	4.918	1.090
ln(income)	natural logarithm of household's financial year disposable income	10.899	0.725	10.815	0.766
Health shock	1 if there is personal injury or illness that has happened to life over the past 12 months, otherwise 0	0.091	0.287	0.082	0.274
Activity limiting condition	1 if there is any long-term health condition, impairment or disability that restricts everyday activities has lasted for 6 months or more, otherwise 0	0.263	0.440	0.258	0.438
		42 375		48 056	

TABLE 2 Transition probabilities of labour force participation for 2002–2009

	Male			Female		
yi,t−1	***yi,t*** **ILF (%)**	***yi,t*** **NILF (%)**	***yi,t*** **Total (%)**	***yi,t*** **ILF (%)**	***yi,t*** **NILF (%)**	***yi,t*** **Total (%)**
ILF	94.92	5.08	100	91.15	8.85	100
NILF	15.10	84.90	100	14.87	85.13	100
Total	74.71	25.29	100	61.99	38.01	100

signs for explanatory variables. Both health variables and older age dummies have negative effects, and the lagged dependent variable y_{it-1} has a positive effect.

It is interesting to note that the absolute magnitude of the coefficients of health shock variable (HS) relative to the activity limiting condition variable (ALC) are reversed between the RE and the FE specification. The estimated coefficients for HS and ALC for the RE specification for the static model (Model 2) for males are approximately −0.7 and −1.4, respectively, and for females are

TABLE 3 Coefficient estimates for Models 1–4

	Model 1: no lagged, pooled			Model 2: no lagged, RE			Model 3: no lagged, FE			Model 4: w/lagged, pooled		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**	**Male**	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
Lagged Labour Force										3.64	3.291	3.491
Participation (y_{it-1})										[0.044]***	[0.033]***	[0.026]***
Male			0.845			1.59			NA			0.595
			[0.020]***			[0.064]***						[0.027]***
Age5559	−0.845	−0.777	−0.755	−1.79	−1.61	−1.668	−1.325	−1.238	−1.261	−0.827	−0.706	−0.714
	[0.055]***	[0.043]***	[0.034]***	[0.127]***	[0.097]***	[0.078]***	[0.187]***	[0.142]***	[0.113]***	[0.076]***	[0.058]***	[0.046]***
Age6064	−1.884	−1.694	−1.74	−4.097	−3.584	−3.821	−3.224	−2.797	−2.965	−1.632	−1.334	−1.421
	[0.054]***	[0.047]***	[0.035]***	[0.146]***	[0.121]***	[0.093]***	[0.256]***	[0.199]***	[0.156]***	[0.073]***	[0.062]***	[0.047]***
Age65above	−3.753	−3.512	−3.594	−7.552	−6.784	−7.196	−5.716	−4.853	−5.286	−2.632	−2.436	−2.474
	[0.052]***	[0.052]***	[0.035]***	[0.165]***	[0.151]***	[0.110]***	[0.319]***	[0.289]***	[0.210]***	[0.067]***	[0.063]***	[0.044]***
Married	0.861	−0.156	0.243	1.458	−0.046	0.574	0.458	−0.147	0.071	0.407	−0.293	−0.042
	[0.041]***	[0.028]***	[0.022]***	[0.100]***	[0.067]	[0.055]***	[0.151]***	[0.093]	[0.078]	[0.056]***	[0.037]***	[0.031]
Year 12	0.757	0.69	0.663	2.261	1.708	1.94	2.385	1.66	1.974	0.418	0.402	0.374
	[0.050]***	[0.036]***	[0.029]***	[0.110]***	[0.088]***	[0.069]***	[0.140]***	[0.117]***	[0.089]***	[0.068]***	[0.047]***	[0.039]***
Post school	0.797	0.915	0.875	2.142	2.032	2.159	1.948	1.854	1.916	0.378	0.523	0.473
	[0.037]***	[0.031]***	[0.023]***	[0.109]***	[0.089]***	[0.069]***	[0.220]***	[0.144]***	[0.120]***	[0.051]***	[0.042]***	[0.032]***
Degree	1.093	1.348	1.256	3.095	2.914	3.054	4.21	2.844	3.395	0.582	0.798	0.717
	[0.050]***	[0.036]***	[0.029]***	[0.152]***	[0.106]***	[0.088]***	[0.303]***	[0.223]***	[0.178]***	[0.066]***	[0.046]***	[0.038]***
Younger child	0.017	−1.568	−1.135	−0.218	−2.681	−2.043	−0.537	−2.182	−1.886	−0.176	−1.112	−0.854
	[0.070]	[0.033]***	[0.028]***	[0.136]	[0.075]***	[0.062]***	[0.174]***	[0.086]***	[0.074]***	[0.089]**	[0.044]***	[0.038]***
Older child	0.249	−0.176	−0.016	0.466	−0.158	0.105	−0.137	−0.117	−0.082	0.171	−0.024	0.067
	[0.051]***	[0.029]***	[0.024]	[0.117]***	[0.066]**	[0.057]*	[0.165]	[0.084]	[0.075]	[0.067]**	[0.038]	[0.033]**
ln(income)	0.571	0.684	0.631	0.684	0.759	0.715	0.336	0.406	0.38	0.366	0.393	0.369
	[0.022]***	[0.019]***	[0.014]***	[0.043]***	[0.036]***	[0.028]***	[0.051]***	[0.040]***	[0.031]***	[0.029]***	[0.024]***	[0.019]***

TABLE 3 (Continued)

	Model 1: no lagged, pooled			Model 2: no lagged, RE			Model 3: no lagged, FE			Model 4: w/lagged, pooled		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**	**Male**	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
Unemployment rate	−0.008	0.006	−0.004	−0.017	−0.057	−0.042	0.05	−0.047	−0.014	0.004	−0.002	−0.004
	[0.014]	[0.011]	[0.009]	[0.026]	[0.020]***	[0.016]***	[0.030]*	[0.022]**	[0.018]	[0.020]	[0.015]	[0.012]
Health shock	−0.315	−0.268	−0.285	−0.722	−0.449	−0.563	−0.68	−0.369	−0.498	−0.57	−0.384	−0.458
	[0.049]***	[0.045]***	[0.033]***	[0.084]***	[0.074]***	[0.056]***	[0.091]***	[0.079]***	[0.060]***	[0.068]***	[0.060]***	[0.045]***
Activity limiting	−1.262	−0.821	−0.968	−1.367	−0.749	−0.983	−0.669	−0.307	−0.45	−0.977	−0.575	−0.713
condition	[0.033]***	[0.029]***	[0.021]***	[0.071]***	[0.058]***	[0.045]***	[0.084]***	[0.067]***	[0.052]***	[0.046]***	[0.038]***	[0.029]***
Number of observations	42 375	48 056	90 431	42 375	48 056	90 431	9 516	16 429	25 945	39 419	45 175	84 594
Likelihood ratio test H_0: Pooling	LR $\chi^2(13) = 1982.86$***			LR χ^2 (14) = 830.05***			LR χ^2 (13) = 159.44***			LR χ^2 (14) = 538.35***		

Notes. Standard errors are in parentheses.

***Significant at 1%. **Significant at 5%. *Significant at 10%.

TABLE 4 Coefficient estimates for Models 5–6

	Model 5: w/ lagged, RE			Model 6: w/ lagged, FE, c = 8			Model 6: w/ lagged, FE, c = 16		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
Lagged Labour Force	3.311	2.833	3.107	1.631	1.704	1.678	1.662	1.731	1.713
Participation (y_{it-1})	[0.060]***	[0.048]***	[0.037]***	[0.142]***	[0.100]***	[0.080]***	[0.171]***	[0.117]***	[0.092]***
Male			0.793			NA			NA
			[0.037]***						
Age5559	−0.958	−0.891	−0.862	−0.94	−0.723	−0.794	−0.947	−0.711	−0.802
	[0.090]***	[0.073]***	[0.056]***	[0.491]*	[0.380]*	[0.300]***	[0.569]*	[0.429]*	[0.327]***
Age6064	−1.989	−1.871	−1.855	−2.181	−1.394	−1.696	−2.244	−1.382	−1.73
	[0.096]***	[0.088]***	[0.064]***	[0.724]***	[0.562]**	[0.446]***	[0.835]***	[0.623]**	[0.477]***
Age65above	−3.426	−3.472	−3.369	−3.219	−2.152	−2.63	−3.327	−2.237	−2.723
	[0.118]***	[0.109]***	[0.078]***	[0.870]***	[0.794]***	[0.578]***	[1.007]***	[0.875]**	[0.617]***
Married	0.603	−0.238	0.093	0.142	−0.219	−0.094	0.24	−0.236	−0.07
	[0.070]***	[0.049]***	[0.039]**	[0.386]	[0.254]	[0.212]	[0.440]	[0.277]	[0.223]
Year 12	0.681	0.659	0.617	1.847	0.711	1.18	1.671	0.696	1.083
	[0.084]***	[0.065]***	[0.051]***	[0.442]***	[0.317]**	[0.252]***	[0.511]***	[0.360]**	[0.277]***
Post school	0.612	0.836	0.743	0.801	1.304	1.2	0.716	1.23	1.109
	[0.069]***	[0.060]***	[0.045]***	[0.571]**	[0.394]***	[0.323]***	[0.665]	[0.428]***	[0.342]***
Degree	0.933	1.243	1.1	2.321	1.697	1.919	2.196	1.589	1.826
	[0.091]***	[0.070]***	[0.054]***	[0.741]***	[0.624]***	[0.475]***	[0.841]***	[0.666]**	[0.497]***
Younger child	−0.188	−1.515	−1.098	−0.209	−1.467	−1.247	−0.221	−1.465	−1.23
	[0.102]*	[0.061]***	[0.048]***	[0.416]	[0.203]***	[0.177]***	[0.482]	[0.236]***	[0.198]***
Older child	0.275	−0.044	0.105	−0.014	−0.173	−0.125	−0.013	−0.171	−0.112
	[0.081]***	[0.049]	[0.040]***	[0.433]	[0.221]	[0.197]	[0.497]	[0.245]	[0.211]
ln(income)	0.413	0.469	0.43	0.203	0.245	0.231	0.2	0.264	0.239
	[0.034]***	[0.030]***	[0.022]***	[0.146]	[0.115]**	[0.090]**	[0.166]	[0.130]**	[0.098]**
Unemployment rate	−0.004	−0.022	−0.018	0.102	−0.017	0.022	0.081	0.003	0.031
	[0.022]	[0.018]	[0.014]	[0.084]	[0.057]	[0.047]	[0.096]	[0.064]	[0.051]

TABLE 4 (Continued)

	Model 5: w/ lagged, RE			Model 6: w/ lagged, FE, c = 8			Model 6: w/ lagged, FE, c = 16		
	Male	**Female**	**Pooled**	**Male**	**Female**	**Pooled**	**Male**	**Female**	**Pooled**
Health shock	−0.639	−0.447	−0.524	−0.607	−0.453	−0.496	−0.652	−0.445	−0.52
	[0.075]***	[0.068]***	[0.050]***	[0.219]***	[0.189]**	[0.142]***	[0.263]**	[0.217]**	[0.159]***
Activity limiting	−1.079	−0.648	−0.8	−0.384	−0.094	−0.208	−0.391	−0.11	−0.224
condition	[0.055]***	[0.047]***	[0.035]***	[0.202]*	[0.159]	[0.124]*	[0.242]	[0.182]	[0.139]
Number of observations	39 419	45 175	84 594	3413	6248	9661	3413	6248	9661
Likelihood ratio testH_0: Pooling	LR $\chi^2(15) = 583.44$***			LR $\chi^2(14) = 71.73$***			LR $\chi^2(14) = 168.64$***		

Notes. Standard errors are in parentheses.

***Significant at 1%. **Significant at 5%. *Significant at 10%.

approximately −0.4 and −0.8, respectively, while for the dynamic model (Model 5) they are approximately −0.6 and −1 for males and are approximately −0.4 and −0.6, respectively for females. In contrast, the FE estimates for the HS and ALC coefficients of the static model (Model 3) are approximately −0.7 and −0.7, respectively, for males and −0.4 and −0.3, respectively, for females and for the dynamic model (Model 6) are approximately −0.6 and −0.4, respectively, for male and −0.45 and −0.1, respectively, for females. This could be because the health shock variable is usually a one-time event and is likely to be independent of the time-invariant individual specific effects (α_i). In contrast, the *Activity limiting condition* variable is a binary variable based on whether he or she has any long-term health condition, impairment or disability that restricts his or her everyday activities. The ALC variable for an individual is likely to stay constant over time. Thus, when the individual effects are treated randomly and independently of the included covariates, they probably have no impact on the estimated coefficient of the HS variable but the estimated ALC coefficient is likely to pick up both the impact of the ALC and part of the individual specific effects. However, when the impact of the time-invariant individual specific effects are controlled, the impact of the joint dependence between the individual specific effects and the ALC variable is removed.

It is difficult to make a comparison of our findings with that of earlier studies because of differences in model specification and control variables. For instance, Oguzoglu (2007, 2010) uses work limitation rather than activity limitation, and most do not include health shocks and activity limiting conditions together in the same model. Therefore, we shall limit our comparison to the six specifications we used in this paper to highlight the implications of different model specifications.

The marginal impacts of a variable for the logit model is not a constant. It depends on both α_i and x_{it}. In contrast, the relative marginal effect (RME) is independent of α_i and x_{it} because their impacts are cancelled in ratio form. So instead of providing the marginal impacts of each covariate, we report the RME of all variables to the marginal effect of *Age5559* for all six models in Table 5. We pick *Age5559* as the reference of comparison because it is an important variable in labour market decisions and has the same root cause as health variables, as suggested by a referee.[2]

4.2 | Impact of State Dependence

Focusing first on the RME of lagged labour force participation relative to *Age5559*, we find that, for the male sample, Models 4 and 5 have RME equal to around −3.4 to −4.4, while that of Model 6 is only around −1.7.[3] For the female sample, Models 4 and 5 give RME of around −3.2 to −4.6, while Model 6 delivers a value of around −2.4. These results suggest that when an individual effect is not controlled (Model 4) or is controlled via a random effect (Model 5), the estimated RME of labour market status dependence is many times greater than that from the model that controls the time-persistent individual FE (Model 6), relative to *Age5559*. The results also reveal that the labour force participation decision appears to be more persistent for females than males under Model 6 but there is not much difference between the genders under Models 4 and 5.

The results in Table 5 also allows us to use ratios to compare the relative impact of any two regressors as well as provides a unique ranking of the effects of individual regressors. Focusing on the ranking of the RME of lagged LFP, for Model 6 we discover that lagged LFP has the fifth and the second strongest relative impact on current participation probability for males and females, respectively, after *Age65above* for males and females, and additionally *Age6064*, *Degree* and

[2]We have also computed the RME to the marginal effect of *Degree*. It is available upon request.

[3]The RME of the persistence measure is negative because the coefficient of *Age5559* is negative while the coefficient of the lag dependent variable is positive.

TABLE 5 Relative marginal effect between each explanatory variable and "*Age5559*" on the probability of being in the labour force

	Model 1: No lagged, pooled		Model 2: No lagged, RE		Model 3: No lagged, FE		Model 4: w/ lagged, pooled	
	Male	Female	Male	Female	Male	Female	Male	Female
Lagged LFP							−4.40	−4.66
Age5559	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Age6064	2.23	2.18	2.29	2.23	2.43	2.26	1.97	1.89
Age65above	4.44	4.52	4.22	4.21	4.31	3.92	3.18	3.45
Married	−1.02	0.20	−0.81	0.03	−0.35	0.12	−0.49	0.42
Year 12	−0.90	−0.89	−1.26	−1.06	−1.80	−1.34	−0.51	−0.57
Post school	−0.94	−1.18	−1.20	−1.26	−1.47	−1.50	−0.46	−0.74
Degree	−1.29	−1.73	−1.73	−1.81	−3.18	−2.30	−0.70	−1.13
Younger child	−0.02	2.02	0.12	1.67	0.41	1.76	0.21	1.58
Older child	−0.29	0.23	−0.26	0.10	0.10	0.09	−0.21	0.03
ln(income)	−0.68	−0.88	−0.38	−0.47	−0.25	−0.33	−0.44	−0.56
Unemployment rate	0.01	−0.01	0.01	0.04	−0.04	0.04	0.00	0.00
Health shock	0.37	0.34	0.40	0.28	0.51	0.30	0.69	0.54
Activity limiting condition	1.49	1.06	0.76	0.47	0.50	0.25	1.18	0.81

	Model 5: w/ lagged, RE		Model 6: w/ lagged, FE, c = 8		Model 6: w/ lagged, FE, c = 16	
	Male	Female	Male	Female	Male	Female
Lagged LFP	−3.46	−3.18	−1.74	−2.36	−1.76	−2.43
Age5559	1.00	1.00	1.00	1.00	1.00	1.00
Age6064	2.08	2.10	2.32	1.93	2.37	1.94
Age65above	3.58	3.90	3.42	2.98	3.51	3.15
Married	−0.63	0.27	−0.15	0.30	−0.25	0.33
Year 12	−0.71	−0.74	−1.96	−0.98	−1.76	−0.98
Post school	−0.64	−0.94	−0.85	−1.80	−0.76	−1.73
Degree	−0.97	−1.40	−2.47	−2.35	−2.32	−2.23
Younger child	0.20	1.70	0.22	2.03	0.23	2.06
Older child	−0.29	0.05	0.01	0.24	0.01	0.24
ln(income)	−0.43	−0.53	−0.22	−0.34	−0.21	−0.37
Unemployment rate	0.00	0.02	−0.11	0.02	−0.09	0.00
Health shock	0.67	0.50	0.65	0.63	0.69	0.63
Activity limiting condition	1.13	0.73	0.41	0.13	0.41	0.15

Year12 for males. However, with Models 4 and 5, lagged LFP has the highest or second highest relative effect among all regressors. In other words, state dependence is overestimated if an individual effect is not best controlled with an FE model.

4.3 | Impacts of health

Experiencing a *Health shock*, or experiencing a personal injury or major illness in the past 12 months, is found to have a significantly negative effect on current labour force participation for both males and females for all models. There is not much difference between RE and FE estimates. However, their relative impacts are smaller for static models than for dynamic models.

Turning towards the other health variable, *Activity limiting condition* (ALC), a condition that adversely restricts everyday activities has a higher RME (as relative to *Age5559*) for males than for females for all six models. For Model 6, the effect of having an *Activity limiting condition* is approximately 0.4 for men and 0.1 for women. In comparison, this health effect is overestimated in all other models. In particular, Models 4 and 5 estimate the RME of ALC as up to three to six times as large as those from Model 6 for men and women. That is, the effect of ALC will be overexaggerated if static models or dynamic models with no individual effects or random effects are used.

Comparing the ranking of health impact to that of other explanatory variables in Table 5, for Model 6, for males the effects of both health variables are found to be lower than the effects of older age (*Age5559* and *Age6064*), lagged LFP and educational attainment. For females, in addition to older age dummies, education, and already being in the labour force, the health effects are also lower than the effect of having young children.

4.4 | Impacts of other factors

Looking at the age effects first, Model 6 shows that *Age65above* has the highest effect on LFP probability among all regressors, with 340–350 and 300–310% higher effects than *Age5559* for males and females, respectively. This is expected because the retirement age has increased gradually from 61 since 2001 to 65 in 2016. *Age65above* also has the highest or second highest effect (after lagged LFP for Model 4) for all other models, and the magnitudes of the RME tend to be slightly higher than that of Model 6, except for the male sample under Model 4. When comparing the impact of each age category (*Age5559*, *Age6064* and *Age65above*) on LFP probability based on the relative marginal effect, the effect appears to be monotonically increasing with age. This holds true for all models, both static and dynamic ones.

Turning next to educational attainment, the impact of education is also found to be monotonically increasing as women become more educated. For example, Model 6 in Table 5 shows that the relative marginal effects of *Year12*, *Post school* and *Degree* are approximately −2.3, −1.8 and −1, respectively. For males, the effect of *Year12* is more pronounced than *Post school* while both variables still yield lower marginal effect than *Degree*. Finally, being married has a positive effect for men (i.e. negative RME relative to *Age5559*) and a negative effect for women (i.e. positive RME relative to *Age5559*) on LFP for all models; however, the magnitudes of the RME for males are much smaller for Model 6 than for other models.

5 | DYNAMIC RESPONSE PATHS TO HEALTH SHOCKS

We next consider the LFP response paths from a one-time health shock. Static models (Models 1–3) assume that previous LF experience has no bearing on the current LF decisions, so the impact of a health shock on the LFP decisions is immediate and permanent. In contrast, a dynamic model allows the impact of a one-time health shock to gradually diminish and eventually evaporate (if the dynamic process is stationary).

We consider the short-run and long-run response paths of LFP probabilities from a health shock for two groups of people: those who were in LF at $t = 0$ and those who were not in LF at $t = 0$.[4] The standard method considering dynamic response is with a continuous dependent variable. Here

[4]The initial period for this section (i.e. $t = 0$) is the 2001 HILDA, which is the first wave of HILDA available. We use the 2001 HILDA to separate individuals into four cohorts of males and females who were initially in and out the LF.

our LFP is a binary outcome. We therefore suggest considering the dynamic response using the following method.

Let $P_{it+1} = P(y_{it+1} = 1| x_{it+1}, \alpha_i, y_{it} = 1)$ and $\tilde{P}_{it+1} = P(y_{it+1} = 1|x_{it+1}, \alpha_i, y_{it} = 0)$. Then, conditional on $y_{it} = 1$,

$$P^*_{it+2} = P(y_{it+2} = 1|x_{it+1}, x_{it+2}, \alpha_i, y_{it} = 1) = P_{it+1} \cdot P_{it+2} + (1 - P_{it+1}) \cdot \tilde{P}_{it+2}, \quad (5.1)$$

$$P^*_{it+3} = P(y_{it+3} = 1|x_{it+1}, \ldots, x_{it+3}, \alpha_i, y_{it} = 1) = P^*_{it+2} \cdot P_{it+3} + \left(1 - P^*_{it+2}\right) \cdot \tilde{P}_{it+3}, \quad (5.2)$$

and

$$P^*_{it+j} = P\left(y_{it+j} = 1|x_{it+1}, \ldots, x_{it+j}, \alpha_i, y_{it} = 1\right) = P^*_{it+j-1} \cdot P_{it+j} + \left(1 - P^*_{it+j-1}\right) \cdot \tilde{P}_{it+j}, j > 0. \quad (5.3)$$

Conditional on $y_{it} = 0$,

$$\tilde{P}_{it+2}{}^* = P(y_{it+2} = 1|x_{it+1}, x_{it+2}, \alpha_i, y_{it} = 0) = \tilde{P}_{it+1} \cdot P_{it+2} + \left(1 - \tilde{P}_{it+1}\right) \cdot \tilde{P}_{it+2} \quad (5.4)$$

and

$$\tilde{P}_{it+j}{}^* = P\left(y_{it+j} = 1|x_{it+1}, \ldots, x_{it+j}, \alpha_i, y_{it} = 0\right) = \tilde{P}_{it+j-1}{}^* \cdot P_{it+j} + \left(1 - \tilde{P}^*_{it+j-1}\right) \cdot \tilde{P}_{it+j}, j > 0. \quad (5.5)$$

We can use the above formula to compute the short-run and long-run response to a health shock on the LFP probability for the population using the formula

$$P_t = \int P(y_{it} = 1|x_{it}) f(x_{it})\, dx_{it}. \quad (5.6)$$

The population (or average) probability Equation (5.6) may be approximated by $\frac{1}{N}\sum_{i=1}^{N} P(y_{it} = 1|x_{it})$ if samples are random draws from the population. As we do not estimate α_i for all individuals in Model 6, we cannot estimate $P(y_{it} = 1|x_{it}, y_{it-1}) = \frac{e^{\alpha_i + \beta x_{it} + \gamma y_{it-1}}}{1 + e^{\alpha_i + \beta x_{it} + \gamma y_{it-1}}}$ for each individual. To compare the difference in response path due to different model specifications, we propose to evaluate Equations (5.3) or (5.5) for a hypothetical individual male or female, aged 55–59, married, with post-school education, with younger children, having the mean of ln(income) and the mean of unemployment rate at a particular period, and with or without initial period's employment.

The FE model requires knowledge of α_i. Although in principle we can plug in any hypothetical value of α_i and evaluate the dynamic response path conditional on α_i, we hope to obtain an α_i that is close to the representative individual under consideration. To obtain a reasonable α_i for comparison, we follow Deaton's (1985) cohort approach assuming individuals belonging to a cohort to have identical α_i, with $\alpha_i = \overline{\alpha}$ for all $i \in C = \{$il i ϵ cohort of our specification$\}$. We obtain an estimate of $\overline{\alpha}$ by noting that

$$\log\frac{P}{1-P} = \overline{\alpha} + \beta x + \gamma y_{t-1}. \quad (5.7)$$

The probability for individuals belonging to the cohort can be estimated by $\widehat{P_1} = \frac{\sum_{i \in C} y_{i1}}{n^*}$, where n^* denotes the number of individuals belonging to this cohort. We divide the male and female cohorts into two: those who are in LF at $t = 0$ and those who are not in LF at $t = 0$. Then for the $(y_{i1} = 1, y_{i0} = 1)$ cohort, $\overline{\alpha}$ is estimated by

$$\hat{\overline{\alpha}} = \log\frac{\hat{P}}{1-\hat{P}} - \gamma - \beta x. \quad (5.8)$$

For the $(y_{i1} = 1, y_{i0} = 0)$ cohort,

$$\hat{\bar{\alpha}}^{*} = \log\frac{\hat{P}}{1-\hat{P}} - \beta x. \tag{5.9}$$

Substituting $\hat{\bar{\alpha}}$ or $\hat{\bar{\alpha}}^{*}$ in lieu of α_i into Equations (5.1)–(5.5), we can compare the LFP probability paths from Model 6 to those from the other two dynamic models (Models 4 and 5). For each of the cohorts of $y_{i0} = 0$ and $y_{i0} = 1$, we compute LFP probability paths for three health shock scenarios: (i) no health shocks and no activity limiting conditions (HS(1) = 0, ALC(t) = 0 for all t); (ii) a one-off health shock with non-absorbing state (HS(1) = 1, ALC(t) = 0 for all t) representing a one-time shock not leading to a long-term condition; and (iii) a one-off health shock with absorbing state (HS (1) = 1, ALC(t) = 1 for all t) representing a one-time shock leading to lasting ALC.

Tables 6–8 trace the probability of being in the labour force for males and females under two different initial employment conditions and three different health shock scenarios for dynamic Models 4 to 6. Figures 1–4 plot these probability paths for each model and each gender separately.

First, for each health shock scenario, the initial condition of whether the person is in LF at the beginning plays no significant role in the long-run equilibrium from Models 4 and 5, but it makes a crucial difference to the long-run equilibrium probability according to Model 6, due to the very different FE individual unobservable factors for the two cohorts in Model 6. For example, when there is a health shock and an absorbing ALC for all time periods after (Table 8), the LFP probabilities approach 0.54 for Model 4 and 0.68 for Model 5 for those males initially not in the labour force and approach 0.61 for Model 4 and 0.71 for Model 5 for those men being initially in the labour force. However, if using Model 6, this equilibrium probability is 0.13 for those males not in LF at the beginning and 0.57 for those males in LF at the start. The disparity arises because of the different cohort FE. The estimated α for males initially in the labour force is −2.77 while for those not in the labour force is −4.46.

TABLE 6 Probability of being in the labour force in period 1 to 8 when $Health\ shock_1 = 0$, $Activity\ limiting\ condition = 0$ in every period

***LFP*$_0$ = 1:**	**Model 4**		**Model 5**		**Model 6, c = 8**		**Model 6, c = 16**	
Period	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
1	0.947	0.732	0.957	0.665	0.806	0.780	0.806	0.780
2	0.915	0.563	0.937	0.481	0.732	0.698	0.732	0.695
3	0.895	0.457	0.928	0.383	0.695	0.670	0.697	0.664
4	0.885	0.393	0.924	0.332	0.684	0.663	0.686	0.655
5	0.880	0.356	0.925	0.310	0.671	0.666	0.676	0.655
6	0.879	0.335	0.927	0.303	0.667	0.670	0.673	0.659
7	0.880	0.324	0.929	0.302	0.666	0.675	0.673	0.663
8	0.882	0.320	0.931	0.303	0.693	0.676	0.695	0.669
***LFP*$_0$ = 0:**								
1	0.319	0.092	0.451	0.104	0.131	0.124	0.131	0.124
2	0.522	0.153	0.682	0.166	0.167	0.165	0.169	0.166
3	0.651	0.193	0.801	0.204	0.171	0.181	0.175	0.180
4	0.733	0.222	0.862	0.230	0.173	0.189	0.179	0.187
5	0.787	0.245	0.895	0.251	0.168	0.195	0.175	0.192
6	0.822	0.263	0.912	0.268	0.167	0.200	0.175	0.196
7	0.845	0.277	0.922	0.282	0.167	0.204	0.175	0.200
8	0.862	0.289	0.928	0.291	0.187	0.205	0.192	0.205

TABLE 7 Probability of being in the labour force in period 1 to 8 when *Health shock*$_1$ = 1, *Activity limiting condition* = 0 in every period

LFP_0 = 1:	Model 4		Model 5		Model 6, c = 8		Model 6, c = 16	
Period	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
1	0.910	0.650	0.922	0.559	0.694	0.693	0.684	0.695
2	0.891	0.511	0.919	0.422	0.692	0.664	0.687	0.662
3	0.881	0.423	0.919	0.349	0.681	0.657	0.680	0.650
4	0.876	0.371	0.920	0.313	0.678	0.658	0.680	0.650
5	0.875	0.341	0.923	0.299	0.669	0.664	0.673	0.653
6	0.876	0.326	0.926	0.296	0.666	0.670	0.672	0.658
7	0.878	0.318	0.928	0.298	0.666	0.675	0.672	0.663
8	0.881	0.317	0.931	0.301	0.693	0.676	0.695	0.669
LFP_0 = 0:								
1	0.210	0.065	0.302	0.069	0.076	0.083	0.073	0.084
2	0.453	0.135	0.607	0.146	0.151	0.152	0.151	0.152
3	0.608	0.182	0.763	0.193	0.166	0.177	0.170	0.176
4	0.707	0.215	0.844	0.224	0.172	0.187	0.177	0.186
5	0.771	0.240	0.886	0.247	0.168	0.195	0.175	0.192
6	0.812	0.259	0.908	0.266	0.167	0.200	0.175	0.196
7	0.839	0.275	0.920	0.281	0.167	0.204	0.175	0.200
8	0.858	0.288	0.927	0.290	0.187	0.205	0.192	0.205

TABLE 8 Probability of being in the labour force in period 1 to 8 when *Health shock*$_1$ = 1, *Activity limiting condition* = 1 in every period

LFP_0 = 1:	Model 4		Model 5		Model 6, c = 8		Model 6, c = 16	
Period	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
1	0.792	0.511	0.801	0.399	0.607	0.673	0.594	0.671
2	0.722	0.338	0.754	0.241	0.583	0.638	0.575	0.631
3	0.674	0.245	0.725	0.172	0.562	0.628	0.559	0.617
4	0.642	0.195	0.710	0.144	0.556	0.629	0.555	0.615
5	0.622	0.170	0.704	0.134	0.545	0.634	0.546	0.618
6	0.610	0.158	0.703	0.133	0.541	0.640	0.544	0.622
7	0.605	0.153	0.706	0.135	0.540	0.646	0.544	0.627
8	0.605	0.153	0.711	0.137	0.570	0.647	0.569	0.634
LFP_0 = 0:								
1	0.091	0.037	0.128	0.038	0.053	0.076	0.050	0.075
2	0.217	0.076	0.307	0.076	0.104	0.139	0.104	0.137
3	0.310	0.098	0.429	0.096	0.111	0.161	0.113	0.157
4	0.380	0.113	0.513	0.108	0.114	0.170	0.116	0.166
5	0.434	0.123	0.574	0.117	0.110	0.176	0.114	0.170
6	0.475	0.131	0.618	0.125	0.110	0.181	0.114	0.174
7	0.508	0.138	0.651	0.131	0.110	0.185	0.114	0.178
8	0.535	0.144	0.675	0.135	0.124	0.185	0.126	0.182

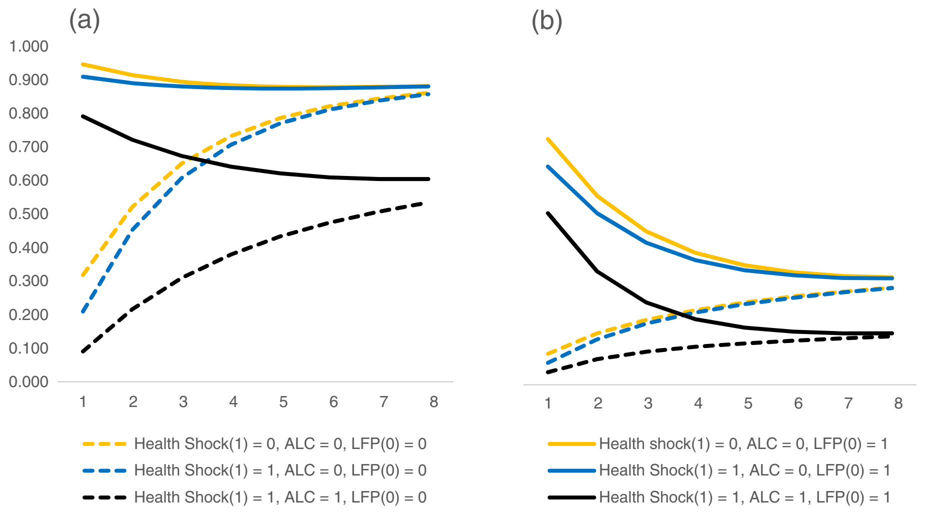

FIGURE 1 Model 4: (a) male and (b) female [Color figure can be viewed at wileyonlinelibrary.com]

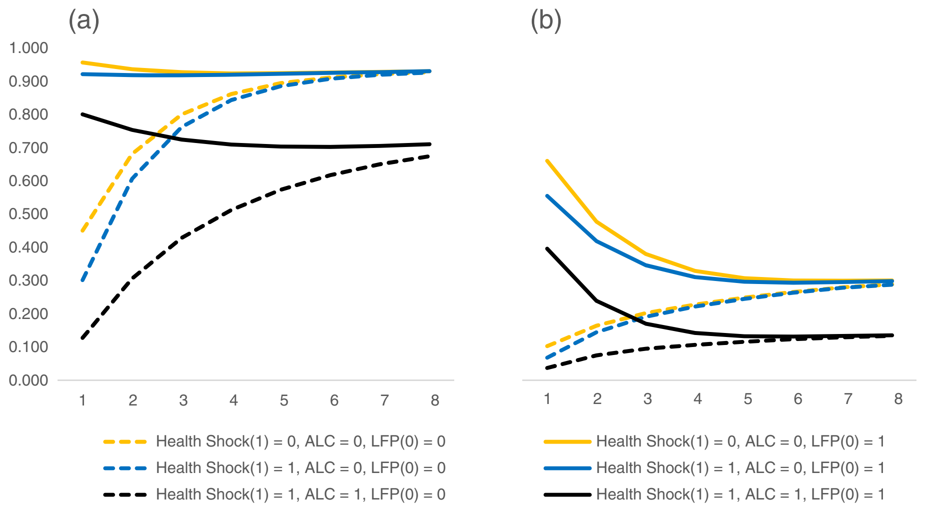

FIGURE 2 Model 5 [Color figure can be viewed at wileyonlinelibrary.com]

Second, not only the equilibrium probabilities are very different for Model 6, the time taken to reach the LR equilibrium is also very different. Due to their higher state dependence, it takes approximately eight periods to return to the equilibrium for Models 4 and 5 for both cohorts and for all health shock scenarios. It only needs around four periods for Model 6. In the short run for Models 4–5, however, adjustment probabilities do depend on the initial conditions. In general for Models 4–5, for those who were initially out of the LF (the dotted lines), their probability in the labour force started fairly small but gradually increases over time towards the equilibrium probability (see dotted lines on Figures 1 and 2). In contrast, for those who started being in the LF (solid lines), the probability tends to be higher for the first few years and then gradually decreases towards equilibrium probability over time to be similar to those for males not initially in LF for the same health shock scenario (see solid lines on Figures 1 and 2). A similar pattern is also found for females, although with much smaller probability in the labour force.

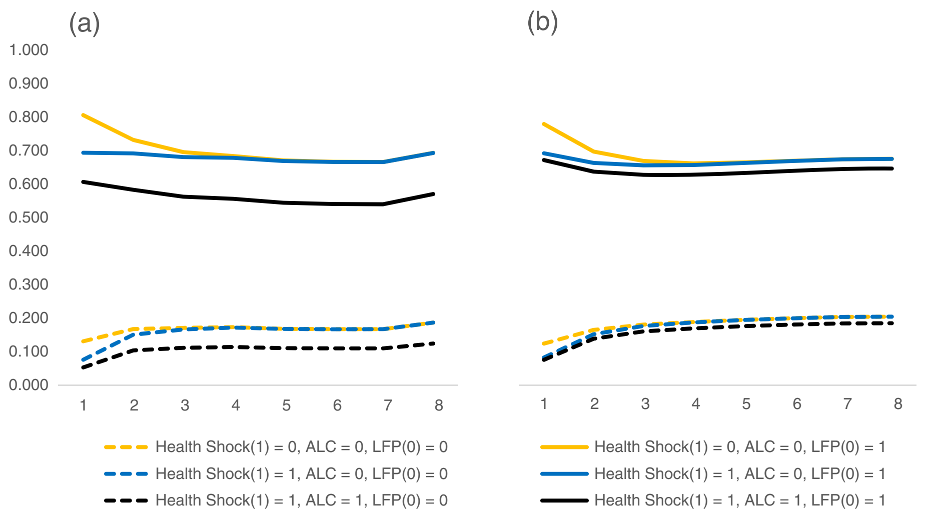

FIGURE 3 Model 6, c = 8 [Color figure can be viewed at wileyonlinelibrary.com]

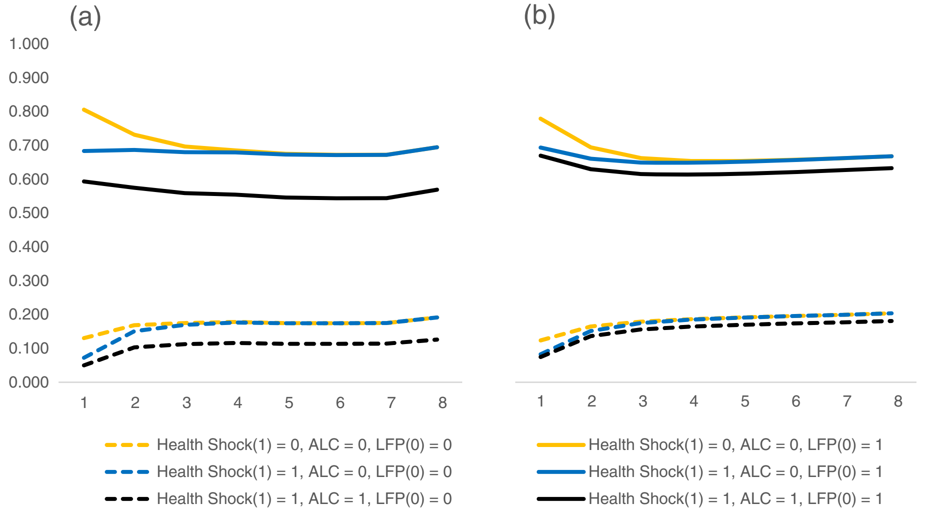

FIGURE 4 Model 6, c = 16 [Color figure can be viewed at wileyonlinelibrary.com]

Finally, the impact of a health shock depends on the seriousness of the shock but the difference in equilibrium probabilities for the three health shock scenarios are different across the models. For Models 4–6, a one-time health shock without the absorbing state in scenario (ii) lowers the LFP probabilities temporarily but the probability eventually converges to the same equilibrium as scenario (i) for without any health shock or ALC for both cohorts. However, a one-time health shock that leads to a long-term health condition in scenario (iii) can have substantial and lasting negative effects on LFP probability, with the converging equilibrium probabilities varying by model. For instance, for Models 4–5, for a male that is not initially in the LF, scenario (iii) lowers the probability to 0.09–0.13 in the first period and slowly climbs back to an equilibrium probability of around 0.54–0.68. However, using Model 6, this cohort of males with an absorbing health shock (iii) are estimated to have an LFP probability of 0.05 in period 1 before increasing quickly to the equilibrium of 0.13, much lower than that from Models 4–5.

6 | SPECIFICATION ANALYSIS

We have estimated six different models for pooled sample and separate male and female subsamples. We have shown that the results are sensitive to the specification. For instance, the estimated magnitudes of state dependent effects and health shock impacts for Models 4 and 5 when individual effects are not best controlled can be up to 5–10 times greater than those from Model 6 when individual effects are better controlled. Which one is a better approximation of the observed phenomena? We first look at the issue of whether to pool the male and female samples to produce a common estimate. We note that under the maintained hypothesis that the model is correctly specified, the issue of whether or not to pool can be decided by using the likelihood ratio tests. The bottom rows of Tables 3 and 4 provide the likelihood ratio test results for homogeneity between males and females. They clearly reject the homogeneity assumption and suggest that there is substantial difference between male and female labour force participation decision for all the models.

Second, we note that Model 1 is nested within Model 4, Model 2 is nested within Model 5 and Model 3 is nested within Model 6. Thus, a standard *t*-test for $\gamma = 0$ can be conducted to choose between static versus dynamic specifications. Because the *t*-statistics for Models 4, 5 and 6 are all highly significant at the 1% level, we reject the static model specification.

Finally, to choose between Models 4, 5, and 6, we note that Model 6 is the most general one, allowing the presence of individual-specific effects, α_i, as well as the correlation between α_i and $(y_{i,\,t-1}, x_{it})$. Model 5 allows the presence of α_i and correlation between α_i and $y_{i,\,t-1}$ but assumes α_i are uncorrelated with x_{it}. Model 4 is the most restrictive one, with the error in the y^*_{it} equation, ε_{it}, being uncorrelated with $y_{i,\,t-1}$ and x_{it}. Under the assumptions that the errors in the y^*_{it} equation consist of $\alpha_i + \varepsilon_{it}$ and that α_i and x_{it} are uncorrelated, the RE MLE is consistent and efficient. However, if the individual-specific effects are correlated with x_{it}, the RE MLE is inconsistent, but the HK FE estimates are consistent under both the null and alternative. Thus, a Hausman (1978) specification test statistic can be constructed to choose between a dynamic RE model (i.e. Model 5) and a dynamic FE model (i.e. Model 6). The test result is provided in the left panel of Table 9, in which we clearly reject the null hypothesis of the RE model in favour of the FE model. By narrowing down the valid models to Models 4 and 6, we can now identify the nature of state dependence by again employing a Hausman specification test. Under the null hypothesis of no individual time-invariant effect, the MLE for Model 4 provides efficient estimates because it utilizes the complete sample and assumes no individual-specific effect and, thus, $E(\alpha_i x_{it}) = 0$. On the other hand, under the alternative hypothesis, the MLE for Model 4 gives biased estimates. In contrast, the coefficient estimator of the FE model (i.e. Model 6) is always consistent under both H_0 and H_1. The right panel

TABLE 9 Hausman specification tests

	Model 5 versus Model 6				Model 4 versus Model 6			
	Male		Female		Male		Female	
	c = 8	c = 16	c = 8	c = 16	c = 8	c = 16	c = 8	c = 16
Model under H0	Model 5	Model 5	Model 5	Model 5	Model 4	Model 4	Model 4	Model 4
Model under H1	Model 6	Model 6	Model 6	Model 6	Model 6	Model 6	Model 6	Model 6
Df	14	14	14	14	14	14	14	14
χ^2 test stat	201.62	125.63	196.24	126.82	250.06	160.62	309.7	209.77

Note. All χ^2-test statistics on Panel (A) and (B) above are statistically significant at the 1% level.

of Table 9 provides the results of the Hausman test between Models 4 and 6. Our results show that the null hypothesis of Model 4 being the correct model is always rejected at the 1% significant level regardless of the bandwidth size. In summary, our specification tests choose Model 6 for separate male and female samples as our preferred model.

7 | CONCLUDING REMARKS

We use eight waves of HILDA data to study labour market state dependence and to investigate the impacts of health shocks and other factors on Australians' labour force participation decisions. We considered six different models: pooled static and dynamic models, static FE and RE models, and dynamic FE and RE models. We find that the empirical results are very sensitive to the specification of the model and the assumption of the errors of an equation. For instance, under the i.i.d. assumption of the errors, the relative marginal effects of health shock to *Age5559* (RME) for the static model (Model 1) shows that it is 0.37 for male and 0.34 for females while the dynamic model (Model 4) shows that it is 0.69 for males and 0.54 for females. So is the difference between the i.i.d. errors and the decomposition of the errors as the sum of individual-specific errors and the errors that vary across individuals and over time. The RMEs of the lag dependent variable for males and females are −4.4 and −4.66 respectively under the i.i.d. errors (Model 4), −3.46 and −3.18 respectively under error components assumption (Model 5), and −1.74 and −2.36 respectively under the FE assumption (Model 6, $c = 8$). In this paper, we have also suggested a method to evaluate the dynamic response of a shock for a binary outcome. Based on our suggested method, under the i.i.d. error assumption Model 4 shows that it takes approximately eight periods (years) to return to the equilibrium path for a health shock that does not have long-term health implications, but it only needs four periods under the FE specification (Model 6).

Our specification analysis demonstrates that it is important to: (i) use a dynamic specification to capture the inertia in human behaviour; (ii) control the impact of unobserved individual-specific effects; (iii) separate the impact of a health shock that is temporary from that of a chronic health condition; and (iv) separate the male and female samples in estimating a labour participation model. We find that the FE dynamic logit model appears to be most compatible with the data. The advantages of an FE specification are that it allows the separation of time-persistent individual effects and state dependence. It also allows correlations between observed covariates and the unobserved individual-specific effects. The disadvantage is that the Honore and Kyriazidou (2000) method puts severe restrictions on the usable sample observations. The eight waves of HILDA data substantially expand the quantity of usable data, hence allowing us to obtain more accurate estimates of unknown parameters.

Our analysis for the dynamic binary outcome model shows that although there could be an experience-enhancing effect, such an effect eventually evaporates as shown by the effect of a one-time health shock that does not lead to a long-term activity limiting condition. An analogous argument could be made on the government labour market policies. Any policy that aims at the short-term job creation schemes could have experience-enhancing effects that last more than one period, but such experience-enhancing effects eventually evaporate. Only government policies that focus on fundamentals such as job training schemes and public investment in education at different stages of life could have permanent lasting impacts.

Our exercise also shows that we must be humble in reporting our findings. We must bear in mind that statistical analysis of causal relationships is not proof of the causal relationships. Information contained in the data may be limited and statistical inference could be fragile and sensitive to inferential procedures. We have to think of as many consequences of the hypotheses as possible and verify the consequences they follow. "Any causal relationship we claim must come with an explanation of the mechanism by which the effect is produced" (Cochran, 1965). We are still only in the process of groping towards the truth, not discovering the truth. Otherwise, just like Mark Twain has said:

> "There are lies.
> There are damned lies.
> There is Statistics!"

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APPENDIX: HONORE-KYRIZIDOU PROCEDURE FOR ESTIMATING DYNAMIC FIXED EFFECTS BINARY MODEL

We first outline the simplest setting of Model 6 with four time periods (see Honore & Kyriazidou (2000), Chintagunta, Kyriazidou, & Perktold (2001) and Hsiao (2014) for details) and later give the explanation of how we apply this method to our eight periods' panel data.

There are a few requirements that need to be satisfied for this model to be identified. First, there must be at least four or more observations per individuals (i.e. at least four periods of panel data). Second, there must be a switching of labour force participation in the middle periods. If assuming that there are exactly four observations for each individual, then the dependent variable for each person can be represented by $\{y_{i0}, y_{i1}, y_{i2}, y_{i3}\}$ for period 0 to period 3. When considering switching of labour force participation in the middle periods, there are two possible scenarios: A = $\{y_{i0}, y_{i1} = 0, y_{i2} = 1, y_{i3}\}$ and B = $\{y_{i0}, y_{i1} = 1, y_{i2} = 0, y_{i3}\}$. y_{i0} and y_{i3} can either be 0 or 1. If it is further assumed that $x_{i2} = x_{i3}$, then we can obtain:

$$\Pr(A|AUB) = \frac{1}{1 + e^{\beta'(x_{i1} - x_{i2}) + \gamma(y_{i0} - y_{i3})}}, \tag{A1}$$

and

$$\Pr(B|AUB) = \frac{e^{\beta'(x_{i1} - x_{i2}) + \gamma(y_{i0} - y_{i3})}}{1 + e^{\beta'(x_{i1} - x_{i2}) + \gamma(y_{i0} - y_{i3})}}, \tag{A2}$$

which has a binary logit form and no longer depends on incidental parameter α_i. We can use Equations (A1) and (A2) to form a log-likelihood function. Nonetheless, it is quite difficult to have $x_{i2} = x_{i3}$ in most cases, especially when the explanatory variables are continuous variables. Thus, Honore and Kyriazidou (2000) propose using a kernel density function as a weight for each observation and maximizing the following weighted likelihood function to obtain the estimated β and γ:

$$\sum_{i=1}^{n} 1\{y_{i1} + y_{i2} = 1\} K\left(\frac{x_{i2} - x_{i3}}{\sigma_n}\right) \ln\left(\frac{\left[e^{\beta'(x_{i1} - x_{i2}) + \gamma(y_{i0} - y_{i3})}\right]^{y_{i1}}}{1 + e^{\beta'(x_{i1} - x_{i2}) + \gamma(y_{i0} - y_{i3})}}\right). \tag{A3}$$

It should be noted that $1\{y_{i1} + y_{i2} = 1\}$ is an indicator function for switching labour force participation in the middle periods, $K\left(\frac{x_{i2} - x_{i3}}{\sigma_n}\right)$ is a kernel density that gives more weight to those observations whose x_{i2} are closer to x_{i3} and σ_n is a bandwidth that shrinks towards 0 when n increases.

When there are more than four observations per individual (i.e. more than four periods of panel data), the main identification strategy is that there must be switching of labour force participation in any two of the middle $T-1$ periods. Honore and Kyriazidou (2000) extend the weight likelihood function Equation (A3) to accommodate longer panel as follows:

$$\sum_{i=1}^{n}\sum_{1\le t<s\le T-1}1\{y_{it}+y_{is}=1\}K\left(\frac{x_{it+1}-x_{is+1}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{it}-x_{is})+\gamma(y_{it-1}-y_{is+1})+\gamma(y_{it+1}-y_{is-1})1\{s-t>1\}}\right]^{y_{it}}}{1+e^{\beta'(x_{it}-x_{is})+\gamma(y_{it-1}-y_{is+1})+\gamma(y_{it+1}-y_{is-1})1\{s-t>1\}}}\right). \tag{A4}$$

Our data is an unbalanced panel covering 8 years. We can write a sequence of labour force participation for each individual i as $\{y_{i0}, y_{i1}, y_{i2}, y_{i3}, y_{i4}, y_{i5}, y_{i6}, y_{i7}\}$ for period 0 to period 7. Because the main identification strategy for this model is that there must be some switching of labour force participation in any two middle periods, there are 15 possible pairs of switching that can take place with 8 years of data:

$$L(\beta,\gamma)=\sum_{i=1}^{n}1\{y_{i1}+y_{i2}=1\}K\left(\frac{x_{i2}-x_{i3}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i1}-x_{i2})+\gamma(y_{i0}-y_{i3})}\right]^{y_{i1}}}{1+e^{\beta'(x_{i1}-x_{i2})+\gamma(y_{i0}-y_{i3})}}\right)+$$

$$1\{y_{i1}+y_{i3}=1\}K\left(\frac{x_{i2}-x_{i4}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i1}-x_{i3})+\gamma(y_{i0}-y_{i4})}\right]^{y_{i1}}}{1+e^{\beta'(x_{i1}-x_{i3})+\gamma(y_{i0}-y_{i4})}}\right)+$$

$$1\{y_{i1}+y_{i4}=1\}K\left(\frac{x_{i2}-x_{i5}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i1}-x_{i4})+\gamma(y_{i0}-y_{i5})+\gamma(y_{i2}-y_{i3})}\right]^{y_{i1}}}{1+e^{\beta'(x_{i1}-x_{i4})+\gamma(y_{i0}-y_{i5})+\gamma(y_{i2}-y_{i3})}}\right)+$$

$$1\{y_{i1}+y_{i5}=1\}K\left(\frac{x_{i2}-x_{i6}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i1}-x_{i5})+\gamma(y_{i0}-y_{i6})+\gamma(y_{i2}-y_{i4})}\right]^{y_{i1}}}{1+e^{\beta'(x_{i1}-x_{i5})+\gamma(y_{i0}-y_{i6})+\gamma(y_{i2}-y_{i4})}}\right)+$$

$$1\{y_{i1}+y_{i6}=1\}K\left(\frac{x_{i2}-x_{i7}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i1}-x_{i6})+\gamma(y_{i0}-y_{i7})+\gamma(y_{i2}-y_{i5})}\right]^{y_{i1}}}{1+e^{\beta'(x_{i1}-x_{i6})+\gamma(y_{i0}-y_{i7})+\gamma(y_{i2}-y_{i5})}}\right)+$$

$$1\{y_{i2}+y_{i3}=1\}K\left(\frac{x_{i3}-x_{i4}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i2}-x_{i3})+\gamma(y_{i1}-y_{i4})}\right]^{y_{i2}}}{1+e^{\beta'(x_{i2}-x_{i3})+\gamma(y_{i1}-y_{i4})}}\right)+$$

$$1\{y_{i2}+y_{i4}=1\}K\left(\frac{x_{i3}-x_{i5}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i2}-x_{i4})+\gamma(y_{i1}-y_{i5})}\right]^{y_{i2}}}{1+e^{\beta'(x_{i2}-x_{i4})+\gamma(y_{i1}-y_{i5})}}\right)+$$

$$1\{y_{i2}+y_{i5}=1\}K\left(\frac{x_{i3}-x_{i6}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i2}-x_{i5})+\gamma(y_{i1}-y_{i6})+\gamma(y_{i3}-y_{i4})}\right]^{y_{i2}}}{1+e^{\beta'(x_{i2}-x_{i5})+\gamma(y_{i1}-y_{i6})+\gamma(y_{i3}-y_{i4})}}\right)+$$

$$1\{y_{i2}+y_{i6}=1\}K\left(\frac{x_{i3}-x_{i7}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i2}-x_{i6})+\gamma(y_{i1}-y_{i7})+\gamma(y_{i3}-y_{i5})}\right]^{y_{i2}}}{1+e^{\beta'(x_{i2}-x_{i6})+\gamma(y_{i1}-y_{i7})+\gamma(y_{i3}-y_{i5})}}\right)+$$

$$1\{y_{i3}+y_{i4}=1\}K\left(\frac{x_{i4}-x_{i5}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i3}-x_{i4})+\gamma(y_{i2}-y_{i5})}\right]^{y_{i3}}}{1+e^{\beta'(x_{i3}-x_{i4})+\gamma(y_{i2}-y_{i5})}}\right)+$$

$$1\{y_{i3}+y_{i5}=1\}K\left(\frac{x_{i4}-x_{i6}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i3}-x_{i5})+\gamma(y_{i2}-y_{i6})}\right]^{y_{i3}}}{1+e^{\beta'(x_{i3}-x_{i5})+\gamma(y_{i2}-y_{i6})}}\right)+$$

$$1\{y_{i3}+y_{i6}=1\}K\left(\frac{x_{i4}-x_{i7}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i3}-x_{i6})+\gamma(y_{i2}-y_{i7})+\gamma(y_{i4}-y_{i5})}\right]^{y_{i3}}}{1+e^{\beta'(x_{i3}-x_{i6})+\gamma(y_{i2}-y_{i7})+\gamma(y_{i4}-y_{i5})}}\right)+$$

$$1\{y_{i4}+y_{i5}=1\}K\left(\frac{x_{i5}-x_{i6}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i4}-x_{i5})+\gamma(y_{i3}-y_{i6})}\right]^{y_{i4}}}{1+e^{\beta'(x_{i4}-x_{i5})+\gamma(y_{i3}-y_{i6})}}\right)+$$

$$1\{y_{i4}+y_{i6}=1\}K\left(\frac{x_{i5}-x_{i7}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i4}-x_{i6})+\gamma(y_{i3}-y_{i7})}\right]^{y_{i4}}}{1+e^{\beta'(x_{i4}-x_{i6})+\gamma(y_{i3}-y_{i7})}}\right)+$$
$$1\{y_{i5}+y_{i6}=1\}K\left(\frac{x_{i6}-x_{i7}}{\sigma_n}\right)\ln\left(\frac{\left[e^{\beta'(x_{i5}-x_{i6})+\gamma(y_{i4}-y_{i7})}\right]^{y_{i5}}}{1+e^{\beta'(x_{i5}-x_{i6})+\gamma(y_{i4}-y_{i7})}}\right)+$$

With the constructed log-likelihood function, we can maximize it with respect to β and γ following the suggestion of Honore and Kyriazidou (2000) and Chintagunta et al. (2001) by taking the kernel function to be a standard normal density function.[5] The bandwidth σ_n is a normal reference rule-of-thumb bandwidth with a form $\sigma_n = c \times n^{-\frac{1}{5}}$ where n is the total number of observations, and c is a positive constant set at 8 and 16. It should be noted that because Model 6 requires switching of labour market outcomes in any two middle periods and uses the weighting scheme $K\left(\frac{x_{it+1}-x_{is+1}}{\sigma_n}\right)$, the number of observations used to estimate Model 6 is substantially smaller than for Models 1–5, which may lead to some loss of precision.

[5] $K\left(\frac{x_{it+1}-x_{is+1}}{\sigma_n}\right)=\frac{1}{\sqrt{2\pi}\sigma_n}e^{-\frac{1}{2}\left(\frac{(X_{it+1}-X_{is+1})}{\sigma_n}\cdot\frac{(X_{it+1}-X_{is+1})}{\sigma_n}\right)}$, where $\frac{(X_{it+1}-X_{is+1})}{\sigma_n}$ is a K-dimensional vector of independent variables.