The Relationship between Health and Labour Force Participation: Evidence from a Panel Data Simultaneous Equation Model

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Abstract

A concern when estimating the effect of health on labour supply is that health might be endogenous, and in particular that people might use poor health to justify non-participation. This would result in the effect of health being overestimated if health were treated as exogenous. The paper employs a simultaneous equation model to explore the relationship between health and labour force status, allowing for the endogeneity of health. In addition, the paper takes advantage of panel data to control for unobserved heterogeneity so that more efficient estimation results can be obtained than using cross-sectional data. The results confirm the finding in the literature that health has a positive and significant effect on labour force participation for both males and females. As for the reverse effect, it is found that labour force participation has a negative effect on male health but a positive effect on female health, implying that the justification hypothesis is rejected for males but not for females. The exogeneity hypothesis on the health variable is rejected for both samples based on a joint test.

1. Introduction

Health is often regarded as an important factor in individuals' labour supply decision, not only because health is a form of human capital, valued by both employers and employees (Becker, 1964; Grossman, 1972), but also because individuals' preferences between work and leisure may change following a health shock. For example, a deterioration of health may lead a person to value leisure more. In addition, changes in health may change the time horizon over which labour supply decisions are made because life expectancy is determined by health (Chiricos, 1993). As a result, the impact of health on labour supply has been under extensive examination particularly in industrialized countries (see, for example, Currie and Madrian (1999) for an extensive review of the US literature).

However, a common concern in the literature is that health may be endogenous to labour supply. For example, employment or long working hours may have adverse impacts on an individual's health, or individuals may use health conditions to justify their labour force status. If this is the case, and health is treated as an exogenous variable in labour supply models, the estimated effect of health is likely to be biased. In addition, the endogeneity of health to labour supply may result from both simultaneity and unobserved heterogeneity, suggesting a simultaneous equation model is required to obtain efficient estimates of the impact of health on labour supply. There are a few published studies that employ simultaneous equation models to examine the relationship between health and labour supply, but they use cross-sectional data (e.g., Stern, 1989; Cai and Kalb, 2006).[1] Two studies that use panel data to estimate the effect of health on labour force status are Sickles and Taubman (1986) and Cai and Kalb (2005), who use a recursive model in which health is allowed to affect labour force status, but the reverse effect of labour force status on health is assumed to be zero.

This paper contributes to the literature by estimating a panel data simultaneous equation model to examine the relationship between health and labour force status and

[1] When the self-reported health variable takes a polychotomous form, Stern (1989) uses the two-stage method to estimate the simultaneous equation model. Only when the health variable takes a dichotomous form, Stern estimates the model using the full-information maximum likelihood (FIML) method. In Cai and Kalb (2006) study, the health variable takes the polychotomous form and they use the FIML method to estimate the model, while two-stage estimation is carried out for comparison. When using the two-stage estimation method, a true test for exogeneity of health cannot to be conducted.

test the hypothesis of exogeneity of health. Using a simultaneous equation model, the reverse effect of labour force status on health can be examined. The use of panel data allows unobserved heterogeneity to be better controlled for than could be achieved using cross-sectional data.

The paper is organized as follows: Section 2 discusses the endogeneity issues of the health variable to labour supply. Section 3 describes the statistical model and estimation strategies. Section 4 describes the data and model specifications. Section 5 presents the estimation results and Section 6 concludes.

2. Endogeneity of health

Although health is partly predetermined as an endowment at birth, health is not exogenous to individuals' labour market behaviour, particularly over one's lifetime. Like other forms of human capital, people can make investments into health to improve or reduce depreciation of health capital.[2] Because this investment requires resources, such as time for recreation or exercise and income for health care services, health is endogenous in the sense that people have to make choices in health capital production jointly with labour supply and other consumption (Grossman, 1972). In addition, labour market activity may have a direct impact on individuals' health. For example, boredom or general lack of activity in non-participation may lead to a deterioration of health (Stern, 1989; Sickles and Taubman, 1986). Alternatively, it is possible that stress associated with employment and work pressure leads to health deterioration; or, some jobs may have bad working conditions and be detrimental to health. These arguments suggest that labour force status could also affect health, although the direction of the impact can only be determined empirically. The potential reverse effect of current labour force status on health introduces a simultaneity bias to the effect of health if health is treated as exogenous in labour supply models.

The endogeneity of health described above could be estimated if we could measure health accurately. However, often an individual's health cannot be measured precisely, and in most of the survey data only self-reported health measures are available. Although there is a large literature showing that self-reported health is a strong and independent predicator of mortality and morbidity (Idler and Kasl, 1995; McCallum et

[2] Unlike education, however, health as a form of human capital is subject to adverse shocks, such as the occurrence of illness or an accident, which may reduce the health stock dramatically. Health investments can be used to improve health or to prevent adverse health shocks.

al., 1994; Connelly et al., 1989; Okun et al., 1984; Lundberg and Manderbacka, 1996), there remains a concern over the use of self-reported health measures in labour supply models. This is because self-reported health may introduce another source of endogeneity resulting from the possibility that people out of the labour force report poor health to justify their non-participation (Anderson and Burkhauser, 1984, 1985; Stern 1989; Bound, 1991; Dwyer and Mitchell, 1999; Kreider, 1999). The consequence of this justification is that when self-reported health is used in labour supply models, the health variable becomes endogenous and the effect of health on labour force participation can be overestimated. We refer to the endogeneity associated with self-reported health as justification endogeneity and the endogeneity associated with (unmeasurable) true health as true endogeneity.[3]

Both the justification endogeneity and true endogeneity result from simultaneity of health and labour force status. However, another source of endogeneity of health is possible, which results from unobserved heterogeneity. For example, there may exist some unobserved factors, such as preferences, that have effects on both health and labour supply. Therefore, we need to allow for the correlation between the health and labour supply equations in order to obtain efficient estimation results. Consequently, a true test of the exogeneity hypothesis on the health variable requires both the coefficient on the labour force status variable and the correlation between the two equations to be examined.

To account for the justification endogeneity associated with self-reported health, some authors have used more objectively measured health such as subsequent mortality (Parsons, 1982; Anderson and Burkhauser, 1984, 1985) or specific health conditions to instrument self-reported health (Bound, 1991; Bound *et al.*, 1999; Dwyer and Mitchell, 1999; Campolieti, 2002). However, an objective measure of health, even if available in a dataset, is not free of problems (Bound, 1991)[4]. The instrumental variable approach does not itself solve the problem of endogenous self-reported health (Bound, 1991; Kreider, 1999).

Evidence on the justification hypothesis is not conclusive so far in the literature.

[3] Self-reported health may also suffer from measurement errors (Bound, 1991), but it is the justification endogeneity that raises the major concern in the literature.
[4] Since mortality is a rare event at the individual level, as a health measure it is often defined at the population level to examine its effect on macroeconomic outcomes, such as economic growth.

Studies that use objective health measures such as subsequent mortality tend to find a smaller effect of health than that estimated from using subjective health measures (Parsons, 1982; Anderson and Burkhauser, 1984, 1985), suggesting that the justification endogeneity may exist. However, Bound (1991) shows that the smaller effect could be due to measurement error in objective health measures in the sense that these measures are not perfectly correlated with those aspects of health that affect labour supply. Using simultaneous equation models, Stern (1989) and Cai and Kalb (2006) do not find strong evidence supporting the justification hypothesis, neither do Dwyer and Mitchell (1999) find evidence for the hypothesis using an instrumental variable approach.

There is a small but growing literature that directly evaluates reporting biases of self-reported health measures; the evidence is again mixed. For example, while Bazzoli (1985) shows that the importance of self-reported health may be overstated in early-retirement studies, Boaz and Muller (1990) find that the early retirees do not exaggerate their health problems to justify their retirement status. By benchmarking self-reported health of workers, Kreider (1999) finds that non-workers overstate their health problems. However, the underlying assumption in Kreider's study that workers provide an unbiased report on their health is questionable (Myers, 1982; Stern, 1989). For example, if subjective measures of health reflect leisure preferences, workers may down-play their health problems because they enjoy working (Dwyer and Mitchell, 1999; Benitez-Silva *et al.*, 2004). Benitez-Silva *et al.* (2004) use the definition of disability by the US Social Security Administration (SSA) as a social standard to assess potential biases of self-reported disability status in the Health and Retirement Survey (HRS). They find no evidence of reporting biases in the sense that disability benefit applicants in the HRS do not exaggerate their health problems, compared with the standards used by the SSA.

3. Statistical model and estimation strategy

3.1 The model

To explore the relationship between self-reported health and labour force status and test for the exogeneity of the health variable, the current paper employs a simultaneous equation model. The modelling strategies draw on Stern (1989), but extend Stern's model to a panel data context to better control for unobserved heterogeneity. The first equation describes the determination of health,

(1) $h_t^{**} = \gamma_1 l_t^* + x_{h,t}\beta_h + \varepsilon_{1,t}$,

where h_t^{**} is latent true health at time *t*, which depends on the latent value of labour force status at time *t* l_t^* , and a set of exogenous variables $x_{h,t}$; $\varepsilon_{1,t}$ is a disturbance term. The latent value of labour force status enters equation (1) because of the endogeneity of true health as discussed earlier. The justification endogeneity has not been accounted for in equation (1) because this equation is about the determination of true health, not self-reported health.

The labour force participation equation is specified as

(2) $l_t^* = \gamma_2 h_t^{**} + x_{L,t}\varphi_L + \varepsilon_{2,t}$,

where the latent value of labour force status l_t^* is determined by true health h_t^{**}, and a set of exogenous variables $x_{L,t}$; $\varepsilon_{2,t}$ is a disturbance term. $x_{h,t}$ and $x_{L,t}$ may have some variables in common.

Because true health is not observed, another equation is introduced to relate true health and observed self-reported health,

(3) $h_t^* = h_t^{**} + \alpha l_t^* + \varepsilon_{3,t}$,

where h_t^* is the latent measure of self-reported health status, which depends on true health and the latent value of labour force status. The dependence of self-reported health on labour force status reflects the justification endogeneity of self-reported health, which is made explicit in equation (3). A positive α implies that those in the labour force overstate their health and those out of the labour force understate their health.

By taking advantage of panel data, each of the three disturbance terms, $\varepsilon_{1,t}$, $\varepsilon_{2,t}$ and $\varepsilon_{3,t}$, can be decomposed into two independent parts: a time-invariant component and a time-variant component,

$\varepsilon_{m,t} = \mu_m + \nu_{m,t} \quad for\ m = 1,2,3.$

Substituting equation (1) into equation (3) yields:

(4) $h_t^* = \theta_1 l_t^* + x_{h,t}\beta_h + \varepsilon_{h,t}$,

where $\theta_1 = \gamma_1 + \alpha$, $\varepsilon_{h,t} = \mu_h + \nu_{h,t}$, $\mu_h = \mu_1 + \mu_3$ and $\nu_{h,t} = \nu_{1,t} + \nu_{3,t}$. In the model, only θ_1 can be identified. γ_1 and α cannot be separately estimated because there are no true health measures in the data. This means that the two types of simultaneity endogeneity (i.e., true endogeneity and justification endogeneity) cannot be separated and only the overall simultaneity endogeneity can be empirically examined. However, the sign of θ_1 can provide useful information in terms of which of the two types of simultaneity endogeneity dominates. For example, if θ_1 is estimated to have a negative sign, γ_1 must be negative, given that the justification hypothesis predicts a positive sign for α. This means that the true endogeneity must be negative and dominates the justification endogeneity. If θ_1 is positive, there are two possible explanations: the true endogeneity has a positive effect (i.e., γ_1 >0), or the true endogeneity has a negative effect but is dominated by the justification endogeneity.

It follows from (3) that $h_t^{**} = h_t^* - \alpha l_t^* - \varepsilon_{3,t}$. Substituting this equation into (2) gives:

(5) $l_t^* = \theta_2 h_t^* + x_{L,t}\beta_L + \varepsilon_{L,t}$,

where $\theta_2 = \dfrac{\gamma_2}{(1+\gamma_2\alpha)}$, $\beta_L = \dfrac{\varphi_L}{(1+\gamma_2\alpha)}$, $\varepsilon_{L,t} = \mu_L + \nu_{L,t}$, $\mu_L = \dfrac{\mu_2 - \gamma_2\mu_3}{1+\alpha\gamma_2}$ and $\nu_{L,t} = \dfrac{(\nu_{2,t} - \gamma_2\nu_{3,t})}{(1+\gamma_2\alpha)}$. μ_h and μ_L are correlated through μ_3, and ν_h and ν_L are correlated through $\nu_{3,t}$, even if μ_1 and μ_2, and $\nu_{1,t}$ and $\nu_{2,t}$ were assumed to be independent. As a result, $\varepsilon_{h,t}$ and $\varepsilon_{L,t}$ are correlated. Ignoring the correlation would result in inefficient estimation results.

Although μ_m (for $m = h, L$) can be estimated either as a fixed or random effect in a general panel data model framework, the latent nature of the dependent variables in our data necessitates the assumption of a random effect for the time-invariant components (Hsiao, 2003). The covariance between $\varepsilon_{h,t}$ and $\varepsilon_{L,t}$ is specified as,

$$(6)\,\mathrm{cov}(\varepsilon_{i,s},\varepsilon_{j,t}) = \begin{cases} \delta_{i(\mu)} + \delta_{i(\nu)} & if \quad i = j \text{ and } s = t \\ \delta_{i(\mu)} & if \quad i = j \text{ and } s \neq t \\ \delta_{hL(\mu)} + \delta_{hL(\nu)} & if \quad i \neq j \text{ and } s = t \\ \delta_{hL(\mu)} & if \quad i \neq j \text{ and } s \neq t \end{cases} \quad for \quad \begin{matrix} i,j = h,L; \text{ and} \\ s,t = 1,\ldots,T \end{matrix},$$

where $\delta_{i(\mu)}$ and $\delta_{i(\nu)}$ (for $i,j = h,L$) are the variances of the time invariant and time variant error components respectively; $\delta_{hL(\mu)}$ is the covariance of the two time invariant error components; and $\delta_{hL(\nu)}$ is the covariance of the two time variant error components.

The latent dependent variables underlying the model need to be linked to their observed discrete counterparts. For the health variable we use the five levels of self-reported health status as recorded in the data. For labour force status we distinguish two states: labour force participation and non-participation, with participation including unemployment.[5] The corresponding observed values of the endogenous variables are:

$$(7)\ h_t = \begin{cases} 4 \quad (= excellent) & if \quad m_3 < h_t^* < m_4 = +\infty \\ 3 \quad (= very\ good) & if \quad m_2 < h_t^* \leq m_3 \\ 2 \quad (= good) & if \quad m_1 < h_t^* \leq m_2 \\ 1 \quad (= fair) & if \quad m_0 < h_t^* \leq m_1 \\ 0 \quad (= poor) & if \quad -\infty = m_{-1} < h_t^* \leq m_0 \end{cases},$$

where (m_0, m_1, m_2, m_3) are unobserved cut-off points to be estimated, and

$$(8)\ l_t = \begin{cases} 1 \quad (= in \quad labour \quad force) & if \quad l_t^* > 0 \\ 0 \quad (= not \quad in \quad labour \quad force) & if \quad l_t^* \leq 0 \end{cases}.$$

Equations (4), (5), (7) and (8) constitute a simultaneous equation system. The parameters to be estimated are the structural coefficients θ_1 , θ_2 , β_h and β_L in equations (4) and (5), the cut-off points m_0 to m_3 in equations (7), and the variance-covariance parameters in equation (6).

3.2 Estimation method

[5] An alternative division of labour force status is employed versus not employed. Participation versus non-participation is preferred because whether an individual participates or not is a personal choice (that is, a labour supply decision), while whether a persons is employed or not also depends on labour demand. In other words, by using participation versus non-participation, we focus on individuals' labour supply decisions.

Two methods are used to estimate the simultaneous equation system: the two-stage method, which is a partial information maximum likelihood method; and the full-information maximum likelihood (FIML) method. The former provides consistent parameter estimates, while the estimates from the latter method are also efficient. In addition, the FIML method provides estimates for all parameters in the variance-covariance matrix of the two disturbance terms (i.e., in equation (6)), which are required to conduct a true test for the exogeneity of the health variable.

Equations (4) and (5) can be rewritten in their reduced forms,

(9) $h_t^* = \frac{1}{1-\theta_1\theta_2}[x_{h,t}\beta_h + x_{L,t}\beta_l \cdot \theta_1] + \varepsilon_{h,t}^* = x_t\pi_h + \varepsilon_{h,t}^*$,

(10) $l_t^* = \frac{1}{1-\theta_1\theta_2}[x_{h,t}\beta_h \cdot \theta_2 + x_{L,t}\beta_L] + \varepsilon_{L,t}^* = x_t\pi_L + \varepsilon_{L,t}^*$,

where x_t is the set of all exogenous variables in $x_{h,t}$ and $x_{L,t}$; π_h and π_L are the reduced-form coefficient parameters; $\varepsilon_{h,t}^* = \eta_h + \omega_{h,t}$, $\varepsilon_{L,t}^* = \eta_l + \omega_{L,t}$; $\eta_h = \frac{\mu_h + \theta_1\mu_L}{1-\theta_1\theta_2}$ and $\eta_L = \frac{\theta_2\mu_h + \mu_L}{1-\theta_1\theta_2}$ are the time-invariant error components in the reduced form equations; and $\omega_{h,t} = \frac{v_{h,t} + \theta_1 v_{L,t}}{1-\theta_1\theta_2}$ and $\omega_{L,t} = \frac{\theta_2 v_{h,t} + v_{L,t}}{1-\theta_1\theta_2}$ are the time-variant error components.

3.2.1 Two-stage method

In the first stage, equations (9) and (10) (combined with (7) and (8)) can be estimated using random effect ordered probit and random effect probit respectively. The consistent estimates of π_h and π_L, denoted as $\hat{\pi}_h$ and $\hat{\pi}_L$, can be used to construct predicted values of latent health and labour force status,

(11) $\hat{h}_t^* = x_t\hat{\pi}_h$

(12) $\hat{l}_t^* = x_t\hat{\pi}_{L,t}$

The second stage is to replace h_t^* and l_t^* in equations (4) and (5) by $\hat{h}_t^*$ and $\hat{l}_t^*$ and estimate the random effect ordered probit and random effect probit again. The standard errors of the second stage parameter estimates need to be adjusted to reflect the fact that $\hat{\pi}_h$ and $\hat{\pi}_L$ are estimated from the first stage. For the methods of adjustment, see Stern (1989) or Amemiya (1979).

Although the two-stage method produces consistent estimates for the structural equation parameters, it is inefficient because the correlation between the two equations is not taken into account. In addition, a true test for the exogeneity of the health variable cannot be conducted by the two stage method because not all parameters in the variance-covariance matrix of the two disturbance terms are estimated. The FIML method overcomes these deficiencies.

3.2.2 FIML method

Although we illustrate the approach for four waves of data, which are used in the paper, the method can be readily extended to data with more than four waves.

Given the variance-covariance parameters in equation (6), the variance-covariance matrix of the error terms of the structural equations (4) and (5) is,

(13)
$$\begin{aligned}&\operatorname{cov}(\varepsilon_{h,1},\varepsilon_{h,2},\varepsilon_{h,3},\varepsilon_{h,4};\varepsilon_{L,1},\varepsilon_{L,2},\varepsilon_{L,3},\varepsilon_{L,4})\\ &\equiv \Omega = \begin{pmatrix} I_4\delta_{h(\mu)} + e_4e_4'\delta_{h(\nu)} & I_4\delta_{hL(\mu)} + e_4e_4'\delta_{hL(\nu)} \\ I_4\delta_{hL(\mu)} + e_4e_4'\delta_{hL(\nu)} & I_4\delta_{L(\mu)} + e_4e_4'\delta_{L(\nu)} \end{pmatrix},\end{aligned}$$

where I_4 is a four-dimensional identity matrix, and e_4 a column vector with four ones as its elements. Then the covariance matrix of the reduced-form error terms in equations (9) and (10) can be written as,

(14) $$\operatorname{cov}(\varepsilon^*_{h,1},\varepsilon^*_{h,2},\varepsilon^*_{h,3},\varepsilon^*_{h,4};\varepsilon^*_{L,1},\varepsilon^*_{L,2},\varepsilon^*_{L,3},\varepsilon^*_{L,4}) \equiv \Omega^* = A\Omega A',$$

where $A = \dfrac{1}{1-\theta_1\theta_2}\begin{pmatrix} I_4 & I_4\theta_1 \\ I_4\theta_2 & I_4 \end{pmatrix}$.

Using the variance-covariance matrix in equation (14), the system can be estimated with the maximum likelihood estimator (MLE) by assuming a joint density $f(\varepsilon_{h,t},\varepsilon_{L,t})$. To implement the FIML method in this paper, μ_h and μ_L, and $\nu_{h,t}$ and $\nu_{L,t}$ are assumed to follow joint normal distributions with means zero and covariance parameters as specified in equation (6). Both $\delta_{h(\nu)}$ and $\delta_{L(\nu)}$ need to be normalised to one for identification purposes; then $\delta_{hL(\nu)}$ becomes the correlation coefficient between the two time-variant error components. Then

$(\varepsilon_{h,1},\varepsilon_{h,2},\varepsilon_{h,3},\varepsilon_{h,4};\ \varepsilon_{L,1},\varepsilon_{L,2},\varepsilon_{L,3},\varepsilon_{L,4})$ jointly follow a multivariate normal distribution and the probability of a given configuration of health-labour force states can be spelled out using the reduced-form error terms $(\varepsilon^*_{h,1},\varepsilon^*_{h,2},\varepsilon^*_{h,3},\varepsilon^*_{h,4};\ \varepsilon^*_{L,1},\varepsilon^*_{L,2},\varepsilon^*_{L,3},\varepsilon^*_{L,4})$. For example, the probability of observing $(h_1=1,\ h_2=2,\ h_3=3,\ h_4=4;\ l_1=0,\ l_2=1,\ l_3=0,\ l_4=1)$ is

$$\Pr(h_1=1,\ h_2=2,\ h_3=3,\ h_4=2;\ l_1=0,\ l_2=1,\ l_3=0,\ l_4=1)$$
$$=\int_{\mathrm{m}_0-x_1\pi_h}^{\mathrm{m}_1-x_1\pi_h}\int_{\mathrm{m}_1-x_2\pi_h}^{\mathrm{m}_2-x_2\pi_h}\int_{\mathrm{m}_2-x_3\pi_h}^{\mathrm{m}_3-x_3\pi_h}\int_{\mathrm{m}_3-x_3\pi_h}^{\mathrm{m}_4-x_3\pi_h}\int_{-\infty}^{-x_1\pi_L}\int_{-x_2\pi_L}^{+\infty}\int_{-\infty}^{-x_3\pi_L}\int_{-x_2\pi_L}^{+\infty}$$
$$\phi(\varepsilon^*_{h,1},\varepsilon^*_{h,2},\varepsilon^*_{h,3},\varepsilon^*_{h,4};\ \varepsilon^*_{L,1},\varepsilon^*_{L,2},\varepsilon^*_{L,3},\varepsilon^*_{L,4}\,|\,\Omega^*)d\varepsilon^*_{L,4}d\varepsilon^*_{L,3}d\varepsilon^*_{L,2}d\varepsilon^*_{L,1}d\varepsilon^*_{h,4}d\varepsilon^*_{h,3}d\varepsilon^*_{h,2}d\varepsilon^*_{h,1}.$$

An evaluation of eight-dimensional integrals for observing each specific configuration of health-labour force states over the four time periods would be required if the conventional MLE were to be used. This renders such estimation infeasible.[6] However, recently developed simulation-based estimation techniques provide a feasible approach to overcoming this problem (Stern, 1997; Lerman and Manski, 1981).

Simulation-based estimation procedures replace functions (usually integrals), which are computationally intractable when using numerical or analytical methods, with random approximations for these functions. There are generally two approaches to simulation-based estimators: direct simulation of the likelihood function or indirect likelihood simulation by using an expression for the score of the likelihood (Hyslop, 1999). In this paper we use the former approach, known as maximum simulated likelihood (MSL).[7] Following Hyslop (1999), let the log-likelihood function for the unknown parameter vector θ, given the random sample of observations $(x_i,\ i=1,\dots,N)$, be

(15) $$L_N(\theta)=\sum_{i=1}^{N}\ln(L(\theta;x_i)).$$

[6] See Hajivassiliou and Ruud (1994, p. 2399-2400) for an example of this.

[7] See Hyslop (1999) and Stern (1997) for a discussion on advantages and disadvantages of different simulation estimators.

Let $\{\xi_i\} = \{\xi_{i1},...,\xi_{iR}\}$ be a sequence of primitive simulators, independent of the parameters of the model and the data.[8] These are used in the following way,

$$(16) \qquad \tilde{L}(\theta; x_i, \xi_i) = (1/R)\sum_{r=1}^{R} \tilde{L}(\theta; x_i, \xi_{ri}),$$

where $\tilde{L}(\theta; x_i, \xi_{ir})$ is an unbiased simulator for $L(\theta; x_i)$ and R is the number of simulation replications. The maximum simulated likelihood estimator for θ is defined as:

$$(17) \qquad \hat{\theta}_{MSL} = \arg\max_{\theta} \sum_{i=1}^{N} \ln(\tilde{L}(\theta; x_i, \xi_i).$$

MSL estimation requires obtaining an unbiased simulator for the likelihood function. The simulator used here is the smooth recursive conditional (SRC) simulator, or Geweke-Hajivassiliou-Keane (GHK) simulator. This simulator is continuous in the parameters, strictly bounded by zero and one, unbiased and consistent in the number of replications R.[9] Although the GHK simulator is unbiased for the likelihood function, the resulting log (simulated) likelihood function will be biased with a finite number of replications due to the nonlinear logarithmic transformation. Therefore, the MSL estimator obtained will be inconsistent for finite R. However, MSL is consistent if the number of replications $R \to \infty$ as the sample size $N \to \infty$, and is asymptotically efficient if $R/\sqrt{N} \to \infty$ (Hajivassiliou and Ruud, 1994).

In addition, we use antithetic acceleration in simulating the random draws. These simulators use the original set of uniform random draws along with their reflections or mirror images to estimate the likelihood function.[10] Antithetic acceleration is a powerful variance reduction method (Geweke, 1988). Hajivassiliou (2000) presents Monte-Carlo evidence suggesting that the antithetically accelerated simulator for multivariate normal rectangle probabilities is superior to the standard GHK simulator. In this paper, 500 replications (that is, 250 random draws plus their reflections) are used in simulating the likelihood function.

[8] The asymptotic theory developed for the simulation-based estimators requires that the same fixed values of the primitive random draws be used at each iteration of the estimation.

[9] For a detailed discussion of the GHK simulator and its properties, see Hajivassiliou (1993), Börsch-Supan and Hajivassiliou (1993), Keane (1993, 1994) or Stern (1997).

[10] If z is a draw from the uniform distribution, $z_r = 1 - z$ is its reflection or mirror image.

4. Data and variables

The data used in this paper come from the first four waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Details of this survey are documented in Watson and Wooden (2002). In the first wave, 7683 households representing 66 percent of all in-scope households were interviewed, generating a sample of 15,127 persons who were 15 years or older and eligible for interviews, of whom 13,969 were successfully interviewed. Subsequent interviews for later waves were conducted about one year apart. In addition to the data collected through personal interviews, each person completing a personal interview was also given a self-completion questionnaire to be returned on completion by mail or handed back to the interviewer at a subsequent visit to the household. Attrition is a common problem with longitudinal survey data. The HILDA attrition rates for waves 2, 3 and 4 were 13.2, 9.6 and 8.4 percent respectively, which is not much higher than other longitudinal surveys (Melbourne Institute of Applied Economic and Social Research, 2006).

The HILDA survey contains detailed information on each individual’s labour market activity and history. Information relating to individual health was collected in both the personal interviews and self-completion questionnaires. In the personal interviews, individuals were asked whether they had a long-term condition, impairment or disability that restricted everyday activities and had lasted or was likely to last for six months or more. Specific examples of these long-term conditions were shown on a card, examples of which are limited use of fingers or arms, or problems with eyesight that could not be corrected with glasses or contact lenses.

In the self-completion questionnaire, the Short Form 36 health status questions (SF-36) were asked. The SF-36 is a measure of general health and wellbeing, and produces scores for eight dimensions of health (Ware *et al.,* 2000). The first question in the SF-36 is the standard self-reported health status question, with five levels scaled from poor to excellent health. This self-reported health status is used as the discrete observed counterpart of the latent health stock in the model.

Table 1 tabulates labour force status against self-reported health status using the pooled sample from wave 1 to wave 4. The sample is restricted to working-age Australian men and women, which comes down to men aged between 25 and 64 years and women between 25 and 60 years (inclusive). People aged over the upper age bound are eligible for the Age Pension and are expected to behave differently as a result. We exclude people under 25 years from the analysis because many of them would not have completed their studies. In addition, anyone who was still undertaking full-time studies was also excluded.

A positive relationship between labour force participation and health status appears for both males and females from the simple tabulation. That is, the better the health, the more likely an individual is in the labour force.[11]

Table 1: Labour force status by self-reported health status of working-age Australian men and women

	Health status					
Labour force status	Poor (0)	Fair (1)	Good (2)	Very good (3)	Excellent (4)	All
	Males					
% not in labour force	72.2	30.27	9.02	5.39	5.08	11.67
% in labour force	27.8	69.73	90.98	94.61	94.92	88.33
Observations	259	1,110	3,225	3,304	1,062	8,960
	Females					
% not in labour force	74.11	43.26	28.56	22.09	18.63	27.03
% in labour force	25.89	56.74	71.44	77.91	81.37	72.97
Observations	197	994	3,288	3,903	1,326	9,708

Table 2 provides definitions of the variables included in the models, together with their means across the four waves. The grouping of the variables also describes the model specifications. The variables in panel B are included in both the health and labour force participation equations, while those in panel C are only included in the labour force participation equation; and those in panel D are only included in the health equation. Therefore, the exclusion restrictions required to identify the simultaneous equation model are satisfied with this specifications and we do not merely rely on the nonlinearity of the model to identify the parameters. In the following section we report some test results on the validity of these exclusion restrictions.

[11] This pattern holds in each wave of the HILDA.

Table 2: Variable definitions and means

Variable name	Definition of variables	Mean value	
A. Endogenous variables		Male	Female
labour force status	0 non-participation, 1 participation	0.88	0.73
health	self-reported health status, 0=poor, 1=fair, 2=good, 3=very good, 4=excellent	2.42	2.53
B. Variables appearing in both equations (x_h and x_L)			
Demographic and education			
age	age deviation from 16	44.43	42.93
married	1 if married or in de facto	0.79	0.76
born overseas En	1 if born overseas English speaking country	0.13	0.11
born non-En country	1 if born in a non-English speaking foreign country	0.10	0.11
degree	1 if has a bachelor or higher degree	0.25	0.26
other post-sch qual	1 if has other non-degree post-school qualifications	0.41	0.23
completed year 12	1 if highest education completed is year 12	0.10	0.14
year 11 or lower	1 if highest education completed is lower than 12	0.25	0.37
Job history, occupation and spouse's labour force status			
employ history	years in employment since first leaving full-time education	25.31	18.63
unemploy history	years in unemployment since first leaving full-time education	0.74	0.51
white collar 1	1 if last or current job as a manager, administrator or professional	0.34	0.30
white collar 2	1 if last or current job as a clerical, sales or service worker	0.28	0.55
blue collar	1 if last or current job as a tradesperson, labourer, production or transport worker or related worker	0.38	0.15
spouse in LF	1 if married and the spouse in the labour force	0.54	0.64
Income and whether living in a capital city			
own NL income	monthly income from investment (for example interest and dividend), private transfer and windfall income in previous financial year ($)	324.94	294.31
spouse income	monthly spouse's income in previous financial year ($)	1760.42	3400.39
capital city	1 if living in a capital city[(a)]	0.57	0.57
C. Additional variables appearing in the labour force participation equation (x_L)			
child 0-4	1 if has child(ren) aged 0 to 4	0.18	0.19
child 5-14	1 if has child(ren) aged 5 to 14	0.30	0.37
married*child 0-4	interaction between married and child 0-4	0.18	0.17
married*child 5-14	interaction between married and child 5-14	0.29	0.31
Aged 55p	1 if aged 55 years or over	0.17	0.11
D. Additional variables appearing in the health equation (x_h)			
smoker	1 if currently smoking or ever smoked	0.61	0.51
health condition	1 if has long-term health conditions	0.23	0.18
lack physical activity	1 if lack of physical activity, defined as no physical activity at all or less than once per week	0.09	0.10
heavy drinker	1 if a heavy drinker, defined as drinking more than 6 standard drinks a day when drinking	0.09	0.02
physical functioning	Index of physical functioning, ranging from 0 to 100.	87.06	86.78
Number of observation (four waves pooled)		8960	9708

Note (a), The capital cities do not include Hobart and Darwin because they cannot be identified from the data.

The variables excluded from the health equation are indicators of whether an individual is aged 55 years or over and whether the person has young children. The presence of young children represents an obstacle to labour force participation, particular for women, because of childcare responsibility. The impact of young children is expected to depend on whether the person has a partner or not because partnered persons can share the responsibility of childcare. Therefore, the interaction between marital status and the presence of young children is included in the labour force participation equation. While many studies show that the presence of young children has adverse effects on labour supply, there is no evidence on the effects of young children on individuals' health. Therefore, the presence of young children variables should be valid instruments in the labour force participation equation. In Australia, people aged 55 years or over are allowed to withdraw from private pension funds, which may provide an incentive to retire earlier than the official retirement age. However, this provision itself is unlikely to affect individuals' health. The variable aged 55 years or over should therefore not be included in the health equation, given that the impacts of ageing on health have been controlled for through the variables age and age squared.

The health risk variables *Smoker, heavy drinker and lack of physical activitie*s are included in the health equation only. There is no reason to believe that these variables would affect labour force participation directly rather than indirectly through health. Therefore these variables are legitimate instruments in the health equation.[12] To explain the difference in health status between individuals, it would be ideal to have some specific and objective health indicators as instruments in the health equation, such as symptoms, types and severity of disability or health conditions. Unfortunately, such detailed objective health measures are not available in the HILDA survey. However, two summary indicators of health problems are available in the data and are included in the health equation. The first is the existence of long-term health conditions (*health condition*). This variable is included, although it is self-reported, following a suggestion by Bound, Schoenbaum and Waidmann (1995) that it is reasonable to treat self-reported chronic health conditions as exogenous. Bound, Schoenbaum and Waidmann (1996) argue that survey questions that are more specific

[12] It has been argued that smoking and heavy drinking may reflect the rate of time preference (Barsky *et al.*, 1997), but there is no strong empirical evidence on this from the HILDA survey (Cai and Kalb, 2006).

and concrete should be less subjective and therefore less susceptible to the justification endogeneity problem. The variable *health condition* is used here in a similar way to Stern (1989). The difference is that Stern (1989) includes a list of specific long-term health conditions in his health equation, while in this paper only a summary indicator is used. However, when the health condition question is asked, HILDA respondents are shown a card listing specific examples of these conditions, including severe sight problems, hearing problems, speech problems, blackouts, limited use of arms or fingers, etc. As such, the health condition variable can be regarded as a summary measure of specific health conditions.[13] Another variable excluded from the labour force equation is one of the SF-36 indices, the index for physical functioning. Because this index is constructed based on individuals' answers to questions about specific physical functioning limitations, such as climbing one flight of stairs, lifting or carrying groceries, or bending, kneeling or stooping, it can be treated as an exogenous variable. The index value ranges from 0 to 100, with 0 indicating that there is no physical functioning limitation (see Ware *et al.*, (2000) for the construction and interpretation of the index.)

For the variables included in both equations, some justification may be needed for the inclusion of these variables in the health equation, although they are commonly used variables in labour supply models. Age is included because it is often observed that health deteriorates with age (Kenkel, 1995). Australian survey data show that the disability incidence rate increases with age (ABS, 1998) and the probability of entering the disability benefit program is higher among older people than among younger people (Cai and Gregory, 2003). In other studies, it has been noticed that health and marital status are closely correlated (for example, see Wilson and Oswald (2005) and references therein). Education may improve health through increased health-related knowledge and is often found to be an important factor in health production (Grossman, 1999). Occupation is a key indicator of socio-economic status (SES). In addition, occupation may serve to control for job quality in terms of health impacts. Finally, education, occupation, age and age squared are key factors in the determination of individuals' wages. Since wages are only observed for labour force

[13] The health condition variable can be thought of as being derived from a list of specific health condition variables. If people had been asked whether they had each of the health conditions listed on the card, a dummy variable could have been generated indicating whether a person had any of the conditions. This derived variable would have been equivalent to the health condition variable used in this paper.

participants and (potential) wages are likely to influence both health and labour supply, we include education, occupation, age and age squared as instruments for wage in both the health and labour force equations. The variable, *capital city,* is included because individuals living in capital cities may have better access to health services, although living in a capital city at the same time can be more stressful.

The impact of unemployment on health has been discussed frequently (Wilson and Walker, 1993; Jin, Shah and Svoboda, 1995; Mathers and Schofield, 1998) and is included in the model as well. The inclusion of an employment history variable can also be justified in theory although its expected effect is ambiguous. On the one hand, employment may put stress on individuals and bad work conditions may be harmful to health; but on the other hand, employment may make people happier and enhance self-confidence which could have a positive effect on health. In addition, wealth and income, which are important factors in health determination, depend to some extent on employment experience. Family income and wealth depend at least partly on the spouse's employment. In addition, the spouse's participation in the labour force may reduce pressure on the individual by reducing the consequences arising from the risk of unemployment. Therefore, the spouse's labour force participation could also have an impact on an individual's health status. Two income variables, the individual's own non-labour income and the spouse's income (if married), are included to control for the impacts of non-labour income on labour supply and health.

5. Estimation results

5.1 Validity of exclusion restrictions

Although nonlinearity of our model helps identification, equation-specific variables are used to further facilitate model identification. However, one may ask whether the exclusion restrictions, as specified in the preceding section, are valid. This question is the same as asking whether a set of excluded instruments are valid in an instrumental variable (IV) framework, because the variables excluded from one equation are essentially used to instrument the endogenous variable in that equation. For example, the variables *health condition, smoker, heavy drinker, lack of physical activity and physical functioning* are excluded instruments to the endogenous health variable in the labour force participation equation. The frequently employed tests for the validity of instrumental variables are overidentification tests. However, this test is often used for linear models (Davidson and Mackinnon, 1993) and may not apply to the model here because the endogenous variables in our model (i.e. health and labour force status) enter the equations as latent variables. For models like ours, Lee (1992) proposes a method to test overidentification restrictions. The test statistics are obtained as by products of a minimum distance (MD) estimator of simultaneous equation models with limited or qualitative dependent variables. Like in linear models, Lee's overidentificaion tests can only be carried out for equations that are overidentified. Because both the health and labour force equations are overidentified in our model, we can conduct the test for each of the equations. The overidentification test results using Lee's methods are reported in the first panel in Table 3. Because applied researchers are often used to overidentification tests in linear models, we also conducted tests by treating observed discrete health and labour force status as continuous variables. With latent values of the endogenous variables replaced by their observed values, equations (4) and (5) become linear (probability) models and they can be estimated using generalised method of moment (GMM) to obtain the overidentification test statistics (Baum, Schaffer and Stillman, 2003). The second panel in Table 3 reports the test results from the GMM estimation.

Table 3: Overidentification test results

	Males		Females	
	Health equation	LF equation	Health equation	LF equation
(1) Lee's method				
$\chi^2(4)$	6.8652	7.5572	4.4620	3.2066
$p \geq \chi^2$	0.1432	0.1092	0.3471	0.5239
(2) GMM method				
$\chi^2(4)$	0.8120	5.1220	1.8650	11.4740**
$p \geq \chi^2$	0.9368	0.2750	0.7606	0.0217

From Table 3, using Lee's (1992) method, for both males and females the exclusion restrictions are valid for both the health and labour force equations, because the statistics are not significant at any conventional significance levels. Using the GMM method, the test statistics indicate that for the female labour force equation, the exclusion restrictions might be violated. But it is not clear to what extent this violation is due to (improperly) treating discrete variables as continuous ones. In addition, a further investigation shows that it was the health condition variable that led to the violation. When the health condition variable was removed from the excluded instruments of the female labour force participation equation, the GMM overidentification test statistic became insignificant at conventional significance levels. But the removal of the health condition variable from the female model did not change the main results. Consequently the estimation results with the health condition variable remaining in the model are reported in the following subsections.

5.2 Estimates for the endogenous variables

The coefficient estimates for the explanatory variables from the two estimation methods are not directly comparable since the estimated variances of the error terms are different between the two methods. For ease of comparison we standardize the coefficient estimates by dividing each of the coefficients by the square root of the estimated variance of the corresponding error term. Table 4 presents such standardized coefficient estimates and the estimates of the variance-covariance parameters. The original coefficient estimates are reported in Table A1 in the Appendix. The level of significance indicated in Table 4 refers to that of the original estimates. From Table 4, it appears that the results from the two methods are similar not only in terms of statistical significance, but also in terms of the direction and the order of magnitude of the estimated effects.[14]

Because the relationship between health and labour force status is the focus of the paper, here we only discuss the results on the two endogenous variables. It would be enough to say that there are no surprising estimation results for other explanatory variables because, as shown in Table 4, all significant variables appear to have the expected sign.

First, for both males and females, a positive and significant effect of health on labour force participation is found independent of the estimation method. This confirms the common finding in the literature that better health increases the probability of labour force participation. Due to the non-linearity of the model, the coefficient estimate does not represent a marginal effect and the effect of health will be assessed in a later subsection. Literately the standardized coefficients indicate that a one unit increase in latent health increases the latent value of participation by about 40 percentage points for males and 10 percentage points for females.

[14] The results from the first-stage estimation are reported in Tables A2 and A3 in the Appendix.

Table 4: Standardized coefficient estimates and estimates of the variance-covariance parameters

	Males		Females	
	FIML	Two-stage	FIML	Two-stage
Labour force equation				
health	0.4323***	0.4489***	0.1061***	0.1016***
Constant	-0.2741	-0.1259	-0.1086*	-0.1161**
age (minus 25) /10	-0.6217***	-0.7365***	0.0652	0.0699
age deviation squared /100	-0.1696***	-0.2122***	-0.0882***	-0.0837***
born overseas En	0.0396	0.0312	-0.0603	-0.0581*
born non_En country	0.0675	0.0694	-0.0513	-0.0455
married	0.0368	0.0391	-0.1905***	-0.1705***
child 0-4	-0.7105**	-1.0910	-0.3119***	-0.3088***
child 5-14	-0.5052***	-0.6419***	-0.1769***	-0.1548***
married*child 0-4	0.7724**	1.0914	-0.0818*	-0.0520
married*child 5-14	0.5078***	0.6229***	0.1501***	0.1232***
spouse in LF	0.3068***	0.3462***	0.1592***	0.1432***
degree	0.5456***	0.6042***	0.2450***	0.2255***
other post-sch qual	0.0693	0.0694	0.0993***	0.0914***
completed year 12	0.1520	0.1670	0.1030***	0.0948***
employ history/10	1.0082***	1.1738***	0.3394***	0.3107***
unemploy histroy	0.0347**	0.0391**	0.0240***	0.0228***
white collar 2	-0.0369	-0.0350	-0.0559**	-0.0492**
blue collar	0.0293	0.0417	-0.0952***	-0.0854***
capital city	0.1059*	0.1229*	-0.0163	-0.0160
own NL income /1000	-0.0175*	-0.0202*	0.0005	0.0004
spouse income /1000	-0.0062	-0.0080	-0.0012	-0.0009
Aged 55p	-0.1461*	-0.0476	-0.0707*	-0.0560
Health equation				
Labour force	-0.3353***	-0.1726	0.0277*	0.0276**
age (minus 25) /10	-0.8878***	-0.9326***	-0.2159***	-0.2165***
age deviation squared /100	-0.0873*	-0.0144	0.0317**	0.0325**
born overseas En	0.1043	0.0990	0.0327	0.0326
born non_En country	0.1457*	0.1392*	-0.0785*	-0.0775*
married	0.0201	-0.0117	0.0011	0.0002
spouse in LF	0.2886***	0.2407**	0.0411	0.0420
degree	0.7768***	0.6884***	0.0607	0.0562
other post-sch qual	0.1865***	0.1781***	-0.0027	-0.0034
completed year 12	0.2796***	0.2539**	0.0461	0.0447
employ history/10	0.9196***	0.7352**	0.0085	0.0051
unemploy history	0.0225	0.0167	-0.0351***	-0.0353***
health condition	-0.5159***	-0.5797***	-0.3452***	-0.3374***
smoker	-0.2274***	-0.2628***	-0.1175***	-0.1171***
heavy drinker	-0.0523	-0.0470	-0.1014**	-0.1151**
lack physical activity	-0.2424***	-0.2428***	-0.1246***	-0.1227***
physical functioning /10	0.1670***	0.1819***	0.1241***	0.1248***
white collar 2	-0.1679***	-0.1711***	-0.0473**	-0.0483**
blue collar	-0.1184**	-0.1349***	-0.0793**	-0.0825**
capital city	0.1872***	0.1723***	-0.0207	-0.0211
own NL income /1000	-0.0085	-0.0048	0.0089**	0.0089**
spouse income /1000	0.0023	0.0040	0.0038**	0.0036**
cut_1 (m_0)	-0.9735***	-1.4179***	-1.1478***	-1.1334***
cut_2 (m_1)	0.0175	-0.1563	-0.2690***	-0.2614***
cut_3 (m_2)	1.0477***	1.1581***	0.6838***	0.6869***
cut_4 (m_3)	2.0686***	2.4622***	1.6402***	1.6404***

Estimates of covariance parameters

$\delta_{h(\mu)}$	2.3634***	1.8247***	1.3438***	1.3427***
$\delta_{L(\mu)}$	2.3681***	3.1603***	2.8053***	3.1240***
$\delta_{hL(\mu)}$	0.2398		-0.5430***	
$\delta_{hL(v)}$	-0.1954		-0.4385***	

*** Significant at 1% level; ** 5% and * 10%.

As for the reverse effect of labour force status on health, a negative estimate is obtained for males from both estimation methods, but with different accuracy. While the estimate from the FIML method is strongly significant, the one from the two-stage method is insignificant. This inconsistency may be because the variation of the predicted latent value of labour force participation used in the two-stage method is small due to the fact that about 90 percent of males are in the labour force, while in the FIML method there is no predicted value involved. For females, the estimate is positive from both methods, with the one from the FIML method being weakly significant and the one from the two-stage method being significant at the 5 percent significance level.

The model specification in Section 3 shows that the coefficient on the labour force status variable is derived from the combined effects of the true endogeneity and justification endogeneity. While the impact direction of the true endogeneity is ambiguous, the justification hypothesis predicts that labour force status should have a positive effect on self-reported health. Therefore, the negative estimate for the labour force status variable of males suggests that for males justification endogeneity of self-reported health, if it does exist, must be small and outweighed by the negative effects resulting from the true endogeneity.

However, the results for females suggest that justification endogeneity might have occurred. This is a surprising result because females are normally under less pressure socially than males to attribute non-participation to poor health. For example, using data from the National Survey of Families and Households and from the Survey of Income and Program Participation, Ettner (1997) finds that among women self-reported measures of health are not affected by employment status. That is, justification endogeneity of self-reported health is unlikely to occur among women. Therefore, the positive sign for females may not due to justification, rather it may be due to self-selection into labour force status and the selection of jobs by women. That is, those women who choose to be in the labour force are in good health and they are in jobs that are less likely to harm their health.

5.2 Test for exogeneity of health

With the FIML estimation results, we can conduct a true test on the exogeneity hypothesis of the health variable. If self-reported health were exogenous to labour force participation, the coefficient on the labour force status variable (θ_1), the covariance of the time-invariant error components ($\delta_{hL(\mu)}$) and the correlation coefficient of the time-variant error components ($\delta_{hL(\nu)}$) should all be zero. Hence, the null and alternative hypotheses for the exogeneity of health are,

$$H_0: \ \theta_1 = 0, \ \ \delta_{hL(\mu)}=0, \ and \ \ \delta_{hL(\nu)} = 0 ;$$

$$H_1: \ \theta_1 \neq 0, \ \ \delta_{hL(\mu)} \neq 0, \text{ or } \ \delta_{hL(\nu)} \neq 0 .$$

The Wald statistics for testing the joint significance of the three parameters are 105.56 and 51.73 for males and females respectively. These statistics are significant at any conventional significance levels, implying that health should not be treated as an exogenous variable in the labour force participation equation. This result is different from that inferred from the two-stage estimation method where only the coefficient on the labour force status variable can be examined. By only looking at the two-stage results, based on the significance of the estimate for the labour force status variable in the health equation, for males the exogeneity hypothesis can be accepted at any conventional significance levels; for females the exogeneity hypothesis can be accepted at the 1 percent significance level, but is rejected at the 5 percent significance level. Therefore, if relying only on the two-stage estimation method, incorrect inferences on the endogeneity of health could have been drawn.

Focusing on the results from the FIML method, it appears that the sources of endogeneity are different between males and females. For males the endogeneity mainly results from the reverse effect of labour force participation on health since the two covariance parameters are insignificant, while for females the endogeneity mainly results from unobserved factors that have opposite effects on health and labour force participation. Since for males the reverse effect of labour force participation on health is negative, treating health as an exogenous variable would underestimate the effect of health on labour force participation, but for females it appears impossible to theoretically predict the direction of the bias caused by the endogeneity of the health variable. On the one hand, the positive reverse effect of labour force participation on health would lead to an upward bias in the effect of health; on the other hand, the negative correlation between the two error terms of the equations would cause a downward bias. These results are in general consistent with the finding in Cai and Kalb (2006), who use only the first wave of the HILDA.[15]

The estimates for the variances of the time invariant error components in both equations are strongly significant and very large in magnitude from both estimation methods, suggesting that controlling for unobserved heterogeneity should have improved estimation efficiency.

5.3 Assessing the effect of health

Given the nature of the model, it is impossible to calculate the marginal effects of health. To get a flavour of the effect of health on labour force participation, we predict the probabilities of participation conditional on five ranges of latent health using the estimated parameters from the FIML method. The five ranges of latent health are defined by the estimates for the cut-off points in the health equation and correspond to the five health categories. These results are reported in Table 5.

The first data column in Table 5 shows the predicted conditional probabilities of participation averaged across individuals in the sample, the second and third data columns present changes in the probabilities due to health changes. For example, the results in the second data column indicate that a change from fair to poor health on average reduces the probability of participation by 2 percentage points for males and 3.5 percentage points for females. A change from excellent to poor health reduces the probability of participation by about 7 and 13 percentage points for males and females respectively. The effect of health appears to be nonlinear. From the table, changes in health at the lower end of health status seem to have a larger effect on the probability of participation than a change at the upper end. The effect of health on labour force participation is clearly larger for females than for males.

[15] The results here cannot be compared with Stern (1989), who also uses simultaneous equation models, because Stern pools males and females in the models.

Table 5: Predicted conditional probabilities of labour force participation using estimates from the FIML method

Health status	Predicted probability of participation	Percentage point change compared with higher health status	Percentage point change compared with excellent health
		Males	
poor	0.8552	-2.0066	-6.6189
fair	0.8753	-1.7143	-4.6122
good	0.8924	-1.5105	-2.8980
very good	0.9075	-1.3874	-1.3874
excellent	0.9214		
		Females	
poor	0.6500	-3.4784	-13.0012
fair	0.6848	-3.3267	-9.5228
good	0.7180	-3.1082	-6.1962
very good	0.7491	-3.0879	-3.0879
excellent	0.7800		

6. Conclusion

The paper used a panel data simultaneous equation model to examine the relationship between health and labour force participation. The two-stage and full information maximum likelihood estimation methods were used to estimate the model. Using the HILDA data, we confirmed the common finding in the literature that health had a positive and significant effect on labour force participation for both males and females. However, the reverse effect from labour force status to health was found to be different between males and females. For males a negative and strongly significant reverse effect was found, while for females the effect was positive and weakly significant. The negative reverse effect for males suggests that the commonly held view that those men who are out of the labour force may overstate their health problems to justify their non-participation might not be true. On the other hand, the positive effect for females may not result from justification, rather it may be due to how women self-select themselves into the labour force and how they choose jobs.

The negative reverse effect of labour force participation on health for males, together with the insignificant estimates for the correlation of the unobserved heterogeneity in the health and labour force participation equations, implies that treating health as an exogenous variable could lead to an underestimation of the effect of health on labour force participation for males. But for females the potential bias arising from using health as an exogenous variable could not be determined from the data. The results also suggested that there were efficiency gains in using panel data, because the variances of the unobserved heterogeneity terms in both the health and labour force equations were found strongly significant and very large in magnitude. In summary, the simultaneous equation model estimated in this paper provided more insights into the relationship between health and labour force status than a single equation model could and the estimates are also more efficient due to better controlling for unobserved heterogeneity using panel data.

Appendix: Additional results

Table A1: Coefficient estimates

	Males				Females			
	FIML method		Two-stage method		FIML method		Two-stage method	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Labour force equation								
health	0.7934***	0.0999	0.9273***	0.0682	0.4444***	0.0399	0.4950***	0.0466
constant	-0.503	0.5436	-0.5162	0.4677	-0.4546*	0.2528	-0.5658**	0.2778
age (minus 26) /10	-1.1410***	0.3159	-1.3541***	0.4011	0.2732	0.2257	0.3408	0.2453
age deviation squared /100	-0.3112***	0.0667	-0.4307***	0.0872	-0.3691***	0.0636	-0.4080***	0.0693
born overseas En	0.0727	0.169	0.0455	0.2252	-0.2523	0.1626	-0.2829*	0.1697
born non_En country	0.1239	0.1865	0.1212	0.2439	-0.2147	0.1546	-0.2219	0.1689
married	0.0675	0.1377	0.0816	0.1815	-0.7976***	0.1365	-0.8307***	0.1481
child 0-4	-1.3040**	0.627	-2.1998	1.6825	-1.3060***	0.1744	-1.5044***	0.1961
child 5-14	-0.9272***	0.257	-1.3125***	0.3249	-0.7408***	0.1534	-0.7542***	0.1719
married*child 0-4	1.4175**	0.6371	2.2314	1.6953	-0.3423*	0.1808	-0.2533	0.2067
married*child 5-14	0.9320***	0.2716	1.2660***	0.3639	0.6284***	0.1572	0.6004***	0.1758
spouse in LF	0.5630***	0.1113	0.7070***	0.144	0.6664***	0.098	0.6978***	0.1051
degree	1.0014***	0.2248	1.2277***	0.2725	1.0259***	0.1518	1.0986***	0.1607
other post-sch qual	0.1272	0.1443	0.1438	0.189	0.4157***	0.1194	0.4453***	0.1294
completed year 12	0.279	0.2236	0.3427	0.2972	0.4312***	0.1486	0.4619***	0.1589
employ history/10	1.8503***	0.1944	2.3487***	0.2179	1.4212***	0.087	1.5138***	0.0857
unemploy histroy	0.0636**	0.0272	0.0791**	0.0366	0.1006***	0.0228	0.1109***	0.0251
white collar 2	-0.0678	0.1209	-0.0602	0.1599	-0.2342**	0.0925	-0.2398**	0.0991
blue collar	0.0538	0.1316	0.108	0.1742	-0.3985***	0.1253	-0.4162***	0.1343
capital city	0.1944*	0.1156	0.2497*	0.1515	-0.0683	0.0887	-0.078	0.0968
own NL income /1000	-0.0322*	0.0181	-0.0425*	0.0234	0.0023	0.0199	0.0021	0.0216
spouse income /1000	-0.0114	0.018	-0.0158	0.0243	-0.0049	0.0064	-0.0046	0.0069
aged 55p	-0.2682*	0.161	-0.2002	0.2369	-0.2962*	0.1535	-0.2726	0.1733
Health equation								
labour force	-0.6149***	0.2038	-0.2549	0.1643	0.0610*	0.0314	0.0606**	0.0291
age (minus 25) /10	-1.6281***	0.3242	-1.2936***	0.3781	-0.4746***	0.1125	-0.4758***	0.1126
age deviation squared /100	-0.1601*	0.0827	-0.0568	0.0759	0.0696**	0.0318	0.0715**	0.0318
Born overseas En	0.1912	0.1357	0.1592	0.1127	0.0720	0.0888	0.0717	0.0868

Born non-En country	0.2672*	0.1478	0.2232*	0.1263	-0.1726*	0.0886	-0.1704*	0.0885
married	0.0368	0.102	-0.023	0.0804	0.0024	0.0728	0.0004	0.0723
spouse in LF	0.5292***	0.1456	0.3692**	0.1503	0.0903	0.0635	0.0922	0.0633
degree	1.4246***	0.2774	1.0877***	0.3204	0.1335	0.0855	0.1234	0.0852
other post-sch qual	0.3421***	0.1196	0.2854***	0.1092	-0.0059	0.0726	-0.0074	0.0723
completed year 12	0.5127***	0.1917	0.4130**	0.1729	0.1013	0.0846	0.0983	0.084
employ history	1.6865***	0.4081	1.1292**	0.4687	0.0187	0.0619	0.0113	0.0615
unemploy history	0.0413	0.0267	0.0226	0.0243	-0.0772***	0.0148	-0.0775***	0.0146
health condition	-0.9461***	0.0661	-0.9453***	0.1448	-0.7590***	0.0426	-0.7414***	0.0454
smoker	-0.4171***	0.0739	-0.4249***	0.1112	-0.2583***	0.0478	-0.2574***	0.0496
heavy drinker	-0.0959	0.082	-0.0795	0.0788	-0.2230**	0.1032	-0.2529**	0.1063
lack physical activity	-0.4445***	0.0779	-0.4088***	0.0726	-0.2739***	0.0465	-0.2697***	0.049
physical functioning /10	0.3063***	0.0163	0.2979***	0.037	0.2728***	0.0082	0.2743***	0.0081
white collar 2	-0.3080***	0.089	-0.2775***	0.077	-0.1041**	0.0508	-0.1062**	0.0506
blue collar	-0.2171**	0.0947	-0.2202***	0.0727	-0.1744**	0.08	-0.1813**	0.0795
capital city	0.3434***	0.098	0.2769***	0.0942	-0.0455	0.0529	-0.0463	0.0529
own NL income /1000	-0.0155	0.0148	-0.0066	0.0125	0.0195**	0.0091	0.0195**	0.009
spouse income /1000	0.0042	0.0157	0.0072	0.0115	0.0083**	0.0037	0.0080**	0.0037
cut_1 (m_0)	-1.7854***	0.4185	-2.2531***	0.2299	-2.5235***	0.1591	-2.4908***	0.157
cut_2 (m_1)	0.0321	0.3053	-0.1324	0.2279	-0.5913***	0.1533	-0.5745***	0.1523
cut_3 (m_2)	1.9215***	0.2949	2.0764***	0.2281	1.5033***	0.1522	1.5095***	0.1518
cut_4 (m_3)	3.7938***	0.4018	4.2676***	0.2277	3.6060***	0.1506	3.6050***	0.1511
covariance matrix parameters								
$\delta_{h(\mu)}$	2.3634***	0.321	1.8247***	0.0775	1.3438***	0.0575	1.3427***	0.0567
$\delta_{L(\mu)}$	2.3681***	0.2604	3.1603***	0.3880	2.8053***	0.2316	3.1240***	0.2484
$\delta_{hL(\mu)}$	0.2398	0.4621			-0.5430***	0.1257		
$\delta_{hL(v)}$	-0.1954	0.1745			-0.4385***	0.0526		
log-likelihood of TS LF equation				-1344.01				-3188.45
log-likelihood of TS health equation				-8879.49				-9723.48
log-likelihood of FIML		-10213.62				-12899.17		
Number of observations		2240				2427		

Table A2: The first-stage labour force status equation

	Males		Females	
	Coef.	s.e.	Coef.	s.e.
constant	-0.0112	0.4888	0.1276	0.3624
age (minus 25) /10	-2.3271***	0.3418	-0.3834	0.2821
age deviation squared /100	-0.3548***	0.0785	-0.2470***	0.0806
born overseas En	0.1874	0.2111	-0.2496	0.1831
born non_En country	0.2974	0.2253	-0.4154**	0.1763
married	0.0838	0.1707	-0.9327***	0.1792
spouse in LF	0.8353***	0.1352	0.8824***	0.1177
degree	1.7887***	0.2560	1.2525***	0.1798
other post-sch qual	0.3134*	0.1756	0.5186***	0.1413
completed year 12	0.5687**	0.2826	0.5745***	0.1677
employ history	2.7827***	0.2064	1.5968***	0.0961
unemploy history	0.0867**	0.0344	0.0793***	0.0263
health condition	-0.8189***	0.1138	-0.6635***	0.1013
smoker	-0.5098***	0.1515	-0.1070	0.1049
heavy drinker	0.0275	0.1667	0.2384	0.2303
lack physical activity	-0.0684	0.1374	-0.153	0.1151
physical functioning /10	0.2149***	0.0243	0.1167***	0.0216
white collar 2	-0.2640*	0.1530	-0.4528***	0.1229
blue collar	-0.086	0.1638	-0.6829***	0.1604
capital city	0.3906***	0.1399	-0.1108	0.1037
own NL income /1000	-0.0380*	0.0228	0.019	0.0339
spouse income /1000	-0.0085	0.0219	-0.0017	0.0081
child 0-4	-1.9304	1.6901	-1.7050***	0.2234
child 5-14	-0.9295***	0.2968	-0.6470***	0.2102
married*child 0-4	1.8545	1.7026	-0.4612**	0.2320
married*child 5-14	0.8847***	0.3346	0.6290***	0.2127
aged 55p	-0.1242	0.2092	-0.5315**	0.2114
$\delta_{L(\mu)}$	3.1504***	0.3976	3.4067***	0.3202

Table A3: The first-stage health equation

	Males		Females	
	Coef.	s.e.	Coef.	s.e.
age (minus 25) /10	-0.8580***	0.1531	-0.4796***	0.1373
age deviation squared /100	0.0586*	0.0347	0.0645	0.0404
born overseas En	0.1119	0.0945	0.0622	0.0885
born non_En country	0.1499	0.1007	-0.1922**	0.0903
married	-0.0062	0.0710	-0.0636	0.0823
spouse in LF	0.1519***	0.0508	0.1620**	0.0663
degree	0.6402***	0.1035	0.1680**	0.0809
other post-sch qual	0.2113***	0.0816	0.0294	0.0743
completed year 12	0.2648**	0.1198	0.1414*	0.0855
employ history	0.4268***	0.0914	0.1104***	0.0399
unemploy history	0.0020	0.0167	-0.0635***	0.0147
health condition	-0.7381***	0.045	-0.8370***	0.0491
smoker	-0.2962***	0.0571	-0.2481***	0.0521
heavy drinker	-0.0886	0.0658	-0.0840	0.1177
lack physical activity	-0.3873***	0.0608	-0.3090***	0.0577
physical functioning /10	0.2443***	0.0076	0.2925***	0.009
white collar 2	-0.2120***	0.0537	-0.1452**	0.0577
blue collar	-0.2028***	0.0589	-0.2440***	0.0866
capital city	0.1746***	0.0611	-0.0764	0.0544
own NL income /1000	0.003	0.0090	0.0232**	0.0105
spouse income /1000	0.0087	0.0101	0.0126***	0.0044
child 0-4	0.2153	0.4680	0.1962	0.1347
child 5-14	0.4081***	0.1552	-0.0796	0.1004
married*child 0-4	-0.2948	0.4698	-0.3000**	0.1422
married*child 5-14	-0.4066**	0.1618	0.1440	0.1082
aged 55p	0.1446	0.1068	-0.0218	0.1146
cut_1 (m_0)	-2.3933***	0.1780	-2.2820***	0.1687
cut_2 (m_1)	-0.2718	0.1753	-0.3821**	0.1627
cut_3 (m_2)	1.9399***	0.1750	1.6937***	0.1629
cut_4 (m_3)	4.1343***	0.1739	3.7248***	0.1632
$\delta_{h(\mu)}$	1.8303***	0.0779	1.2788***	0.0621

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