Health status and labor market outcome: empirical evidence from Australia

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Abstract

This paper uses nine waves of the Household, Income, and Labor Dynamics in Australia data to evaluate the impact of health on labor market outcome and the presence of labor market state dependence. We specify six alternative panel data binary dependent variable models with different ways of modeling labor market dynamics and individual heterogeneity, and compare key results for pooled sample as well as male and female subsamples. Likelihood ratio tests point out that separate analysis for male and female is more appropriate for our data. Generalized Hausman (1978) specification tests are developed to test whether there is any presence of true state dependence in labor force participation decision. Our preferred model is a less frequently used dynamic fixed-effect logit model following Honore and Kyriazidou (2000) which requires a rich panel dataset. Our empirical results show that both the labor market state dependence and the effect of health could be over-estimated for both male and female by many folds if individual-specific effect is not properly controlled in dynamic binary dependent variable models.

JEL Classification: I10, I12, J21, J24
Keywords: health status, labor force participation, state dependence, dynamic fixed-effect binary logit model

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1. Introduction

It is well established both in theory and in empirical studies that health plays an important role in an individual's labor participation decision. For example, Beck (1964), Grossman (1972), Currie and Madrian (1999), etc. regard health as a type of human capital akin to education. Chirikos (1993) and Dwyer and Mitchell (1999), etc. argue that poor health makes work more difficult and less fulfilling, thus increases the utility of leisure relative to the utility derived from work. On the other hand, Dwyer and Mitchell (1999) and Cai and Kalb (2006), etc. argue that the income effect from lower earnings associated with poor health could dominate the substitution effect. There are also many empirical studies measuring the impact of health on labor participation decisions (e.g. Cai and Kalb (2006), Cai (2010), Garcia-Gomez et al. (2010), Zissimopoulos and Karoly (2007), Dwyer and Mitchell (1999), Disney et al. (2006), Siddiqui (1997), Bound et al. (1999), Bazzoli (1985), and Zhang et al. (2009)). Many of them use cross-sectional data and their estimates on the magnitude of health impact are also widely different.

This paper uses nine waves of the Household, Income, and Labor Dynamics in Australia data to evaluate the impact of health on labor market outcomes. The advantages of using panel data over cross-sectional data are several. First, labor 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. Moreover, this unobserved individual-specific effects could also be correlated with the observed confounding covariates. Panel data provide a way to control the impact of unobserved individual-specific effects on the estimation of the coefficients of the observed covariates, in particular, health condition variables. Second, labor market outcomes are inherently dynamic, namely, current outcomes depend on past outcomes. Separation of the individual-specific effects and true or spurious state dependence (e.g. Heckman (1981a, 1981b) and Hsiao (2003)) is critical in providing a correct assessment of the magnitude of health impacts on labor market outcomes. Third, panel data provide information to distinguish the impact of persistent health condition and health changes.

In Australia, there are a few studies that also have employed panel data and tried to model for both individual heterogeneity and state dependence. Oguzoglu (2010) uses dynamic linear probability fixed-effect model. However, the outcome of interest is qualitative in nature. Knights et al. (2002), Oguzoglu (2007, 2010), and Zucchelli et al. (2012)) use dynamic discrete choice random-effects model assuming the individual-specific effects are uncorrelated with the confounding covariates. If they are correlated, the estimates are biased. Moreover, there is also the initial condition problem (Heckman (1981c), Hsiao (2003), Chintagunta et al. (2001), and Honore and Kyriazidou (2000)). Initial realization of labor force participation is usually unobserved for most people in the data but this initial realization has a critical impact on the entire path of labor market outcomes. Typically, when random-effect estimation is used, initial condition is assumed to be exogenous. However, this exogeneity assumption is violated when there is presence of unobserved individual-specific effect that is serially correlated overtime, leading to inconsistent estimation of all parameters.

We use nine waves of the Household, Income, and Labor Dynamics (HILDA) in Australia to evaluate the impact of health status on labor market outcome. Our main contributions consist of the following. First, we try to overcome the drawbacks of random-effect estimation in the existing literature by adopting a dynamic *fixed-effect* binary logit model as outlined in Honore and Kyriazidou (2000). This modeling approach allows us to take into account both unobserved individual heterogeneity as well as state dependence. It allows us to separately identify true state dependence in labor force participation from the spurious type due to time-invariant heterogeneity. Our use of Honore and Kyriazidou (2000) approach also avoids the so-called incidental parameter problem (Hsiao 2003) for a large N panel by bypassing the estimation of nuisance parameters of individual fixed-effect, whilst still allows for correlation between individual fixed-effect and observables. Second, we compare estimates from six alternative model specifications in terms of dynamic state dependence and individual heterogeneity, and show how key results can be mis-estimated. Third, after taking account of state dependence and heterogeneity, we can accurately assess the impact of health status on labor market outcome by considering two different measures of health status including health shock and activity limiting condition. Fourth, we estimate our models separately for male and female subsamples, which allows us to assess the varying impact of each factor on labor market outcome across gender. Finally, our data spans the period of nine years exceedingly longer than other existing studies on the topic, though it complicates the fixed-effect estimation. However, it is essential to have a larger number of data points to yield reliable estimates as the conditions for the HK conditional method are so stringent. These include for each four periods under consideration (i) individuals in the two intermediate periods must switch positions; (ii) individuals must have identical x values for the third and fourth period; (iii) to get good estimates of β, there must be significant true variation for x values for the second and third period; (iv) to get estimate of the coefficient for the lagged state variable, individuals must also switch positions in the first and the last period.

This paper is organized as follows. Section 2 introduces the econometric models. Section 3 provides a description of our data and some empirical observations from the data. Section 4 reports our estimation results. Conclusions are given in Section 5.

2. Econometric models

This paper assumes that there are two alternative labor market states: participating in the labor force ($y_{it} = 1$) and being out of the labor force ($y_{it} = 0$). Each individual is presumed to choose between these two mutually exclusive labor market states during each time period. We assume y_{it} depends on a continuous latent 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:

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

Model 2 and Model 3:

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

Model 4:

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

Model 5 and Model 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}, α_i denotes the unobservable individual-specific factors. Models 1 and 4 assumes that the impact of unobservable factors is independent of the included explanatory variables. Models 2, 3, 5 and 6 assumes that the impact of unobservable factors is the sum of two components, the time-invariant individual-specific effects (α_i), and individual and time varying component (ε_{it}). Models 1, 2, and 3 assume there is no state dependence. Model 4 assumes y_{it} (or y_{it}^{*}) depends on y_{it-1}. However, the magnitude of the impact of y_{it-1}, γ, could either be an approximation of the impact of the individual-specific effects, not an indication of true state dependence or an approximation of the sum of the individual-specific effects and the true state dependence effects. Model 4, 5, and 6 tries to assess if there is true state dependence and the magnitude of the true state dependence after controlling the impact of time persistent individual-specific effects, α_i. Model 2 and 5 assume α_i are independent of x_{it}. Model 3 and 6 assume they are correlated.

Our goal is to assess the effect of health on labor market outcome while also taking into account whether the past labor market outcome affects the current decision to be in the labor force. In addition, we also try to identify the nature of persistency in labor force participation whether it is of true or spurious state dependence. If there is no individual-specific effect, a test of whether there is state dependence is a test of $\gamma = 0$ in model 4. If unobservable individual-specific effects also affect the outcomes, a test of true state dependence ($\gamma = 0$ or not) must control the impact of α_i.

For models 1 and 4, we employ a pooled binary logit approach treating x_{it} and/or lagged choice as uncorrelated with ε_{it}. For models 2 and 5, we use random-effect binary logit regression to obtain the coefficient estimates where in the latter model initial value is treated as fixed constant. For model 3, we use Chamberlain (1982) conditional maximum likelihood estimates. Finally, for model 6, we use Honore and Kyriazidou (2000) conditional MLE. Since the HK method is not widely implemented in empirical studies and the implementation of HK conditional MLE involves 21 possible switching with nine years of data, we spell out the detail in the Appendix A.

3. Data

This paper employs the first nine waves (2001-2009) of the Household, Income and Labor Dynamics in Australia (HILDA) survey. It is a household-based panel data that was started in 2001 and subsequent surveys have been conducted annually. People aged 15 and older are eligible for interview. Both personal interviews and self-completed questionnaires are used to obtain personal information including health variables. Our final sample size varies depending on the model since each model has its own requirements. After deleting missing observations, the resulting samples comprise 42375 observations for male and 48056 observations for female under model 1 and 2; 9516 observations for male and 16429 observations for female under model 3; 39416 observations for male and 45175 observations for female under model 4 and 5; and finally, 3488 observations for male and 6368 observations for female under model 6.

Definitions of all variables are provided in Table 1. The main dependent variable for individual's labor market outcome is a discrete binary choice variable y_{it}, which is equal to 1 if a person is in a labor force during the past seven days and 0 if not. By definition, individuals who are employed or unemployed but currently looking for work are both considered to be in a labor force. HILDA also provides information on explanatory variables such as gender (*Male*), age (*Age1554*, *Age5559*, *Age6064*, *Age65above*), marital status (*Married*), dependent children (*No child*, *Younger child*, *Older child*), educational status (*Less than year 12*, *Year 12*, *Post school*, *Degree*), region of residence's unemployment rate (*Unemployment rate*), and log of household annual disposable income (*ln income*). The final set of explanatory variables included in this study are health related variables. We consider two different health variables. First, each individual answers whether there is personal injury or illness that has happened to his/her life over the past 12 months (*Health shock*). Second, each person is asked whether he/she has any long-term health condition, impairment or disability that restricts his/her everyday activities that has lasted or is likely to last for 6 months or more (*Activity limiting condition*). In this study, both health variables above are treated as exogenous. Furthermore, since *Health shock* captures injury or illness that has happened in the *past* year prior to the survey, one may even regard it as an indication if there was a significant change in one's health condition in the previous year. Table 2 provides summary statistics of dependent and independent variables for male and female subsamples under each model separately.

(Table 1 and 2 around here)

Table 3 presents transition probabilities of being in and out of the labor force between successive periods between 2001-2009 for each subsample. The rows of the table show the lagged period's labor market state while the columns present the current labor market state. At any given time, approximately 75% of male sample participates in the labor market, which is higher than the 60% participation rate of female. Among those currently in the labor market, the majority of them also used to be in the labor market in the previous period for both genders (i.e. 70-90% varying on the model). Furthermore, at any given period, it is found that generally 25% of the Australian male do not participate in the labor force while about 40% of the female are non-participants. Among those outside the labor force, a large proportion of 60-85% for both male and female was found to have no participation in the past. Thus, we can observe high degree of persistency in labor market outcome of people in Australia over the span of 2001-2009. Nonetheless, this strong degree of persistence is detected without controlling for other explanatory variables. Once multivariate analysis is conducted, we will be able to further identify whether this strong persistence is due to true or spurious state dependence.

(Table 3 around here)

Table 4 shows cross-tabulations between current labor force participation and current health status variables. We only present the cross-tabulations for the largest subsample (i.e. subsample of model 1-2) for both male and female since other subsamples follow similar trend. The first cross-tabulation is between labor force participation and *Health shock*. Among male and female who participate in the labor force, 93% (i.e. 29378/31604 for male and 27897/29736 for female) of them do not experience any personal injury or illness during the past 12 months. The cross-tabulation between labor force participation and *Activity limiting condition* reveals that 83% (i.e. 26276/31604 for male and 24962/29736 for female) of men and women who are in the labor market do not have any condition that restricts their everyday activities for 6 months or more. In sum, this finding indicates that on average people who are in labor market tend to be associated with better health status as captured by these two measures of health.

(Table 4 around here)

4. Empirical Analysis

4.A. Estimation Results

This paper employs six different econometric models to investigate the effect of health factors on labor market outcomes. Models 1 – 3 are static. Models 4 – 6 assume the current state also depends on past labor participation decision. Table 5, 6 and 7 report coefficient estimates for models 1 – 3, model 4 – 5, and model 6 with two different bandwidths, respectively. For each model, we estimate three different regressions for pooled, male, and female samples. Although the estimated coefficients are different for each model specification, they all indicate that:

1. Both health status measures, *Health shock* and *Activity limiting condition*, have significant and negative impact on labour participation decisions.
2. Aging plays a significant and progressively negative impact on employment decisions, but being married and more educated have positive impact, so is the income effect.
3. The coefficient of lagged dependent variable, γ, is highly significant, indicating strong state dependence. However, if the impact of individual time-invariant effects are controlled, the magnitude of γ is reduced by one-half.
4. There is a significant difference between male and female towards health status changes and other social-demographic factors.

(Table 5, 6, and 7 around here)

4.B. Specification Analysis

We have estimated six different models with pooled sample or separate male and female sample. Which one is a better approximation of the observed phenomena? We first look at the issue of whether to pool the male and female sample to produce a common estimate. We note that under the maintained hypothesis that the model is correctly specified, to pool or not to pool issue can be decided by using the likelihood ratio tests. The bottom of Table 5, 6, and 7 provides the likelihood ratio test of homogeneity between male and female. They clearly reject the homogeneity assumption and suggest that there is substantial difference between male and female labor force participation decision for all the models.

Secondly, we note that model 1 is nested within model 4, model 2 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 vs. dynamic specification. Since the t-statistics for models 4, 5, and 6 are all highly significant at 1% level, we reject the static model specification.

Thirdly, 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 α_i but assumes α_i are uncorrelated with x_{it}. However, α_i remain correlated with $y_{i,t-1}$. Model 4 is the most restrictive one, the error in y_{it}^* equation, ε_{it}, are uncorrelated with $y_{i,t-1}$ and x_{it}. Under the assumptions that the errors in y_{it}^* equation consist of $\alpha_i + \varepsilon_{it}$ and α_i are uncorrelated with x_{it}, the random-effect MLE is consistent and efficient. However, if the individual-specific effects are correlated with x_{it}, the random-effect MLE is inconsistent, but the HK fixed-effect estimates are consistent under both the null and alternative. Thus, a Hausman (1978) specification test statistic can be constructed to choose between dynamic random-effect model (i.e. model 5) and dynamic fixed-effect model (i.e. model 6). The test result is provided in Panel (A) of Table 8, in which we clearly reject the null hypothesis of random-effect model in favor of the fixed-effect model. By narrowing down the valid models to models 4 and 6, we can now identify the nature of state dependence by again employing Hausman specification test. Under the null hypothesis, the pooled regression (i.e. model 4) provides efficient estimates since 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 pooled regression (i.e. model 4) gives biased estimator. In contrast, the coefficient estimate of the fixed-effect model (i.e. model 6) is always consistent under both H_0 and H_1. Panel (B) of Table 8 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 1% significant level regardless of the bandwidth size or the health status variable controlled for in model 6. Because the Hausman test favors model 6 over model 4, we find that the estimated magnitude of gamma under model 4 substantially overstates the impact of past experience of an event on the outcome (i.e. the magnitude of gamma under model 4 is twice as large as under model 6).

4.C. Impact Analysis

Our estimation results show that lagged labor force participation has positive and significant effect on current period's labor force participation for both male and female. However, the impact of individuals who participate in the labor force in the past period to be in the labor force again in the present appears to be overestimated after controlling the impact of unobserved individual heterogeneity. Since it is not meaningful to compare the size of this coefficient across these models, we consider two approaches. One is to compare the relative marginal effect between each explanatory variable and a variable '*Degree*' on the probability of being in the labor force for each respective regression, and the other is to provide a comparison of health shocks on a hypothetical person. The main reason for presenting relative marginal effect is because for the fixed-effect models we do not explicitly estimate the time-invariant individual specific-effect (i.e. α_i) because α_i gets differenced out from the model. Thus, it is not possible to compute the exact value of the individual marginal effect of each factor on the probability of the outcome under fixed-effect estimation. However, it is possible to compute relative marginal effect on the probability of being in labor force, because the numerator and the denominator have common elements including α_i that cancel each other out when putting it in a ratio form. As an illustration, Appendix B provides a computation of relative marginal effect for model 6. We pick *Degree* to standardize our results because by standardizing it this way we will be able to discuss the effect of our main explanatory variables (i.e. health status and lagged labor force participation) on current employment on the same basis. Furthermore, we can easily compare our results with existing literature because most papers also include *Degree* as an explanatory variable in their studies. Table 9 provides relative marginal effect between our preferred model and those of other studies. We also compare the difference of labor participation decisions overtime for a hypothetical individual with those of other studies when this hypothetical individual suffers a health injury

(Table 9 around here)

When comparing marginal effect of lagged labor force participation relative to the marginal effect of *Degree* across models as shown on Table 9, we find that for male sample models 4 and 5 have relative marginal effect approximately equal to 3 - 6 while that of model 6 is around 0.5 – 0.6. For female sample, models 4 and 5 give relative marginal effect of 2 - 4; on the other hand, model

6 indicates the relative marginal effect of 0.6 – 1. Because model 6 imposes the least restrictive assumptions and Hausman specification tests favor model 6, these results suggest that, if only pooled and random-effect estimations are employed, one will misleadingly obtain the results that overstate the effect of labor market status dependence. The relative marginal effects also reveal that labor force participation decision appears to be almost 2-folds more persistent for female than male under our preferred model 6; however, in models 4 and 5 when individual specific-effect is not as well controlled for this persistency is found to be about 1.5-folds greater for men than women. Furthermore, because model 6 is the most preferred model according to our specification tests, we can clearly identify that the type of state dependence presented in the Australian labor market is *true* state dependence, and not spurious one. Table 8 also allows us to compare the impact of lagged labor force participation on current labor force participation against the impact of other regressors on current employment (in relation to *Degree*). Specifically, we discover that lagged labor force participation has the third strongest impact on current participation, following age and educational attainment. Our finding is consistent with other existing literature in Australia. Knights et al. (2002), Oguzoglu (2007, 2010), and Zucchelli et al. (2012) also find strong persistence in labor market outcome in Australia; however, their models assume that the individual-specific effect is random and does not correlate with the individual observable variables. For comparison purpose, Oguzoglu (2007) uses five waves of HILDA and finds relative marginal effect between lagged labor force participation and the attainment of bachelor degree or more on current labor market outcome to be 0.72 and 1.01 for male and female samples, respectively while Knights et al. (2002) finds this same relative marginal effect to be 1.35 for male and 1.95 for female. Again, both these studies discover

the marginal effect of lagged labor force participation relative to the marginal effect of *Degree* to be larger than the figure found in our preferred model 6.

After partial out the effect of lagged labor force participation, we can now discuss the impact of health status variables. *Health shock* is found to have significantly negative effect on current labor force participation for both male and female. This matches with our prior expectation that individuals who experience personal injury or major illness in the past 12 months are less likely to participate in the labor force. From Table 8, the marginal effect of *Health shock* on current participation is lower for male than female under model 6; however, for model 1 – 5, this impact appears to be stronger for men than women. For our preferred model 6, marginal effect of *Health shock* for male sample is estimated to be about one-fifth of that of *Degree* (-0.16 to -0.22) and for female is around one-quarter of that of *Degree* (-0.21 to -0.27). This effect will be over-estimated to -0.7 to -0.99 that of *Degree* for men and -0.36 to -0.48 that of *Degree* for women with dynamic models 4 and 5 when individual effect is not as well controlled as in model 6. Interestingly, the effect of *Health shock* estimates in models 1, 2 and 3, when state dependence is not allowed, are quite close to the results in model 6.

Turning towards another health status variable, *Activity limiting condition*, models 1-5 for both male and female groups and model 6 for male group reveal that having condition that restricts everyday activity adversely affects labor force participation. However, for female subsample in model 6, the effect of this variable turns out to be insignificant. This could be because females' labor participation decisions are more dominated by the unobserved individual-specific effects and family factors than males. Thus, unless there is a significant change in their health condition due to health shock, their labor participation decisions are unlikely to be changed. We may also infer from this result that women's overall long-term health condition may be more superior to men (see Table 2) and there are other more important factors that influence female's employment decision rather than *Activity limiting condition*. In term of relative marginal effect, the effect of having *Activity limiting condition* is negative and is estimated as -0.12 to -0.15 that of *Degree* for men and insignificant for women under our preferred specification (i.e. model 6). In comparison, this effect is significantly over-estimated in models 1, 2, 4 and 5 and slightly over-estimated in model 3. This result is quite similar to our earlier observation on the impact of lagged dependent variable. That is, the effect of health factors on labor force participation will be over-exaggerated if researchers only use pooled and random-effect estimations and ignore the fixed-effect estimation from their studies.

Comparing the magnitude of health impact to that of other explanatory variables based on our preferred model 6 as can be seen from Table 8, both *Health shock* and *Activity limiting condition* (for male sample only) are found to have statistically significant stronger effect than that of household's disposable income but smaller effect than lagged labor force participation, categorical age groups, and educational attainment. In addition, for female sample, we also find the effect of *Health shock* on labor market outcome to be smaller than that of having young dependent child in a family. This inference is drawn by comparing the relative marginal effects of these factors (in relation to *Degree*) against each other. For example, for male sample under model 6, the relative marginal effect of *Health shock* and *Activity limiting condition* on current employment (in relation to *Degree*) are approximately -0.2 and -0.15, respectively, while that of household's disposable income is equal to 0.1, that of lagged labor force participation is 0.5, that of *Age5559*, *Age6064* and *Age65above* is -0.3, -0.7, and -1.1, and that of *Year12*, *Postschool*, and *Degree* is 0.7, 0.45, and 1, respectively. Thus, in decreasing order of relative marginal effect (in absolute term), we find the impact of being in the eldest age group to be the strongest, followed by the attainment of Degree, then intermediate level of education, being in the middle age group, lagged labor force participation, health factors, and finally household income. In sum, our findings on health status variables indicate that poor health have negative effect on labor market outcome, which is comparable to previous studies like Knights et al. (2002), Oguzoglu (2007), Cai and Kalb (2006), and Cai (2010). For example, Oguzoglu (2007) finds marginal effect of having work limiting condition relative to marginal effect of *Degree* to be -0.27 and -0.16 for male and female samples, respectively. On the other hand, Knights et al. (2002) finds marginal effect of being disabled relative to marginal effect of *Degree* to be -0.35 for male and -0.9 for female. Cai and Kalb (2006) and Cai (2010) do not control for *Health shock* nor *Activity limiting condition* in their studies instead they take account of self-assessed health status, in which they find that worse self-rating health status lowers the tendency of being in the labor force, a consistent finding to our study.

For other conditional variables, age significantly affects labor force participation in all models. Our preferred model 6 also shows that among all regressors age has the strongest impact on employment outcome for both male and female. In particular, the effect of age appears to monotonically increase as people get older. For example, under our preferred model 6 when bandwidth size is c = 4, relative marginal effects for *Age559*, *Age6064*, and *Age65above* are approximately -0.3, -0.7 and -1.1, respectively, for both men and women. This finding implies that people aged 65 years old or above are less inclined to participate in the labor force in comparison to all the other younger age groups. This is to be expected since the current retirement age in Australia for both male and female is 65 years old, making people of older age unlikely to be active in the labor market. Previous studies give mixed findings on this variable. Cai and Kalb (2006) and Cai (2010) find that an additional year of age decreases the probability of participating in the labor force while Oguzoglu (2007) discovers the coefficient of continuous age variable to be positive and significant for female sample and insignificant for male sample. Finally, Knights et al. (2002) omits age from the estimation completely.

Being married has positive and significant effect on labor market outcome for male but insignificant for female under models that do not control for lagged dependent variable (i.e. models 1-3). When model 4-5 are used, the effect of *Married* is significantly positive for men and significantly negative for women. On the other hand, our preferred model 6 indicates that being married is neither significant for male nor female though the coefficient of the former group possesses positive sign while that of the latter group yields negative sign. Thus, the impact of marital status on labor market outcome varies across different models though our most preferred specification points out to insignificant result. Similar to our study, both Oguzoglu (2007) and Knights et al. (2002) find marital status to have insignificant effect on labor force participation. In contrast, Cai (2010) discovers that married male are more likely to enter the labor force than those who are not married while married female are less likely to be in the labor market in comparison to their never married counterparts.

Turning towards educational attainment, we find that the effect of education on individual's employment decision is positive and significant for all models. When looking at our preferred model 6 on Table 7 and 8, the magnitude of educational coefficients as well as the relative marginal effects is the largest for male and female who obtain bachelor degree or beyond.. The impact of education is also found to be monotonically rise as women become more educated., for example, our preferred model 6 on Table 8 shows that relative marginal effects of *Year12*, *Post school*, *Degree* are approximately 0.4, 0.8 and 1, respectively. For male, the effect of *Year12* is more pronounced than *Post school* while both of these variables still yield lower marginal effect than *Degree*. Our finding is in consensus with previous studies from Australia like Cai and Kalb (2006), Cai (2010), and Oguzoglu (2007, 2010) where they all find positive effect of education on labor force participation.

Having younger dependent children in a family negatively affects the likelihood of being in the labor market for female sample regardless of the models. In this study, we define younger dependent children to be newborn up until 4 years old. Our preferred model 6 shows the effect of children on female's labor force participation to diminish and become insignificant once children become older (i.e. aged 5 to 24 years old). For male, model 6 indicates that having younger or older dependent children has no effect on male's employment choice. This result is again in agreement with Oguzoglu (2007) that finds significantly negative impact of having younger kids among women but insignificant impact for men. Oguzoglu (2007) also discovers that having older kids has no effect on employment for both men and women. Cai (2010)'s preferred model yields the same finding as ours. That is, having 0-4 years old children has no significant effect on men but significantly negative effect on women's participation in the labor market.

Because income can affect labor force participation in either positive or negative direction, empirical evidence is needed to identify its effect for Australia. All our models except model 4 find that income has positive and significant effect on labor force participation for both male and female, meaning that as income rises people tend to work more holding other variables constant. This result implies that substitution effect dominates income effect. Growing income makes opportunity cost of leisure rises. Thus, people would consume less leisure and work more, leading to higher labor force participation. This finding is different from Cai (2010) and Oguzoglu (2010), in which they find insignificant effect of income on labor force participation in their studies.

Lastly, unemployment rate in major statistical region appears to have diverse effect on labor force participation depending on the models. Models 1 and 4 find significantly negative effect of this variable for both genders, models 2 and 3 discovers significantly negative effect for female and insignificant or slightly positive effect for male, while models 5 and 6 obtain insignificant result for both gender groups. Since our specification tests point out that the most valid model is model 6, it appears that in the context of Australia unemployment rate does not play an important role on individual's labor market decision once other relevant factors have been taken account of.

5. Conclusion

In this work, we employ nine waves of HILDA (i.e. 2001-2009) to investigate the effect of health on labor force participation in Australia. Because of the use of panel data, we additionally examine the dynamic of labor market outcome to find out whether past employment affects current employment. Through six different econometrics models namely pooled binary logit regressions with and without lagged dependent variable, fixed-effect and random-effect binary logit estimations with and without lagged dependent variable, we examine how the estimated results for labor market health effect and labor market state dependence vary by different model specifications and different gender groups. Our preferred model is the fixed-effect dynamic logit model which relies on the availability of a rich panel data for estimation.

Our study finds that worse health status has negative and significant effect on labor force participation. That is, people who experience injury or major illness in the past 12 months (for both male and female) or people who encounter with activity limiting condition that lasts for 6 months or more (male only) are less likely to be in the labor market. The magnitude of the effect of a health shock is about one-fifth and about one-quarter of that of having a university degree for male and female, respectively, and the effect of having an activity limiting condition is about one-eighth to one-sixth of the effect of having a university degree for men and appears to be insignificant for women. Our empirical results also indicate that there is indeed true state dependence in labor force participation in Australia. That is, individuals who experience being in the labor force in the past are more likely to participate in the labor force again in the future even after taking into account of individual heterogeneity. The magnitude of the impact of lagged labor force participation on current participation is found to outweigh many factors, except for age and educational attainment; the effect of state dependence is estimated as around one-half of that of having a university degree for men and similar magnitude as that of having obtained a bachelor degree or beyond for women.

Thus, if the goal of policy makers is to induce people to participate in the labor force, one of the main policy variables that they need to focus on is lagged labor force participation. Any short-term policy that attempts to create incentive for people to be in the labor force will have significant experience-enhancing effect because the dynamic of the Australian labor market is captured by habit formation, and not just factors inherent to the individual. Some examples of relevant governmental policies are job creation schemes to make jobs readily available for people even in time of bad economy, job training schemes and public investment on education at all stages of life that help to augment individual's human capital and make people's knowledge up-to-date with their jobs' requirements, and job search assistance schemes aiming towards those who recently become unemployed in order to make them actively looking for job and preventing them from exiting the labor market altogether. However, in comparison the effect of health shock for both genders or having long term conditions for male is not insignificant; it has about one-third of the effect of state dependence. So any public health campaign aimed at reducing the prevalence of chronic conditions could also have a significant positive effect on the labor market.

Our empirical results and specification tests show that it is critically important to control for individual-specific effect with a fixed-effect specification, which allows for better estimation of true labor market state dependence and labor market effect of health. State dependence could be over-estimated by ten times for men and five times for women when individual effect is not properly controlled in dynamic binary dependent variable models. The results also suggest that health effect on labor market participation can be over-estimated by six times when individual-specific effect is not suitably controlled in dynamic models. Interestingly, when static model with individual effect is used, the health effect estimates are rather similar to that from our preferred results. However, the static models do not allow for estimation of labor market state dependence.

6. References

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Table 1: Definition of variables

Variables	Description
Labor force participation (y)	1 if a person is in the labor force during the past 7 days, otherwise 0
Age1554 (omitted)	1 if age 15 to 54 years old, otherwise 0
Age5559	1 if age 55 to 59 years old, otherwise 0
Age6064	1 if age 60 to 64 years old, otherwise 0
Age65above	1 if age 65 years old or above, otherwise 0
Married	1 if married, otherwise 0
Less than year 12 (omitted)	1 if less than 12 years of education, otherwise 0
Year 12	1 if complete 12 years of education, otherwise 0
Post school	1 if more than 12 years of education but less than bachelor degree, otherwise 0
Degree	1 if bachelor degree or above, otherwise 0
No child (omitted)	1 for no dependent children, otherwise 0
Younger child	1 for having at least one child aged 0 to 4 years old, otherwise 0
Older child	1 for having at least one child aged 5 to 24 years old, otherwise 0
Unemployment rate	Unemployment rate in major statistical region
ln(income)	natural logarithm of household's financial year disposable income
Health shock	1 if there is personal injury or illness that has happened to life over the past 12 months, otherwise 0
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

Table 2: Summary Statistics

	Model 1 and 2				Model 3				Model 4 and 5				Model 6			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Labor force participation (y)	0.746	0.435	0.619	0.486	0.605	0.489	0.593	0.491	0.747	0.435	0.615	0.487	0.719	0.450	0.623	0.485
Age1554 (omitted)	0.709	0.454	0.709	0.454	0.659	0.474	0.817	0.387	0.693	0.461	0.696	0.460	0.620	0.485	0.834	0.372
Age5559	0.075	0.263	0.073	0.260	0.091	0.288	0.072	0.259	0.078	0.268	0.076	0.265	0.132	0.339	0.081	0.273
Age6064	0.064	0.245	0.060	0.238	0.109	0.312	0.059	0.236	0.068	0.251	0.063	0.243	0.131	0.337	0.052	0.223
Age65above	0.152	0.359	0.157	0.364	0.141	0.348	0.051	0.221	0.162	0.368	0.165	0.372	0.116	0.320	0.032	0.177
Married	0.653	0.476	0.611	0.487	0.492	0.500	0.624	0.484	0.671	0.470	0.624	0.484	0.602	0.490	0.658	0.475
Less than year 12 (omitted)	0.298	0.458	0.391	0.488	0.372	0.483	0.368	0.482	0.283	0.450	0.383	0.486	0.343	0.475	0.380	0.485
Year 12	0.138	0.345	0.157	0.364	0.176	0.381	0.185	0.388	0.138	0.345	0.158	0.365	0.148	0.355	0.185	0.389
Post school	0.366	0.482	0.234	0.423	0.289	0.453	0.228	0.420	0.375	0.484	0.237	0.426	0.322	0.467	0.215	0.411
Degree	0.198	0.398	0.218	0.413	0.164	0.370	0.219	0.413	0.203	0.402	0.221	0.415	0.188	0.390	0.220	0.414
No child (omitted)	0.697	0.460	0.654	0.476	0.837	0.369	0.552	0.497	0.685	0.464	0.642	0.479	0.787	0.409	0.539	0.499
Younger child	0.119	0.324	0.133	0.339	0.063	0.244	0.234	0.423	0.124	0.329	0.137	0.344	0.086	0.281	0.243	0.429
Older child	0.237	0.426	0.273	0.446	0.129	0.335	0.309	0.462	0.247	0.431	0.284	0.451	0.166	0.372	0.318	0.466
Unemployment rate	4.928	1.098	4.918	1.090	4.915	1.105	4.860	1.100	4.926	1.098	4.917	1.089	5.176	1.096	5.164	1.084
ln(income)	10.899	0.725	10.815	0.766	10.787	0.771	10.845	0.744	10.888	0.731	10.800	0.772	10.745	0.738	10.767	0.704
Health shock	0.091	0.287	0.082	0.274	0.106	0.307	0.078	0.269	0.090	0.286	0.082	0.274	0.101	0.301	0.077	0.267
Activity limiting condition	0.263	0.440	0.258	0.438	0.311	0.463	0.222	0.416	0.269	0.443	0.262	0.440	0.295	0.456	0.207	0.406
Number of observations (N)	42375		48056		9516		16429		39419		45175		3488		6368	

Table 3: Transition probabilities of labor force participation for 2001-2009

Model 1 and 2 - Male

		$y_{i,t}$		
		Out of LF	In LF	Total
$y_{i,t\text{-}1}$	Out of LF	84.90%	15.10%	100%
	In LF	5.08%	94.92%	100%
	Total	25.29%	74.71%	100%

Model 1 and 2 - Female

		$y_{i,t}$		
		Out of LF	In LF	Total
$y_{i,t\text{-}1}$	Out of LF	85.13%	14.87%	100%
	In LF	8.85%	91.15%	100%
	Total	38.01%	61.99%	100%

Model 3 - Male

		$y_{i,t}$		
		Out of LF	In LF	Total
$y_{i,t\text{-}1}$	Out of LF	58.26%	41.74%	100%
	In LF	26.46%	73.54%	100%
	Total	38.85%	61.15%	100%

Model 3 - Female

		$y_{i,t}$		
		Out of LF	In LF	Total
$y_{i,t\text{-}1}$	Out of LF	60.68%	39.32%	100%
	In LF	25.70%	74.30%	100%
	Total	39.86%	60.14%	100%

Model 4 and 5 - Male

		$y_{i,t}$		
		Out of LF	In LF	Total
$y_{i,t\text{-}1}$	Out of LF	86.44%	13.56%	100%
	In LF	4.80%	95.20%	100%
	Total	25.35%	74.65%	100%

Model 4 and 5 - Female

		$y_{i,t}$		
		Out of LF	In LF	Total
$y_{i,t\text{-}1}$	Out of LF	85.95%	14.05%	100%
	In LF	8.64%	91.36%	100%
	Total	38.41%	61.59%	100%

Model 6 - Male

		$y_{i,t}$		
		Out of LF	In LF	Total
$y_{i,t\text{-}1}$	Out of LF	60.99%	39.01%	100%
	In LF	14.82%	85.18%	100%
	Total	26.01%	73.99%	100%

Model 6 - Female

		$y_{i,t}$		
		Out of LF	In LF	Total
$y_{i,t\text{-}1}$	Out of LF	71.96%	28.04%	100%
	In LF	17.21%	82.79%	100%
	Total	36.93%	63.07%	100%

Table 4: Cross-tabulations of labor force participation and health variables, overall sample

Labor force participation and Health shock - Male

		Injury shock		
		0	1	Total
$y_{i,t} = 0$	Out of LF	9,160	1,611	10,771
$y_{i,t} = 1$	In LF	29,378	2,226	31,604
	Total	38,538	3,837	42,375

Labor force participation and Health shock - Female

		Injury shock		
		0	1	Total
$y_{i,t} = 0$	Out of LF	16,218	2,102	18,320
$y_{i,t} = 1$	In LF	27,897	1,839	29,736
	Total	44,115	3,941	48,056

Labor force participation and Activity limiting condition - Male

		Activity limiting condition		
		0	1	Total
$y_{i,t} = 0$	Out of LF	4,974	5,797	10,771
$y_{i,t} = 1$	In LF	26,276	5,328	31,604
	Total	31,250	11,125	42,375

Labor force participation and Activity limiting condition - Female

		Activity limiting condition		
		0	1	Total
$y_{i,t} = 0$	Out of LF	10,698	7,622	18,320
$y_{i,t} = 1$	In LF	24,962	4,774	29,736
	Total	35,660	12,396	48,056

Table 5: Coefficient Estimates for Model 1 - 3

	Model 1: no lagged, pooled			Model 2: no lagged, RE			Model 3: no lagged, FE		
	Male	Female	Pooled	Male	Female	Pooled	Male	Female	Pooled
Male			0.835			1.59			NA
			[0.020]***			[0.064]***			
Age5559	-0.911	-0.901	-0.862	-1.79	-1.61	-1.668	-1.325	-1.238	-1.261
	[0.054]***	[0.042]***	[0.033]***	[0.127]***	[0.097]***	[0.078]***	[0.187]***	[0.142]***	[0.113]***
Age6064	-1.982	-1.889	-1.902	-4.097	-3.584	-3.821	-3.224	-2.797	-2.965
	[0.053]***	[0.046]***	[0.034]***	[0.146]***	[0.121]***	[0.093]***	[0.256]***	[0.199]***	[0.156]***
Age65above	-3.946	-3.807	-3.853	-7.552	-6.784	-7.196	-5.716	-4.853	-5.286
	[0.051]***	[0.051]***	[0.034]***	[0.165]***	[0.151]***	[0.110]***	[0.319]***	[0.289]***	[0.210]***
Married	0.97	0.026	0.403	1.458	-0.046	0.574	0.458	-0.147	0.071
	[0.041]***	[0.027]	[0.022]***	[0.100]***	[0.067]	[0.055]***	[0.151]***	[0.093]	[0.078]
Year 12	0.707	0.633	0.611	2.261	1.708	1.94	2.385	1.66	1.974
	[0.050]***	[0.035]***	[0.028]***	[0.110]***	[0.088]***	[0.069]***	[0.140]***	[0.117]***	[0.089]***
Post school	0.755	0.874	0.839	2.142	2.032	2.159	1.948	1.854	1.916
	[0.037]***	[0.031]***	[0.023]***	[0.109]***	[0.089]***	[0.069]***	[0.220]***	[0.144]***	[0.120]***
Degree	1.144	1.417	1.324	3.095	2.914	3.054	4.21	2.844	3.395
	[0.050]***	[0.036]***	[0.029]***	[0.152]***	[0.106]***	[0.088]***	[0.303]***	[0.223]***	[0.178]***
Younger child	-0.034	-1.629	-1.2	-0.218	-2.681	-2.043	-0.537	-2.182	-1.886
	[0.070]	[0.033]***	[0.028]***	[0.136]	[0.075]***	[0.062]***	[0.174]***	[0.086]***	[0.074]***
Older child	0.29	-0.169	-0.003	0.466	-0.158	0.105	-0.137	-0.117	-0.082
	[0.051]***	[0.029]***	[0.024]	[0.117]***	[0.066]**	[0.057]*	[0.165]	[0.084]	[0.075]
ln(income)	0.185	0.167	0.143	0.684	0.759	0.715	0.336	0.406	0.38
	[0.007]***	[0.005]***	[0.004]***	[0.043]***	[0.036]***	[0.028]***	[0.051]***	[0.040]***	[0.031]***
Unemployment rate	-0.113	-0.12	-0.126	-0.017	-0.057	-0.042	0.05	-0.047	-0.014
	[0.013]***	[0.010]***	[0.008]***	[0.026]	[0.020]***	[0.016]***	[0.030]*	[0.022]**	[0.018]
Health shock	-0.332	-0.299	-0.31	-0.722	-0.449	-0.563	-0.68	-0.369	-0.498
	[0.049]***	[0.044]***	[0.032]***	[0.084]***	[0.074]***	[0.056]***	[0.091]***	[0.079]***	[0.060]***
Activity limiting	-1.346	-0.927	-1.067	-1.367	-0.749	-0.983	-0.669	-0.307	-0.45
condition	[0.033]***	[0.028]***	[0.021]***	[0.071]***	[0.058]***	[0.045]***	[0.084]***	[0.067]***	[0.052]***
test *H_0 : Pooling*	LR chi2(12) = 2114.33***			LR chi2(14) = 830.05***			LR chi2(13) = 159.44***		

Notes: (1) Standard errors are in parentheses, (2) *** significant at 1%, (3) ** significant at 5%, (4) * significant at 10%,

Table 6: Coefficient Estimates for Model 4 - 5

	Model 4: w/ lagged, pooled			Model 5: w/ lagged, RE		
	Male	Female	Pooled	Male	Female	Pooled
Lagged Labor Force	3.691	3.355	3.554	3.311	2.833	3.107
Participation (y_{it-1})	[0.044]***	[0.033]***	[0.026]***	[0.060]***	[0.048]***	[0.037]***
Male			0.588			0.793
			[0.027]***			[0.037]***
Age5559	-0.889	-0.801	-0.802	-0.958	-0.891	-0.862
	[0.075]***	[0.057]***	[0.045]***	[0.090]***	[0.073]***	[0.056]***
Age6064	-1.721	-1.48	-1.548	-1.989	-1.871	-1.855
	[0.072]***	[0.061]***	[0.046]***	[0.096]***	[0.088]***	[0.064]***
Age65above	-2.789	-2.652	-2.668	-3.426	-3.472	-3.369
	[0.065]***	[0.061]***	[0.043]***	[0.118]***	[0.109]***	[0.078]***
Married	0.498	-0.151	0.084	0.603	-0.238	0.093
	[0.055]***	[0.036]***	[0.030]***	[0.070]***	[0.049]***	[0.039]**
Year 12	0.37	0.359	0.329	0.681	0.659	0.617
	[0.067]***	[0.047]***	[0.038]***	[0.084]***	[0.065]***	[0.051]***
Post school	0.327	0.482	0.43	0.612	0.836	0.743
	[0.051]***	[0.041]***	[0.032]***	[0.069]***	[0.060]***	[0.045]***
Degree	0.598	0.829	0.745	0.933	1.243	1.1
	[0.066]***	[0.046]***	[0.038]***	[0.091]***	[0.070]***	[0.054]***
Younger child	-0.225	-1.155	-0.904	-0.188	-1.515	-1.098
	[0.088]**	[0.044]***	[0.038]***	[0.102]*	[0.061]***	[0.048]***
Older child	0.194	-0.03	0.064	0.275	-0.044	0.105
	[0.066]***	[0.038]	[0.032]**	[0.081]***	[0.049]	[0.040]***
ln(income)	0.002	-0.011	-0.031	0.413	0.469	0.43
	[0.009]	[0.007]	[0.006]***	[0.034]***	[0.030]***	[0.022]***
Unemployment rate	-0.101	-0.107	-0.112	-0.004	-0.022	-0.018
	[0.018]***	[0.014]***	[0.011]***	[0.022]	[0.018]	[0.014]
Health shock	-0.59	-0.402	-0.477	-0.639	-0.447	-0.524
	[0.067]***	[0.059]***	[0.044]***	[0.075]***	[0.068]***	[0.050]***
Activity limiting	-1.06	-0.668	-0.803	-1.079	-0.648	-0.8
condition	[0.045]***	[0.038]***	[0.029]***	[0.055]***	[0.047]***	[0.035]***
Likelihood ratio test H_0: Pooling	LR chi2(13) = 568.75***			LR chi2(15) = 583.44***		

Notes: (1) Standard errors are in parentheses, (2) *** significant at 1%, (3) ** significant at 5%, (4) * significant at 10%,

Table 7: Coefficient Estimates for Model 6

	Model 6: w/ lagged, FE					
	c = 8			c = 16		
	Male	Female	Pooled	Male	Female	Pooled
Lagged Labor	1.539	1.641	1.61	1.569	1.679	1.654
Participation (y_{it-1})	[0.126]***	[0.090]***	[0.073]***	[0.151]***	[0.105]***	[0.082]***
Male			NA			NA
Age5559	-0.974	-0.828	-0.879	-0.959	-0.766	-0.841
	[0.442]**	[0.332]**	[0.267]***	[0.506]*	[0.367]**	[0.284]***
Age6064	-2.08	-1.596	-1.792	-2.095	-1.501	-1.734
	[0.639]***	[0.486]***	[0.391]***	[0.729]***	[0.527]***	[0.408]***
Age65above	-3.084	-2.601	-2.85	-3.103	-2.567	-2.806
	[0.788]***	[0.711]***	[0.522]***	[0.901]***	[0.769]***	[0.544]***
Married	0.253	-0.194	-0.035	0.312	-0.213	-0.028
	[0.344]	[0.233]	[0.193]	[0.391]	[0.251]	[0.201]
Year 12	2.007	0.691	1.223	1.876	0.669	1.145
	[0.414]***	[0.302]**	[0.240]***	[0.476]***	[0.338]**	[0.260]***
Post school	1.24	1.353	1.379	1.185	1.274	1.298
	[0.547]**	[0.381]***	[0.314]***	[0.628]*	[0.405]***	[0.325]***
Degree	2.762	1.697	2.093	2.692	1.57	2.003
	[0.707]***	[0.581]***	[0.453]***	[0.795]***	[0.611]**	[0.465]***
Younger child	-0.251	-1.462	-1.247	-0.227	-1.452	-1.22
	[0.393]	[0.189]***	[0.166]***	[0.448]	[0.215]***	[0.182]***
Older child	-0.22	-0.193	-0.166	-0.2	-0.183	-0.15
	[0.386]	[0.195]	[0.174]	[0.437]	[0.215]	[0.185]
ln(income)	0.238	0.259	0.255	0.235	0.276	0.261
	[0.132]*	[0.109]**	[0.084]***	[0.150]	[0.121]**	[0.090]***
Unemployment rate	0.071	0.027	0.036	0.05	0.048	0.044
	[0.086]	[0.061]	[0.050]	[0.098]	[0.068]	[0.053]
Health shock	-0.569	-0.434	-0.465	-0.605	-0.424	-0.483
	[0.206]***	[0.180]**	[0.135]***	[0.244]**	[0.204]**	[0.148]***
Activity limiting	-0.384	-0.117	-0.223	-0.402	-0.151	-0.256
condition	[0.191]**	[0.150]	[0.117]*	[0.226]*	[0.169]	[0.129]**
Likelihood ratio test H_0: Pooling	LR chi2(15) = 59.05***			LR chi2(15) = 191.98		

Notes: (1) Standard errors are in parentheses, (2) *** significant at 1%, (3) ** significant at 5%, (4) * significant at 10%,

Table 8: Hausman specification tests

Panel (A): Hausman test for model 5 (i.e. dynamic RE model) vs model 6 (i.e. dynamic FE model)

	Male		Female	
	c = 8	c = 16	c = 8	c = 16
Model under H0	Model 5	Model 5	Model 5	Model 5
Model under H1	Model 6	Model 6	Model 6	Model 6
Df	14	14	14	14
Chi2 test stat	289.26	182.4	271.9	175.57

Panel (B): Hausman specification test for model 4 (i.e. pooled regression with lagged) vs model 6 (i.e. dynamic FE model)

	Male		Female	
	c = 8	c = 16	c = 8	c = 16
Model under H0	Model 4	Model 4	Model 4	Model 4
Model under H1	Model 6	Model 6	Model 6	Model 6
Df	14	14	14	14
Chi2 test stat	365.86	239.28	452.36	313.63

Note: All Chi-square test statistics on Panel (A) and (B) above are statistically significant at 1% level.

Table 9: Relative marginal effect between each explanatory variable and "Degree" on the probability of being in the labor force

	Model 1: no lagged, pooled		Model 2: no lagged, RE		Model 3: no lagged, FE		Model 4: w/ lagged, pooled		Model 5: w/ lagged, RE	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Lagged LFP							6.17	4.05	3.55	2.28
Age5559	-0.80	-0.64	-0.58	-0.55	-0.31	-0.44	-1.49	-0.97	-1.03	-0.72
Age6064	-1.73	-1.33	-1.32	-1.23	-0.77	-0.98	-2.88	-1.79	-2.13	-1.51
Age65above	-3.45	-2.69	-2.44	-2.33	-1.36	-1.71	-4.66	-3.20	-3.67	-2.79
Married	0.85	0.02	0.47	-0.02	0.11	-0.05	0.83	-0.18	0.65	-0.19
Year 12	0.62	0.45	0.73	0.59	0.57	0.58	0.62	0.43	0.73	0.53
Post school	0.66	0.62	0.69	0.70	0.46	0.65	0.55	0.58	0.66	0.67
Degree	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Younger child	-0.03	-1.15	-0.07	-0.92	-0.13	-0.77	-0.38	-1.39	-0.20	-1.22
Older child	0.25	-0.12	0.15	-0.05	-0.03	-0.04	0.32	-0.04	0.29	-0.04
ln(income)	0.16	0.12	0.22	0.26	0.08	0.14	0.00	-0.01	0.44	0.38
Unemployment rate	-0.10	-0.08	-0.01	-0.02	0.01	-0.02	-0.17	-0.13	0.00	-0.02
Health shock	-0.29	-0.21	-0.23	-0.15	-0.16	-0.13	-0.99	-0.48	-0.68	-0.36
Activity limiting condition	-1.18	-0.65	-0.44	-0.26	-0.16	-0.11	-1.77	-0.81	-1.16	-0.52

	Model 6: w/ lagged, FE			
	c = 8		c = 16	
	Male	Female	Male	Female
Lagged LFP	0.56	0.97	0.58	1.07
Age5559	-0.35	-0.49	-0.36	-0.49
Age6064	-0.75	-0.94	-0.78	-0.96
Age65above	-1.12	-1.53	-1.15	-1.64
Married	0.09	-0.11	0.12	-0.14
Year 12	0.73	0.41	0.70	0.43
Post school	0.45	0.80	0.44	0.81
Degree	1.00	1.00	1.00	1.00
Younger child	-0.09	-0.86	-0.08	-0.92
Older child	-0.08	-0.11	-0.07	-0.12
ln(income)	0.09	0.15	0.09	0.18
Unemployment rate	0.03	0.02	0.02	0.03
Health shock	-0.21	-0.26	-0.22	-0.27
Activity limiting condition	-0.14	-0.07	-0.15	-0.10

Appendix A: 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 and Kyriazidou (2000), Chintagunta et al. (2001), and Hsiao (2003) for details) and later give the explanation of how we apply this method to our nine 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 labor 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 labor 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 get

$$\Pr(A \mid AUB) = \frac{1}{1 + e^{\beta'(x_{i1} - x_{i2}) + \gamma(y_{i0} - y_{i3})}} \quad \text{(A.1)},$$

and

$$\Pr(B \mid AUB) = \frac{e^{\beta'(x_{i1} - x_{i2}) + \gamma(y_{i0} - y_{i3})}}{1 + e^{\beta'(x_{i1} - x_{i2}) + \gamma(y_{i0} - y_{i3})}} \quad \text{(A.2)},$$

which has a binary logit form and no longer depends on incidental parameter α_i. We can use (A.1) and (A.2) to form 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) proposes using kernel density function as a weight for each observation and maximizes the following weighted likelihood function to get the estimated β and γ

$$\sum_{i=1}^{n} 1\{y_{i1}+y_{i2}=1\} K\left(\frac{x_{i2}-x_{i3}}{\sigma_n}\right) \ln\left(\frac{[e^{\beta'(x_{i1}-x_{i2})+\gamma(y_{i0}-y_{i3})}]^{y_{i1}}}{1+e^{\beta'(x_{i1}-x_{i2})+\gamma(y_{i0}-y_{i3})}}\right). \tag{A.3}$$

It should be noted that $1\{y_{i1}+y_{i2}=1\}$ is an indicator function for switching labor 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 labor force participation in any two of the middle T-1 periods. Honore and Kyriazidou (2000) extend the weight likelihood function (A.3) to accommodate longer panel as follows

$$\sum_{i=1}^{n} \sum_{1\le t<s\le T-1} 1\{y_{it}+y_{is}=1\} K\left(\frac{x_{it+1}-x_{is+1}}{\sigma_n}\right) \ln\left(\frac{[e^{\beta'(x_{it}-x_{is})+\gamma(y_{it-1}-y_{is+1})+\gamma(y_{it+1}-y_{is-1})1\{s-t>1\}}]^{y_{it}}}{1+e^{\beta'(x_{it}-x_{is})+\gamma(y_{it-1}-y_{is+1})+\gamma(y_{it+1}-y_{is-1})1\{s-t>1\}}}\right) \tag{A.4}$$

Our data is an unbalanced panel consisting up to nine years. We can write a sequence of labor force participation for each individual i as $\{y_{i0}, y_{i1}, y_{i2}, y_{i3}, y_{i4}, y_{i5}, y_{i6}, y_{i7}, y_{i8}\}$ for period 0 to period 8. Since the main identification strategy for this model is that there must be some switching of labor force participation in any two middle periods, there are twenty-one possible switching that can take place with nine years of data:

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

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

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

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

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

$$1\{y_{i1}+y_{i7}=1\}K\left(\frac{x_{i2}-x_{i8}}{\sigma_n}\right)\ln\left(\frac{[e^{\beta^{'}(x_{i1}-x_{i7})+\gamma(y_{i0}-y_{i8})+\gamma(y_{i2}-y_{i6})}]^{y_{i1}}}{1+e^{\beta^{'}(x_{i1}-x_{i7})+\gamma(y_{i0}-y_{i8})+\gamma(y_{i2}-y_{i6})}}\right)+$$

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

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

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

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

$$1\{y_{i2}+y_{i7}=1\}K\left(\frac{x_{i3}-x_{i8}}{\sigma_n}\right)\ln\left(\frac{[e^{\beta^{'}(x_{i2}-x_{i7})+\gamma(y_{i1}-y_{i8})+\gamma(y_{i3}-y_{i6})}]^{y_{i2}}}{1+e^{\beta^{'}(x_{i2}-x_{i7})+\gamma(y_{i1}-y_{i8})+\gamma(y_{i3}-y_{i6})}}\right)+$$

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

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

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

$$1\{y_{i3}+y_{i7}=1\}K\left(\frac{x_{i4}-x_{i8}}{\sigma_n}\right)\ln\left(\frac{[e^{\beta'(x_{i3}-x_{i7})+\gamma(y_{i2}-y_{i8})+\gamma(y_{i4}-y_{i6})}]^{y_{i3}}}{1+e^{\beta'(x_{i3}-x_{i7})+\gamma(y_{i2}-y_{i8})+\gamma(y_{i4}-y_{i6})}}\right)+$$

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

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

$$1\{y_{i4}+y_{i7}=1\}K\left(\frac{x_{i5}-x_{i8}}{\sigma_n}\right)\ln\left(\frac{[e^{\beta'(x_{i4}-x_{i7})+\gamma(y_{i3}-y_{i8})+\gamma(y_{i5}-y_{i6})}]^{y_{i4}}}{1+e^{\beta'(x_{i4}-x_{i7})+\gamma(y_{i3}-y_{i8})+\gamma(y_{i5}-y_{i6})}}\right)+$$

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

$$1\{y_{i5}+y_{i7}=1\}K\left(\frac{x_{i6}-x_{i8}}{\sigma_n}\right)\ln\left(\frac{[e^{\beta'(x_{i5}-x_{i7})+\gamma(y_{i4}-y_{i8})}]^{y_{i5}}}{1+e^{\beta'(x_{i5}-x_{i7})+\gamma(y_{i4}-y_{i8})}}\right)+$$

$$1\{y_{i6}+y_{i7}=1\}K\left(\frac{x_{i7}-x_{i8}}{\sigma_n}\right)\ln\left(\frac{[e^{\beta'(x_{i6}-x_{i7})+\gamma(y_{i5}-y_{i8})}]^{y_{i6}}}{1+e^{\beta'(x_{i6}-x_{i7})+\gamma(y_{i5}-y_{i8})}}\right)$$

With the constructed log-likelihood function, we can maximize it with respect to β and γ following the suggestion of Honore and Kyrizidou (2000) and Chintagunta et al. (2001) by taking the kernel function to be a standard normal density function[3]. The bandwidth σ_n is a normal

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

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 labor 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 those of model 1 - 5, which may lead to some loss of precision.

Appendix B: Computation of relative marginal effect between x_k and x_j for Model 6

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

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

$$\Pr(y_{it} = 1 \mid x_{it}, y_{it-1}, \alpha_i) = P = \frac{e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}}{1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}}$$

$$\frac{\partial P}{\partial x_{kit}} = \frac{\beta_k e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right) - e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\left(\beta_k e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)^2}$$

$$\frac{\partial P}{\partial x_{kit}} = \frac{\beta_k e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\left[1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i} - e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right]}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)^2}$$

$$\frac{\partial P}{\partial x_{kit}} = \beta_k \frac{e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)} \frac{1}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)}$$

Similarly,

$$\frac{\partial P}{\partial x_{jit}} = \beta_j \frac{e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)} \frac{1}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)}$$

Thus, relative marginal effect is

$$\frac{\frac{\partial P}{\partial x_{kit}}}{\frac{\partial P}{\partial x_{jit}}} = \frac{\beta_k \frac{e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)} \frac{1}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)}}{\beta_j \frac{e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)} \frac{1}{\left(1 + e^{\gamma y_{it-1} + \beta' x_{it} + \alpha_i}\right)}} = \frac{\beta_k}{\beta_j}$$

As one can see, the relative marginal effect does not depend on the time-invariant individual specific-effect, α_i.