Intertemporal Labour Supply of Married Australian Women

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Abstract: Using the first six waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, this study investigates the determinants of labour supply of married Australian women, with a focus on examining whether and to what extent there is state dependence in labour supply of married Australian women. It is found that observed and unobserved heterogeneity and serial correlation of transitory errors play important roles in causing spurious state dependence of labour supply of married Australian women. Once observed and unobserved heterogeneity and serial correlation of transitory errors are accounted for, there is no evidence on state dependence. Among the control variables examined in the analysis, it is found that women's permanent non-labour income, education, health and the number and age of young children have significant effects on their labour supply. In a model specification that treats wages as exogenous, it is found that labour supply of married Australian women is positively associated with their own wages, but negatively associated with their husbands' wages. It is also found that labour supply of a married woman increases with her husband's labour supply.

Key words: Dynamic Tobit model; Female labour supply; State dependence; Unobserved heterogeneity; Serial correlation

JEL codes:

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1. Introduction

Like most other industrialized countries, Australia faces an ageing population. Over the next decade, the baby boomers will reach their retirement age and leave the labour force. Unless some counter measures are taken, population ageing will lead to a significant slowdown in labour force growth and thus present challenges to the sustainability of economic growth and the standard of living of future Australians (Productivity Commission 2005).

One of the broad counter measures recommended by the OECD (2003) is to increase the supply of labour by groups that are currently 'under-represented' in the labour market. Many developed countries facing an ageing population have adopted policies to this end. In Australia, the Council of Australian Government (COAG 2006) has identified women, along with people on welfare and the mature aged, as the groups that have the greatest potential to achieve higher labour force participation.

Developing sound policies to lift female labour force engagement requires a good understanding of the factors affecting the labour supply decisions of women. However, a comprehensive review in 2005 of the literature on the labour supply of Australian women (Birch 2005) pointed out that there remains much to be studied in the field.[1]

A salient feature of female labour market activity — and the focus of this study — is the high degree of 'inter-temporal persistence' (Heckman and Willis 1977; Nakamura and Nakamura 1985; Eckstein and Wolpin 1989; Shaw 1994; Hyslop 1999). That is, women tend to remain in the same labour force 'state' — employed or not employed.

In exploring the reasons for the inter-temporal persistence of female labour market activity, it is important for policy analysts to distinguish persistence due to 'state dependence' from that due to 'persistent individual heterogeneity' (Heckman 1978, 1981a, 1981b).

[1] The Productivity Commission has initiated a series of research projects either to provide background information for the reform agenda, such as Laplagne et al. (2007) and Abhayaratna and Lattimore (2006), or to evaluate the impact of the proposed reforms, such as Productivity Commission (PC, 2006). There are also another three forthcoming studies currently undertaken in the Productivity Commission: *Effects of Health and Education on Wages and Productivity*; *Literacy and Numeracy Skills and Labour Market Outcomes*, and *Labour Force Participation of Women Aged 45 and Over*.

State dependence refers to the situation where an individual's current labour force state depends on his or her past labour force state — so, for example, being employed today improves one's prospects of being employed in the future (and vice versa). State dependence may arise if working leads to accumulation of human capital — skills, know-how, work ethic etc. — and/or not-working leads to depreciation of human capital (Heckman 1981a). Differences in 'search costs' associated with different labour market states may also cause state dependence (Eckstein and Wolpin 1990; Hyslop 1999). For example, there might be a fixed cost to enter the labour market, raising the cost for individuals who are not employed, relative to those already in the labour market.

Persistent individual heterogeneity refers to a range of other factors, related to individual characteristics rather than their labour market history per se, that may explain persistent labour market behaviour. They include differences in preferences between work and leisure, and motivation and ability among individuals. For example, women who prefer work to leisure, who are highly motivated and/or who have high ability may tend to stay in the work force for their entire working life, exhibiting high labour supply persistence.

In addition, *transitory shocks* to labour market decisions that are *serially correlated* may also lead to observed persistence of labour market behaviour. For example, deterioration in a person's health in a year may imply that the person is more likely to experience deterioration in health in subsequent years. If labour force participation is affected by individual health, such positive correlation of health deterioration over time may be reflected in positive correlation in non-participation in the labour force.

The sources of labour market persistence have important policy implications. For example, if there is state dependence in unemployment, policies aimed at preventing people from becoming unemployed would be more effective in reducing unemployment than retraining the unemployed. In addition, in the presence of state dependence, policy interventions targeted at those already unemployed need to be tailor-designed according to duration of unemployment. On the other hand, if persistence can be explained by other factors, the duration of unemployment is less relevant when designing an intervention policy.

This study examines the influence of different sources of observed persistence in the labour market behaviour of married Australia women, using the Household, Income and

Labour Dynamics in Australia (HILDA) Survey. The paper focuses on married women in Australia as they make up of the majority of women of working age, who historically have a lower rate of labour force engagement than single women. At the same time, the study also investigates the effect of various observed factors, such as education, age, health and children, on the labour supply of married women. A number of previous Australian studies have also examined these factors, but have used cross-sectional data which cannot easily capture individual persistent heterogeneity, or adjust for serially correlated transitory shocks, and so may result in biased estimates.

This study finds that there is no evidence that current labour supply of married Australian women is affected by their past labour supply (that is, there is no state dependence in their labour supply). In other words, observed and unobserved individual heterogeneity and serial correlation of transitory shocks play important roles in inter-temporal persistence of labour supply of the women as observed from the data.

Among the control variables examined in the model, the study finds that non-labour income, education, health and the number and age of children of women have significant effects on their labour supply. And in a model specification that treats wages as exogenous, the study finds that the labour supply of married Australian women is positively associated with their own wages, but negatively associated with their partners' wages. It is also found that the labour supply of married women is complementary to their partner's labour supply. That is, an increase in a partner's labour supply is found to be associated with an increase in the woman's supply of labour.

The rest of this paper is structured as follows: Section 2 provides a brief overview of the literature, particularly the studies that examine the dynamic feature of women's labour supply. Section 3 discusses the econometric models and estimation strategies, assumptions of alternative models and their pros and cons. Section 4 describes the data, the model specifications. Section 5 reports the model estimation results, with conclusion drawn in Section 6.

2. Literature review

The labour supply of women has been the subject of extensive study both in Australia and internationally.[2] Despite this, only a few international and Australian studies have examined the inter-temporal labour supply behaviour of women, and it remains a less understood area of labour supply research (Hyslop 1999).[3] However, study in this area is growing rapidly due to the increasing availability of panel data and improved computational power and techniques.

Several international studies have examined inter-temporal persistence in labour supply. Shaw (1994) used the Panel Study of Income Dynamics (PSID) over the period 1967-1987 to measure persistence in (annual) working hours of white women in the United States. She found evidence of (statistically) significant persistence in an individual's labour supply even after controlling for other influencing factors — such as wages, the age and number of children and individual health status. Further, the extent of persistence was found to have changed little over the 20 year period studied. .Shaw also found that unobserved (time invariant) individual heterogeneity played an important role in the persistence. However, the study did not examine whether the persistence also resulted from unobserved transitory shocks (or errors) that might be serially correlated.

Hyslop (1999), also using the PSID data (for the period 1979-1985), examined the dynamics of labour force participation of married women in the US and found evidence of state dependence. While unobserved individual heterogeneity was found to contribute to the persistence of labour force participation, transitory errors were found to be negatively correlated over time, suggesting that failing to control for serially correlated transitory errors would lead to underestimation of state dependence. The non-labour income of married women, measured by their partner's earnings, was also found to have a negative effect on their labour force participation. The pPermanentcy of this non-labour income was found to be more important in affecting a woman's labour force participation than

[2] For a detailed survey of the international literature on women's labour supply, see Killingsworth (1983), Killingsworth and Heckman (1986) and Heckman (1993).

[3] A few studies also examine inter-temporal labour supply behaviour of men, such as Muhleisen and Zimmermann (1994) for Germany and Arulampalam, Booth and Taylor (2000) for the UK.

transitory non-labour income. The age and number of young children were also found to have a significant negative effect on the labour force participation decisions of women.

Inter-temporal persistence in women's labour supply was also examined by Lee and Tae (2005) using the first four waves (1998-2001) of the Korean Labour and Income Panel Study. Without considering serial correlation of transitory errors, the authors found that both state dependence and unobserved individual heterogeneity were important in explaining inter-temporal persistence in the labour force participation of women. They also found that the extent of state dependence of labour force participation varied with education, marital status and age. State dependence was found to increase with age, and was higher for married than for single women and higher for women with a junior college level of education relative to those with other levels of education.

In the Australian context, little research exists on the intertemporal persistence of labour market activity. One study, Knights et al. (2002), examined labour market dynamics of Australian youth (those aged 15-29 years), using the Australian Longitudinal Survey over the period 1985-1988. Dynamic labour market activity of both males and females was analysed separately, with each group being further divided into high and low education groups. High education was defined as the completion of secondary school; with the low education defined as secondary school not being completed. Only two labour force states were examined — employed or not employed (binary variable). The authors found that an individual's employment status in the previous year predicted his/her employment status in the currently year for all the four gender-education groups, suggesting evidence of state dependence of employment status. They also found evidence that unobserved individual heterogeneity was important explanatory factor in the persistence of employment status for all groups examined. Like Lee and Tae (2005), however, Knights et al. (2002) did not examine whether the observed persistence was due to serially correlated transitory errors.

Some studies have also examined the effect of serially correlated transitory errors on inter-temporal persistence. Tatsiramos (2008), for example, examined female employment dynamics in seven European countries (Demark, France, Germany, the Netherlands, Italy, Spain and the UK) to test the effects of fertility had on employment status. State dependence was found in the employment status for women in all countries after controlling for observed and unobserved individual heterogeneity and serially correlated transitory errors. The magnitude of state dependence as measured by average partial effects was very similar across all the countries studied, with the probability of a women being employed being 31 to 49 percentage points higher if employed in the previous year.. Like Hyslop (1999), Tatsiramos (2008) also found that transitory errors are negatively correlated over time for all countries, and only in the case of Denmark, was the serial correlation insignificant. Permanent non-labour income was found to have a significant and negative effect on labour supply for all countries except Denmark and the UK, where the effect was positive. In case of the Netherlands and Italy, a woman's transitory non-labour income was also found to decrease labour supply.

Much of the existing literature of the inter-temporal behaviour of labour supply has focused on whether or not a womaen is involved in paid work — a binary choice measured as labour force participation or employment status. In contrast, the approach taken in this study is to examine working hours as a measure of labour supply, and thus treat non-employment (those with zero working hours) as a censored outcome.[4] Further, there are no Australian (and limited international) studies that have examined both the effect of observed and unobserved individual heterogeneity and serially correlated transitory errors on inter-temporal labour supply.

Despite this, studies of labour force participation by Australian women, comprehensively reviewed by Birch (2005), provide a valuable guide to the choice of explanatory variables. Although the estimates vary across studies and are sensitive to model specifications and estimation techniques, some patterns emerge. Previous studies generally found that increases in a woman's wages, educational attainment, labour market experience, and the cost of living, all have a positive effect on a woman's labour supply. Conversely increases in family income and the number of dependent young children had a negative effect.

[4] In this study the focus is on hours worked of individuals. The individual level measures are used to obtain corresponding aggregate indicators of labour supply such as the labour force participation rate, the employment rate and total hours worked of all employed persons, and average hours worked per employed person.

3. Econometric model and estimation strategy

This chapter sets out the econometric model and estimation strategy used to estimate the factors that drive inter-temporal labour supply of married women in Australia.

3.1. The econometric model

This study explores labour supply in terms of the hours worked rather than participation or employment. Since working hours are censored at zero for those who do not work, the conventional model used is the Tobit model (Killingsworth 1983). Although the Tobit models fit the censored nature of the dependent variable well, it has some limitations.

First, the Tobit model relies on an implicit assumption that working hours vary continuously from zero (at a wage equal to reservation wages) to progressively larger positive hours (at wages greater than reservation wages) with no jumps or discontinuity (Killingsworth and Heckman 1986: p196; Killingsworth 1983: p141-148).[5] While this assumption is consistent with labour supply theory, if a discontinuity is observed in working hours it introduced empirical problems (Killingworth, 1983). This does not appear to be a concern in this study as observed working hours vary continuously between zero and larger positive hours (see Figure 1 in Section 4).

Second, the model treats labour force non-participation and unemployment as the same labour force state as both are represented by zero working hours. Thus, non-participation and unemployment are assumed to be determined by the same decision process, although they may be affected by different driving forces.[6] When interpreting the model estimation results, the limitations of the model and the associated assumptions should be kept in mind.

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[5] A violation of the continuous working hour assumption would suggest that zero working hour should be modelled as a separate decision process that differs from the decision process of generating positive working hours (Killingsworth and Heckman 1986: p196). Maddala (1992) makes a simular point using a different argument. According to Maddala (1992) zero working hour is not due to censoring since individuals cannot in principle working negative hours. The observed zero working hour is instead due to the decisions of individuals. As a result, the decision that produces the zero hour observations should be modelled separately.

[6] Such an assumption is commonly made in estimating a two-step wage equation with Heckman selection correction.

To take advantage of the panel nature of the HILDA data, the conventional Tobit model is augmented by including working hours lagged by one year as an explanatory variable. The resulting model is often called a dynamic Tobit model.

The model can be described as follows. For an individual *i* at time *t* the dynamic model can be expressed as:

$$y_{it}^* = \alpha y_{it-1} + x_{it}^{'}\beta + v_{it}\text{, for } t=1,\ldots,T;\ i=1,\ldots,N\text{, and with} \quad (1)$$

$$y_{it} = \begin{cases} y_{it}^* & \text{if } y_{it}^* > 0 \\ 0 & \text{if } y_{it}^* <= 0 \end{cases}.$$

Where y_{it}^* and y_{it} are the latent and observed working hours of individual *i* respectively; x_{it} is a vector of observed variables that are expected to affect working hours of individual *i*; and v_{it} is an error term, capturing the unobserved factors that affect labour supply decision.

The lagged dependent variable y_{it-1} is included in the right hand side of equation (1) to capture the dynamic feature of working hours, in the sense that current working hours may, all other things being equal, also depend on past working hours. This dependence can be due to things such as the accumulation of skills derived from past work.

With the assumption that v_{it} follows the normal distribution with mean zero and variance σ_v^2 and is independent across individuals and over time for the same individual, equation (1) represents a conventional Tobit model which can be estimated consistently by pooling the panel data to form an enlarged dataset. For the remainder of this paper, this model is termed the ‘pooled Tobit’ model.

However, the assumption that v_{it} is independent over time for the same individual is violated if labour supply is affected by unobserved individual heterogeneity — that is, the characteristics of the individual not captured by the observed variables in the dataset do have an important influence over the individual’s labour supply decisions. An example of this is an individual’s preference to work, which is not directly captured by the observed variables. Other examples include an individual's level of motivation and/or their innate ability. As it would be reasonable to expect that these factors would influence labour supply decisions, it would also be reasonable to expect unobserved heterogeneity exists. In this situation, failure to control for unobserved individual heterogeneity would lead to the estimate for state dependence being biased upwards.

One method to overcome this would be to make use of measures or proxies of these variables, however these are not available in the data used. An advantage of panel data is that it provides a way to control for unobserved individual heterogeneity through decomposing the error terms:

$$v_{it} = \eta_i + \varepsilon_{it}, \qquad (2)$$

where η_i represents the unobserved time invariant individual effects and thus measures unobserved individual heterogeneity; ε_{it} represents the unobserved transitory or time variant shocks/errors to labour supply, and is independent of the observed variables and η_i. In estimation ε_{it} is assumed to follow the normal distribution with mean zero and variance σ_ε^2, i.e. $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$.

The unobserved individual effects η_i can be assumed to be either random or fixed. A random effects assumption implies that η_i is uncorrelated with any of the observed variables included in the model. A fixed effects assumption allows η_i to be correlated with the observed variables. Since the dependent variable working hours is censored and the Tobit model is a non-linear model, it is not technically feasible to use the fixed effects estimator (Hsiao 2003).[7] The model estimated using the random effects assumption is denoted as 'RE Tobit', where η_i is assumed to follow the normal distribution with mean zero and variance σ_η^2.

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[7] In a linear model with fixed effects, the fixed effects can be differenced out and thus do not cause any complication in estimation. But such a differencing approach does not apply to non-linear models. A non-linear model with fixed effects is generally unfeasible for estimation. Logit and Poisson models seem to be the only models that can incorporate fixed effects in estimation (Wooldridge 2002).

Given that unobserved individual factors such as motivation and innate ability are likely to also influence observed outcomes such as education levels and wages for a given education level some modification of the random effects assumption is desirable. One such modification is to use Mundlak's (1978) approach, and allow the unobserved individual effects to be correlated with observed variables through a linear form as denoted in equation (3):

$$\eta_i = \bar{x}_i^{'}\pi + \mu_i \,. \tag{3}$$

With this specification, the unobserved individual effects are assumed to be comprised of two components, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$ and an error term $\mu_i \sim N(0,\sigma_\mu^2)$ which is uncorrelated with any observed variables and the transitory error ε_{it}.[8] Following Wooldridge (2002), this model is called a correlated random effects model (denoted as 'Cor. RE Tobit').

As discussed earlier, even in the absence of state dependence and unobserved individual heterogeneity, labour supply persistence may still be observed if unobserved transitory shocks to labour supply decisions are correlated over time. To control for this source of persistence, an autoregressive relationship between two adjacent transitory errors can be specified:

$$\varepsilon_{it} = \rho\varepsilon_{i,t-1} + \zeta_{it}\,, \tag{4}$$

where $\zeta_{it} \sim N(0,\sigma_\zeta^2)$ and is independent of μ_i and of the observed variables. The model that allows for correlated random effects and serially correlated transitory shocks is denoted as 'AR. Cor. Tobit'.

To summarise, four dynamic Tobit models are to be estimated, each relaxing assumptions of the previous one:

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[8] Since time invariant variables cannot be separately identified from their means in the correlated random effects model, $\bar{x}_i^{'}$ can include only the means of time variant variables. Specifically, this study includes the means of the variables for health, the number of children by age, and whether the individual lives in a capital city in the correlated random effects models.

- *Model I Pooled Tobit*: a conventional Tobit model augmented by including the one-year lagged dependent variable in the right-hand side and being estimated with pooled data. This model assumes that there is no unobserved heterogeneity, working hours in the first wave are exogenous, and the error term is independent across individuals and over time for the same individual. As this model relies on the greatest number of restrictive assumptions, it may be regarded as a 'naïve' model.

- *Model II RE Tobit*: extends Model I to include unobserved individual effects that are assumed to be random and also to endogenize the initial condition using the Heckman (1981c) approach (see the following section). Unobserved transitory shocks to labour supply decisions are assumed to be independent over time for the same individual.

- *Model III Cor. RE Tobit*: extends Model II to allow the unobserved individual effects to be correlated with some time variant observed variables through a linear form. But the assumption of independent transitory shocks is maintained.

- *Model IV AR. Cor. RE Tobit*: Extends Model III to allow the transitory shocks to be (autoregressively) correlated over time.

Assumptions imply restrictions in model estimation. The more numerous the assumptions are, the more restrictive the model is. In this sense Model IV is the most general model since it relies on the least assumptions about the determinants of labour supply. Estimating all four models provides a test for the assumptions embodied in the more restrictive models. The estimation of Models I to III also provide a robust check of the results obtained from the general model.

3.2. The initial condition problem

The dynamic nature of the model implies that current working hours depend on the hours worked in the previous period. In this formulation consistent estimates of the coefficient parameters rely on the assumption that the unobserved error v_{it} is independent across individuals and over time for the same individual. This assumption is only maintained for Model I.

When unobserved individual effects (either random or correlated random effects) are allowed (Models II to IV), the composite error term v_{it} becomes correlated over time for the same individual. Consequently, the lagged dependent variable is correlated with the error term and thus becomes endogenous (Hsiao 2003). One solution, originally suggested by Heckman (1981c), is to approximate the unknown initial conditions (working hours in the first wave) with a static equation that utilises information from the first wave of panel data, and then jointly estimate the dynamic model with the initial condition equation.

Following Heckman (1981c), when random unobserved individual effects are assumed, the static equation for the initial value of the latent dependent variable can be specified as:

$$y_{i0}^* = z_{i0}'\lambda + \gamma\eta_i + \varepsilon_{i0}, \quad \text{with } y_{i0} = \begin{cases} y_{i0}^* & \text{if } y_{i0}^* > 0 \\ 0 & \text{if } y_{i0}^* <= 0 \end{cases} \tag{5}$$

where z_{i0} is a vector of exogenous variables including x_{i0}; and ε_{i0} has the same distribution as ε_{it}.[9]

When correlated random unobserved individual effects are assumed, the initial condition equation takes the form:

$$y_{i0}^* = z_{i0}'\lambda + \bar{x}_i'\pi + \gamma\mu_i + \varepsilon_{i0}, \text{ with } y_{i0} = \begin{cases} y_{i0}^* & \text{if } y_{i0}^* > 0 \\ 0 & \text{if } y_{i0}^* <= 0 \end{cases}. \tag{5′}$$

3.3. Estimation strategies

In the four models, estimates of the coefficients of the parameter for the observed characteristics of married women, (α and β in equation (1)) are of primary interest as they provide insights into what drives inter-temporal labour supply decisions. The auxiliary parameters associated with the error components and the initial condition equation also

[9] The initial condition equation includes the proportion of time employed; the proportion of time unemployed since an individual first left full-time study; and their mother's occupation as additional identification variables (see Table 1 in Section 4).

needs to be estimated. For ease of exposition, θ is used to represent the vector of all parameters to be estimated.[10]

A maximum likelihood estimator (the appropriate estimator for Tobit models) is used to estimate these parameters. This requires the formulation of the likelihood function for the observed sample.

First, the likelihood function is formulated for the pooled Tobit model (Model I). Assuming that v_{it} follows the normal distribution and is independent across time for the same individual *i*, the conditional (on the observed variables) probability of observing a sequence of y_{it} (for *t*=1,…,T) is:

$$L_i^1(\theta) = \prod_{t=1}^{T} [\sigma_v^{-1}\phi(\Delta_{it}^1)]^{D(y_{it}=0)} [\Phi(\Delta_{it}^1)]^{D(y_{it}>0)}, \tag{6}$$

where $\phi(.)$ and $\Phi(.)$ refer to the probability density and cumulative probability functions of the standard normal distribution respectively, with $\Delta_{it}^1 = [y_{it} - (\alpha y_{it-1} + x_{it}^{'}\beta)]/\sigma_v$, and $D(.)$ representing an indicator function equal to 1 if the condition in the bracket holds, and zero otherwise.

When unobserved individual effects are introduced and are assumed to be random (Model II), the probability of observing a sequence of y_{it} (for *t*=1,…,T) can be written in a similar way to equation (6), but with the addition of being conditional on the unobserved individual effects η_i:

$$L_i^2(\theta \mid \eta_i) = \prod_{t=1}^{T} [\sigma_\varepsilon^{-1}\phi(\Delta_{it}^2)]^{D(y_{it}=0)} [\Phi(\Delta_{it}^2)]^{D(y_{it}>0)}, \tag{7}$$

where $\Delta_{it}^2 = [y_{it} - (\alpha y_{it-1} + x_{it}^{'}\beta + \eta_i)]/\sigma_\varepsilon$.

[10] Note that the elements of θ vary depending the model to be estimated.

To account for the initial condition problem, the likelihood function $L_i^2(\theta \mid \eta_i)$ needs to be combined with the probability of observing the initial working hours of individual *i* (the first line on the right hand side of equation (7′)) to form,

$$L_i^{2'}(\theta \mid \eta_i) = \{[\sigma_\varepsilon^{-1}\phi(\Delta_{i0}^2)]^{D(y_{i0}=0)}[\Phi(\Delta_{i0}^2)]^{D(y_{i0}>0)}\} \\ \times\prod_{t=1}^{T}[\sigma_\varepsilon^{-1}\phi(\Delta_{it}^2)]^{D(y_{it}=0)}[\Phi(\Delta_{it}^2)]^{D(y_{it}>0)}, \tag{7′}$$

where $\Delta_{i0}^2 = [y_{i0} - (z_{i0}^{'}\lambda + \gamma\eta_i)]/\sigma_\varepsilon$.

The likelihood function of the correlated random effects model (Model III) is essentially the same as in equation (7′) except that the function is now conditional on μ_i (instead of η_i) and η_i is replaced by $\bar{x}_i^{'}\pi + \mu_i$.

The likelihood function of the model with serially correlated transitory errors is a bit more involved. Conditioning on the random effects μ_i, for a given sequence of the transitory errors $\tilde{\varepsilon}_i = \{\tilde{\varepsilon}_{i0}, \tilde{\varepsilon}_{i1}, ..., \tilde{\varepsilon}_{iT}\}$, the probability of observing a sequence of y_{it} (for *t*=0,…,T) can be written as:

$$L_i^3(\theta \mid \mu_i; \tilde{\varepsilon}_i) = \{[\sigma_\varepsilon^{-1}\phi(\Delta_{i0}^3)]^{D(y_{i0}=0)}[\Phi(\Delta_{i0}^3)]^{D(y_{i0}>0)}\} \\ \times\prod_{t=1}^{T}[\sigma_\zeta^{-1}\phi(\Delta_{it}^3)]^{D(y_{it}=0)}[\Phi(\Delta_{it}^3)]^{D(y_{it}>0)}, \tag{8}$$

where: $\Delta_{i0}^3 = [y_{i0} - (z_{i0}^{'}\lambda + \bar{x}_i^{'}\pi + \gamma\mu_i + \tilde{\varepsilon}_{i0})]/\sigma_\varepsilon$, and

$\Delta_{it}^3 = [y_{it} - (\alpha y_{it-1} + x_{it}^{'}\beta + \bar{x}_i^{'}\pi + \mu_i + \rho\tilde{\varepsilon}_{i,t-1})]/\sigma_\zeta$ (for t=1,…,T).

When working hours are positive ($y_{i,t-1} > 0$), $\tilde{\varepsilon}_{i,t-1}$ can be calculated as $\tilde{\varepsilon}_{i,t-1} = y_{i,t-1} - (\alpha y_{i,t-2} + x_{i,t-1}^{'}\gamma + \bar{x}_i^{'}\pi + \mu_i)$. When working hours are zero ($y_{i,t-1} = 0$), $\tilde{\varepsilon}_{i,t-1}$ need to be simulated as:

$$\tilde{\varepsilon}_{i,t-1} = \sigma_\varepsilon\Phi^{-1}[\xi\Phi(\Delta_{i,t-1}^3)], \tag{9}$$

where ξ is a random draw from a uniform distribution. Fifty Halton sequence draws were used to simulate the likelihood function where required.

In order to estimate the coefficient parameters, the unobserved individual effects in the likelihood equations (7), (7′) and (8) above need to be integrated out. This was carried out using the Gaussian-Hermite quadrature method with the assumption that the unobserved individual effects follow the normal distribution.

The sample likelihood function, which is maximised with respect to the parameters, is obtained by taking the product of the individual likelihood function. All the model estimations are implemented using the Gauss package with code written by the author.

4. Data source, model specification and descriptive analysis

4.1. The HILDA survey

The focus of this study is on labour supply, as measured by working hours. Working hours refer to total hours per week usually worked in all paid employment. This is a more appropriate measure of labour supplied than hours worked per week in an individual's main job, particularly for married women who may be more likely to have several part-time jobs than single women or men (although this may also be the case for younger workers).

The data used in this study are drawn from the first six waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA survey collects information about family composition and dynamics, individual and family incomes, demographic characteristics and labour market activity and history of the respondents. It also collects information on family childcare usage and individual health (for further details of this survey see Watson and Wooden (2004)).

As married women are the focus of the study, the sample included only women aged 18 to 64 years (inclusive) who were either married or in a de facto relationship at the time of the survey. Full-time students were excluded from the analysis.

Respondents could get married or divorced during the six-year data period, or leave the survey over the period examined (known as panel attrition). Accounting for all these factors in the model would substantially complicate the estimation procedure, and therefore, to make the estimation manageable, a balanced panel sample was used. The balanced sample consisted of women who were either married or in a de facto relationship in *all* six years of the survey. It should be noted that the consistency of the model estimation results rely on the assumption that staying married and/or in the sample is independent to labour market activity of the women. To the extent that such an assumption might be violated, caution should be exercised when generalizing the results to the general population of married Australian women.

4.2. Two types of model specifications

For each of the four models described in Section 3, two model specifications have been estimated. The models differ in terms of the inclusion of wages and the treatment of total family income, and have different advantages and disadvantages.

In the first specification, a woman's own wage is excluded from the model. A woman's non-labour income, which is used as an explanatory variable in this specification, includes her individual non-earning income, such as investment income, private transfer and windfall income, and her partner's total income, all measured for the previous financial year. Welfare payments are excluded from non-labour income to avoid endogeneity issues, as the payments are means tested and thus affected by labour supply. This specification is often referred to as a reduced form labour supply model (Killingsworth 1983).

In the second specification, a woman's own wage, along with her partner's wage and working hours are included. Wages are defined as earnings per hour and are obtained by dividing weekly earnings by weekly hours worked. In this specification non-labour income, also measured for the previous financial year, represents total family income net of earnings of both partners. This specification is often referred to as a structural labour supply model.

The reduced form specification is estimated for two reasons. First, wages are not available for those who are not employed. Second, even if wages were all observable, they might be endogenous to labour supply in the sense that individual wages might be affected by working hours and/or both working hours and wages could be determined by some correlated or common unobserved factors. As a result, it seems common in the literature on dynamic labour supply to estimate the reduced form labour supply model, where wages do not enter the model as an explanatory variable (e.g., Hyslop 1999; Knight, Harris, and Loundes 2002; Lee and Tae 2005; Tatsiramos 2008).

Nevertheless, the effect of wages on individual labour supply remains a fundamental question in labour economics. The second specification therefore attempts to shed some light on this question. However, the approach has limitations since wages, particularly own wages, are treated as exogenous. Accounting for endogeneity of a woman's own wages would require instrumental variables which would be selected such that they only affect their wages but not their labour supply. Such instrument variables are not available in the survey. Despite the likelihood of bias if the exogeneity of wages assumption is violated, it is difficult to predict the direction the bias would take since wages might also be measured with error.

Several other assumptions implicit in these models are worth highlighting. In the reduced form specification, a partner's earnings form part of the woman's non-labour income and are assumed to have only an income effect on the woman's labour supply decision. The partner's labour supply itself is assumed to have no independent effects on the woman's labour supply. The validity of this assumption is questionable as there are studies showing that leisure time of a couple may be complementary (Blau and Riphahn 1999). This implies that a couple's labour supply could also be complementary. To test this hypothesis, the partner's working hours are included in the structural specification of the models. Further the wage of a woman's partner is also included to estimate how her labour supply responds to her partner's wages.

4.3. Other model specification issues

In both specifications non-labour income enters the model as two variables: the mean (over the six years) of non-labour income and the deviation from the mean. The mean variable is used to estimate the effect of permanent non-labour income, while the deviation is used to estimate the effect of transitory non-labour income. In the literature, it is often hypothesised that permanent non-labour income should have a larger effect on labour supply than transitory non-labour income.

Following the same logic, a distinction is also made between permanent and transitory wages (both a woman's own wages and her partners') in the structural specification. Mean wages are used to represent permanent earnings capacity, and the deviation from mean wages is used to measure transitory earnings. All financial variables are deflated to 2001 dollar values using the national consumer price index (CPI).

As mentioned, wages are not available for those who are not employed. To include wages in the model for these individuals, wages need to be predicted. The common approach to predicting wages is the three-step Heckman procedure. In the first step a selection equation (on whether an individual is employed or not) is estimated to calculate the inverse Mills' ratio. In the second step the wage equation is estimated for those with positive wages with the inverse Mills' ratio included as one of the explanatory variables. The wages of those who are not employed are then predicted in the third step, using the parameters obtained from the wage equation estimation in the second step. For a detailed description of the procedure and the estimation results of the selection and wage equations, see Appendix A.

Other variables included in both specifications of the models are: age (five age group dummies); education (five dummies indicating the highest qualification obtained); health status (indicating whether an individual has a long-term health condition); the numbers of children aged 0 to 2, aged 3 to 5 and aged 6 to 17; whether they live in a capital city; immigration status (three dummies); and the unemployment rate at the major statistical region level. These are standard variables for modelling labour supply (Birch 2005). In addition, five year- (or wave-) dummies are included to account for the year effects on the labour supply of married women. The definitions of the variables used in the model are shown in Table 1.

4.4. Descriptive statistics

The summary statistics of the sample are reported in Table 1, along with the additional variables used in the initial condition equation.

The average working hours of the women in the sample (including those with zero hours) is just under 22 hours per week. About 29 per cent of women did not work at the time of survey (Figure 1). The next largest group consists of women who worked 40 hours a week, accounting for about 8 per cent. About 5 per cent of the women worked 20 hours a week. Using the Australian Bureau of Statistics (ABS) definition of part-time employment (those working less than 35 hours a week), around 39 per cent of the women in the sample worked part-time, and 32 per cent worked full-time hours.

As most variables appear to fit with prior expectations, the summary statistics are not discussed here in detail.

Figure 1: Distribution of working hours of married women

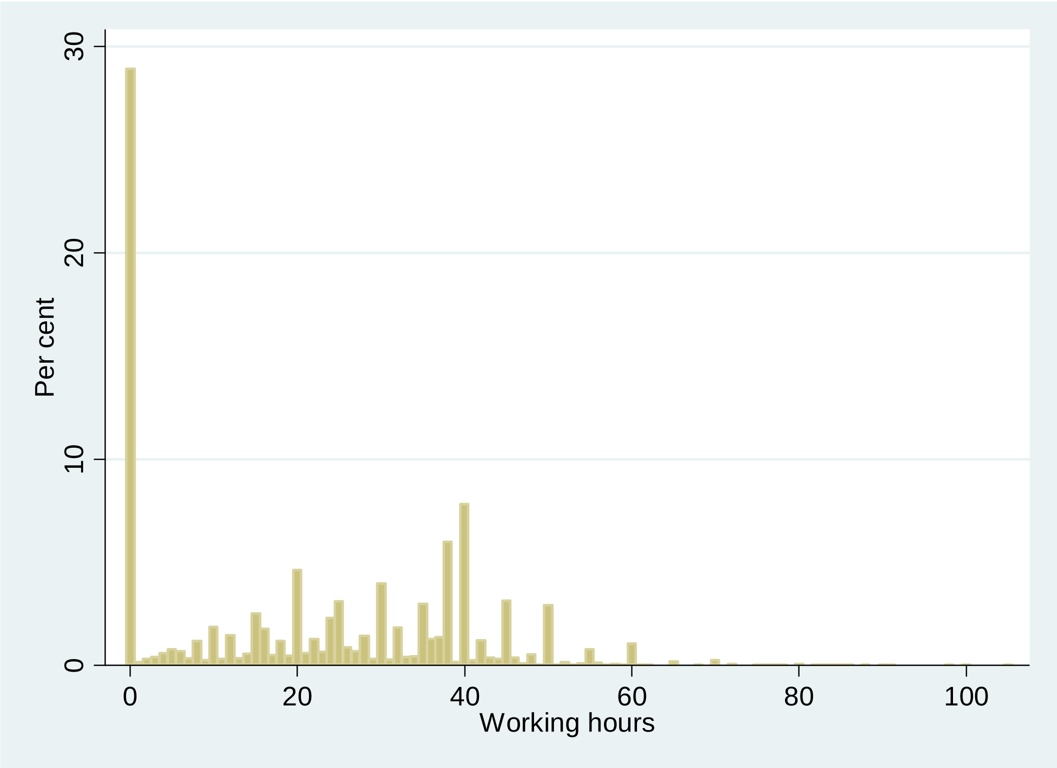

Table 1: Summary statistics and variable definitions

Variables	Definition of variable	Mean
A. Variables used in reduced form specification (9,132 observations)		
Hours	Weekly working hours in all jobs	21.6058
st.d.		18.1971
Aged 18-25	Dummy, =1 if aged 18-25	0.0231
Aged 26-35	Dummy, =1 if aged 26-35	0.2340
Aged 36-45	Dummy, =1 if aged 36-45	0.3717
Aged 46-55	Dummy, =1 if aged 46-55	0.2717
Aged 56 plus	Dummy, =1 if aged 56 and over	0.0995
Degree	Dummy, =1 if have a degree or higher qualification	0.2560
Diploma	Dummy, =1 if have a post-school diploma	0.1090
Certificate	Dummy, =1 if have a post-school certificate	0.1375
Year 12	Dummy, =1 if completed year 12	0.1493
Year 11 or lower	Dummy, =1 if did not completed year 12	0.3482
Health	Dummy, =1 if have a long-term health condition	0.1782
Child 0-2	Number of resident children aged 0 to 2	0.1855
st.d.		0.4501
Child 3-5	Number of resident children aged 3 to 5	0.1708
st.d.		0.4261
Child 6-17	Number of resident children aged 6 to 17	0.8513
st.d.		1.0868
Capital city	Dummy, =1 if live in a capital city	0.5768
OZ born	Dummy, =1 if born in Australia	0.7727
NESC	Dummy, =1 if immigrants from an Eng-speaking country	0.1038
ESC	Dummy, =1 if immigrants from a non-Eng-speaking country	0.1235
Unem rate (%)	Local unemployment rate at the ABS Major Statistical Region level	5.8423
st.d.		1.2569
A woman's non-labour income ($10 000)	Family non-earnings income (including investment income, private transfers and windfall income, but excluding welfare payments), plus partner's earnings	5.7910
st.d.		5.9680
B. Additional variables used in structural specification (9,132 observations)		
A woman's own wage	Hourly wages of women	16.5394
st.d.		14.5375
Partner's wage	Hourly wages of partners	22.1900
st.d.		20.0768
Partner's hours	Weekly working hours of partners	41.3137
st.d.		18.0836
Family non-labour income ($10 000)	Total non-earnings income of the family, including investment income, private transfers and windfall income, but excluding welfare payments	1.6865
st.d.		5.9933

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Table 1: (continued)

Variables	Definition of variable	Mean
C. Additional variables used in the initial condition equation (1,522 observations)		
Mother white collar	Dummy, =1 if mother worked as a manager, administrator or professional	0.1531
Mother other white collar	Dummy, =1 if mother worked as a clerical, sales or service worker	0.3830
Mother blue collar	Dummy, =1 if mother worked as a tradesperson, labourer, production or transport worker or related worker	0.2313
Mother occupation unknown	dummy, =1 if mother's occupation unknown	0.2326
Proportion of life employed	The proportion of time employed since first leaving full-time education	0.7217
st.d.		0.2581
Proportion of life unemployed	The proportion of time unemployed since first leaving full-time education	0.0201
st.d.		0.0742
Number of individuals[a]		1,522

[a] There are 1,522 women in the sample, making to 9,132 (1,522x6) observations. The summary statistics in panels A and C are based on the 9,132 observations of the pooled six-wave data, but those in panel C are based on the 1,522 women in the first wave.

Observed inter-temporal persistence

Examining observed transitions in labour force status provides one indicator of inter-temporal persistence of labour supply. For women in the sample, transitions in labour force status are shown in Table 2. Panel (a) in the table shows the transition on a year-on-year basis, while panel (b) presents the transition between wave 1 (2001) and wave 6 (2006).[11]

The numbers along the diagonal (highlighted in bold) are the proportion of women who do not change labour force status over time, that is, those that show persistence in labour supply. Irrespective of the time window examined, labour force status of the women in the sample exhibits substantial persistence. As expected, short-term persistence (panel (a)) is higher than long-term persistence (panel (b)). On a year-on-year basis, about 80 per cent of the women stay in the same labour force state from one year to the next. Over the six years examined, the proportion of married women staying in the same labour force state is still above 60 per cent.

Table 2: Labour force status transition (row per cent)

Initial LFS	Not-employed	Part-time	LFS transiting to Full-time	Number of observations
	(a). Year-on-year transition			
Not-employed	**79.1**	17.03	3.87	2,225
Part-time	9.93	**78.26**	11.81	2,930
Full-time	5.99	12.83	**81.18**	2,455
All	28.88	39.25	31.87	7,610
	(b). Transition from 2001 to 2006			
Not-employed	**62.3**	28.22	9.48	443
Part-time	13.2	**63.65**	23.15	553
Full-time	12.74	25.29	**61.98**	526
All	27.33	40.08	32.59	1,522

In both the short- and long-term, the probability of transitioning to part-time employment from non-employment is much higher than the probability of transitioning to full-time employment from non-employment. Other relationships are also evident with the probability of transitioning to full-time employment from part-time employment being greater than that of transitioning to non-employment from part-time employment. Also the probability of transitioning to part-time employment from full-time employment is higher than that of transitioning to non-employment from full-time employment.

5. Model estimation results

The results of the estimation of the four models described in Section 3, for both specifications (reduced form and structural specification — Section 4), are presented in this Section. Comparison of the estimates allows the validity of various assumptions about labour supply decisions, to be tested. Particular focus is given to the estimate for the lagged dependent variable, which measures state dependence of labour supply.

[11] Changes in labour force status across years within 2001 and 2006 are not taken into account in panel (b) of Table 2.

Moving from Model I to Model IV involves a gradual relaxation of the assumptions surrounding the estimation of the labour supply decision and requires additional parameters to be estimated. The significance of these additional parameters provides a guide as to whether the assumptions implied in the previous model hold, and therefore, whether the previous model is correctly specified. For example in Model II, unobserved heterogeneity (random effects) is introduced and the lagged dependent variable is treated as endogenous (by simultaneously estimating the dynamic model and the initial condition equation). The significance of the random effects term can be used to test the validity of the assumption made in Model I that unobserved heterogeneity influences labour supply. If the random effects term is found to be significant Model I is misspecified, and the parameter estimates from this model should be biased.

Moving from Model II to Model III, unobserved individual effects are allowed to be correlated with observed time variant variables through including the means of the variables in the model. If the coefficients on the mean variables are jointly statistically significant, the random effects assumption of Model II is not warranted in which case Model II is misspecified, again raising concerns of estimation bias.

Similarly, moving from Model III to Model IV allows for serial correlation of transitory errors. If the correlation parameter is statistically significant, the assumption of no serial correlation of transitory error is unwarranted, suggesting that Model III will be misspecified compared with Model IV.

Before comparing and discussing the model estimation results, it is useful to first illustrate how the coefficient estimates should be interpreted.

5.1. Interpretation of the estimates

As illustrated in Section 3, the Tobit model is formulated based on latent working hours y^*.

Since $E[y^* \mid X] = X'\beta$ in Tobit models, $\beta_k (= \frac{\partial E[y^* \mid X]}{\partial X_k})$ measures the marginal effect of the variable X_k on latent working hours. An advantage of the Tobit model as a method of estimating a censored distribution, is that it allows examining the partial effect of observed variables on alternative outcomes of interest (Wooldridge 2002), such as:

(a) $\Pr ob(y^* > 0 \mid X) = \Phi(X^{'}\beta / \delta)$

(b) $E(y \mid X) = \Phi(X^{'}\beta / \delta)(X^{'}\beta) + \delta\phi(X^{'}\beta / \delta)$

(c) $E(y \mid X, y > 0) = X^{'}\beta + \delta[\phi(X^{'}\beta / \delta) / \Phi(X^{'}\beta / \delta)]$.

In the above equations, δ refers to the square root of the variance of the (composite) error term in the model. Equation (a) measures the probability of being employed (those with positive working hours); (b) measures the expected value of observed working hours (including both zero and positive hours); and (c) is the expected working hours of those who are employed (those with positive hours). Following these equations and by using the coefficient estimates, the marginal effects on each of the three outcomes can be calculated. Since latent working hours are not observed for those who do not work, the marginal effects on the three outcomes described in (a) to (c) are more meaningful than the coefficient estimates themselves.

5.1. Estimation results

In the following two sub-sections the marginal effect estimates on the outcomes depicted in equations (a) $\Pr ob(y^* > 0 \mid X)$ and (b) $E[y \mid X]$, along with the coefficient estimates, are presented. Instead of calculating the marginal effects at the mean of the observed variables, the marginal effects for each observation in the sample are calculated with the mean of the individual marginal effects presented. The resulting marginal effects are often called mean marginal effects (MME).[12] To further facilitate inference, the standard errors of the MME estimates are calculated using the delta method (Greene 2000). The estimation results are presented separately for the reduced form and structural specifications of the four models.

Reduced form estimation

Table 3 presents the coefficient and MME estimates of the reduced form specification of the four models. The estimates of the random effects parameters in Models II to IV are all strongly significant, suggesting that ignoring unobserved individual heterogeneity (as in Model I) would lead to misspecification bias. In Models III and IV, the estimates of the

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[12] The marginal effects evaluated at the mean of the sample are often called the marginal effects at the mean (MEM). The MME estimates are preferred to MEMs since no persons in the sample take the mean values of the variables.

parameters of the mean variables used to explain the random effects are jointly significant at the 5 per cent level, although they are not all individually significant. This indicates that a random effects assumption on unobserved individual effects, as assumed in Model II, may not hold and that a fixed effects approximation is better. In Model IV the estimate on serial correlation is strongly significant, suggesting that ignoring the correlation as in Models I to III would lead to a biased estimate on state dependence and possibly other control variables. All these together suggest that Model IV should be the preferred model among the four.

In the first three models the coefficient and MME estimates for lagged working hours are positive, suggesting positive state dependence of labour supply for married women. However, the estimate on lagged working hours from the preferred model (Model IV) is insignificant. This, together with the positive and significant estimate for the correlation of transitory error, suggests that the evidence of state dependence inferred from Models I to III is largely due to positive correlation of transitory errors, and thus is spurious. That is, while state dependence is observed in the sample, it is a result of a range of unobserved transitory influences such as accumulation (loss) of human capital associated with the employment (unemployment) state.

Comparing the MME estimates between the models, the pooled model (Model I) produces the largest effect for lagged working hours (and thus the largest state dependence estimate). From this model, an additional hour worked in the previous year increases the probability of being employed in the current year by 1.2 percentage points, and increases current working hours by 0.69. The corresponding estimates from Model II are 0.46 percentage point and 0.27 respectively. The estimates from the correlated random effect model (Model III) are very similar to the estimates from Model II in terms of the marginal effects. The reduction of the MME estimate for state dependence from Model I to Models II and III suggests that unobserved individual effects play an important role in inter-temporal ersistence of a married woman's labour supply.

Table 3: Coefficient and MME estimates of the reduced form specification

	Model I: Pooled Tobit			Model II: RE Tobit			Model III: Cor. RE Tobit			Model IV: AR. Cor. RE Tobit		
	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)
Lagged hours	0.9013***	0.0122***	0.6919***	0.3437***	0.0046***	0.2712***	0.3372***	0.0045***	0.2639***	0.0069	0.0001	0.0052
s.e.	*0.0103*	*0.0001*	*0.0076*	*0.0130*	*0.0002*	*0.0102*	*0.0129*	*0.0002*	*0.0101*	*0.0321*	*0.0004*	*0.0242*
Non-labour income: deviation	-0.0230	-0.0003	-0.0177	-0.0288	-0.0004	-0.0227	-0.0298	-0.0004	-0.0233	-0.0268	-0.0003	-0.0201
s.e.	*0.0411*	*0.0006*	*0.0316*	*0.0318*	*0.0004*	*0.0251*	*0.0317*	*0.0004*	*0.0248*	*0.0296*	*0.0004*	*0.0223*
Non-labour income: mean	-0.1692***	-0.0023***	-0.1299***	-0.4334***	-0.0058***	-0.3420***	-0.4622***	-0.0061***	-0.3617***	-0.5951***	-0.0075***	-0.4476***
s.e.	*0.0418*	*0.0006*	*0.0321*	*0.1024*	*0.0014*	*0.0806*	*0.1013*	*0.0013*	*0.0790*	*0.1342*	*0.0017*	*0.1006*
Aged 18-25	2.2506	0.0298	1.7719*	2.8157	0.0345	2.3036*	2.9591	0.0347*	2.4258*	2.6531	0.0305	2.0941
s.e.	*1.5905*	*0.0205*	*1.0684*	*1.8512*	*0.0215*	*1.2161*	*1.8917*	*0.0209*	*1.2665*	*2.3134*	*0.0254*	*1.4144*
Aged 36-45	0.9820*	0.0132*	0.7649**	0.0780	0.0010	0.0625	-0.5005	-0.0063	-0.3999	-0.8994	-0.0109	-0.6911
s.e.	*0.5310*	*0.0072*	*0.3362*	*0.6771*	*0.0088*	*0.4163*	*0.7070*	*0.0088*	*0.4402*	*0.8043*	*0.0097*	*0.4603*
Aged 46-55	-0.2464	-0.0034	-0.1899	-0.7798	-0.0103	-0.6203	-1.9239*	-0.0248*	-1.5195**	-2.0172*	-0.0249*	-1.5361**
s.e.	*0.6227*	*0.0085*	*0.3886*	*0.9365*	*0.0123*	*0.5707*	*1.0067*	*0.0128*	*0.6153*	*1.1871*	*0.0145*	*0.6675*
Aged 56 plus	-4.8570***	-0.0689***	-3.5859***	-5.8866***	-0.0849***	-4.4703***	-7.4002***	-0.1045***	-5.5635***	-8.3707***	-0.1122***	-6.0236***
s.e.	*0.7107*	*0.0100*	*0.4085*	*1.1261*	*0.0164*	*0.6330*	*1.2121*	*0.0170*	*0.6744*	*1.4741*	*0.0197*	*0.7459*
Degree	4.0718***	0.0550***	3.1510***	12.5874***	0.1643***	10.1072***	12.5503***	0.1615***	10.0023***	16.8009***	0.2068***	12.8715***
s.e.	*0.4968*	*0.0066*	*0.3200*	*1.1257*	*0.0132*	*0.7465*	*1.1013*	*0.0129*	*0.7233*	*1.4291*	*0.0159*	*0.8763*
Diploma	2.6090***	0.0358***	1.9933***	7.8962***	0.1131***	6.1035***	7.7802***	0.1095***	5.9661***	10.5949***	0.1430***	7.7200***
s.e.	*0.5646*	*0.0076*	*0.3546*	*1.4242*	*0.0184*	*0.8859*	*1.4084*	*0.0181*	*0.8723*	*1.8181*	*0.0222*	*1.0396*
Certificate	1.7718***	0.0246***	1.3435***	5.0823***	0.0766***	3.8273***	4.7705***	0.0706***	3.5580***	6.2215***	0.0888***	4.3507***
s.e.	*0.5428*	*0.0074*	*0.3344*	*0.9646*	*0.0139*	*0.5590*	*0.9668*	*0.0138*	*0.5528*	*1.2124*	*0.0167*	*0.6228*
Year 12	2.0560***	0.0284***	1.5630***	5.6239***	0.0839***	4.2573***	5.4759***	0.0801***	4.1118***	7.1595***	0.1011***	5.0531***
s.e.	*0.5136*	*0.0070*	*0.3170*	*1.0807*	*0.0154*	*0.6278*	*1.0783*	*0.0151*	*0.6216*	*1.3450*	*0.0183*	*0.6947*
Health	-3.9283***	-0.0547***	-2.9565***	-3.0928***	-0.0430***	-2.4014***	-1.2152*	-0.0163*	-0.9457**	-1.0963*	-0.0141*	-0.8203**
s.e.	*0.4123*	*0.0058*	*0.2367*	*0.5330*	*0.0076*	*0.3077*	*0.6763*	*0.0092*	*0.3987*	*0.6065*	*0.0078*	*0.3290*

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Table 3: (Continued)

	Model I: Pooled Tobit			Model II: RE Tobit			Model III: Cor. RE Tobit			Model IV: AR. Cor. RE Tobit		
	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)
Child 0-2	-6.1477***	-0.0830***	-4.7194***	-10.5131***	-0.1410***	-8.2966***	-9.5885***	-0.1266***	-7.5037***	-12.8591***	-0.1631***	-9.6715***
s.e.	*0.4744*	*0.0062*	*0.3636*	*0.453*	*0.0063*	*0.3635*	*0.5251*	*0.0072*	*0.416*	*0.5392*	*0.0073*	*0.4186*
Child 3-5	-0.8459*	-0.0114*	-0.6494*	-3.7566***	-0.0504***	-2.9646***	-2.9959***	-0.0396***	-2.3445***	-5.1697***	-0.0656***	-3.8882***
s.e.	*0.4603*	*0.0062*	*0.3533*	*0.5144*	*0.0069*	*0.4071*	*0.6382*	*0.0085*	*0.4999*	*0.6852*	*0.0088*	*0.5173*
Child 6-17	-0.0859	-0.0012	-0.0659	-0.7507**	-0.0101**	-0.5924**	-0.4328	-0.0057	-0.3387	-0.5417	-0.0069	-0.4074
s.e.	*0.1818*	*0.0025*	*0.1396*	*0.3073*	*0.0041*	*0.2424*	*0.4740*	*0.0063*	*0.3708*	*0.4737*	*0.006*	*0.3561*
Capital city	-0.0872	-0.0012	-0.067	-0.4997	-0.0067	-0.3946	0.0653	0.0009	0.0511	-0.7631	-0.0097	-0.5745
s.e.	*0.3782*	*0.0051*	*0.2345*	*0.6538*	*0.0087*	*0.3950*	*1.2733*	*0.0168*	*0.7623*	*1.2109*	*0.0153*	*0.6677*
ESC	-0.0853	-0.0011	-0.0658	-0.1232	-0.0016	-0.0979	-0.4493	-0.0058	-0.3538	-0.5231	-0.0065	-0.3965
s.e.	*0.5335*	*0.0072*	*0.3328*	*1.3419*	*0.0177*	*0.8170*	*1.3222*	*0.0173*	*0.7952*	*1.7501*	*0.0220*	*0.9667*
NESC	-1.9929***	-0.0273***	-1.5097***	-3.9546***	-0.0558***	-3.0392***	-4.4715***	-0.0623***	-3.3981***	-5.5143***	-0.0736**	-3.9996***
s.e.	*0.5125*	*0.0071*	*0.3015*	*1.1508*	*0.0169*	*0.6429*	*1.1592*	*0.0168*	*0.6311*	*1.5133*	*0.021*	*0.7446*
Unem rate	0.0335	0.0005	0.0257	0.0071	0.0001	0.0056	0.0350	0.0005	0.0274	-0.0103	-0.0001	-0.0077
s.e.	*0.2025*	*0.0027*	*0.1555*	*0.2103*	*0.0028*	*0.1660*	*0.2103*	*0.0028*	*0.1646*	*0.2235*	*0.0028*	*0.1681*
Health: mean							-12.6297***	-0.1668***	-9.8836***	-17.3743***	-0.2204***	-13.0674***
s.e.							*1.4233*	*0.0183*	*1.1173*	*1.8147*	*0.0223*	*1.3711*
Child 0-2: mean							-3.1861	-0.0421	-2.4933	-1.8129	-0.0230	-1.3635
s.e.							*2.3557*	*0.0310*	*1.8420*	*3.0228*	*0.0383*	*2.2722*
Child 3-5: mean							-6.2744**	-0.0828***	-4.9101**	-10.1854***	-0.1292***	-7.6606***
s.e.							*2.4455*	*0.0322*	*1.9157*	*3.1766*	*0.0400*	*2.3948*
Child 6-17: mean							-0.8172	-0.0108	-0.6395	-1.3247*	-0.0168*	-0.9963*
s.e.							*0.6185*	*0.0082*	*0.4843*	*0.7130*	*0.009*	*0.5367*

(continued next page)

Table 3: (Continued)

	Model I: Pooled Tobit			Model II: RE Tobit			Model III: Cor. RE Tobit			Model IV: AR. Cor. RE Tobit		
	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)
Capital city: mean							-0.7135	-0.0094	-0.5584	-0.2034	-0.0026	-0.1530
s.e.							*1.5273*	*0.0202*	*1.1952*	*1.6471*	*0.0209*	*1.2388*
Wave 3	0.0502	0.0007	0.038	-0.2717	-0.0037	-0.2124	-0.3237	-0.0044	-0.2507	-0.4404	-0.0057	-0.3287
s.e.	*0.5386*	*0.0074*	*0.324*	*0.5258*	*0.0072*	*0.3128*	*0.5238*	*0.0071*	*0.3084*	*0.4759*	*0.0061*	*0.2585*
Wave 4	1.1823**	0.0161**	0.9033**	0.4707	0.0064	0.3704	0.5004	0.0067	0.3903	0.1050	0.0013	0.0788
s.e.	*0.5913*	*0.0080*	*0.3626*	*0.5278*	*0.0071*	*0.317*	*0.5271*	*0.0070*	*0.3138*	*0.5648*	*0.0072*	*0.3087*
Wave 5	1.3919**	0.0189**	1.0654***	0.7437	0.0100	0.5866*	0.8333	0.0110	0.6517*	0.4844	0.0061	0.3645
s.e.	*0.6561*	*0.0089*	*0.4042*	*0.5656*	*0.0076*	*0.3410*	*0.5633*	*0.0075*	*0.3372*	*0.5863*	*0.0074*	*0.3222*
Wave 6	1.6647**	0.0225**	1.2773***	1.0728*	0.0143*	0.8486**	1.2446**	0.0163**	0.9768***	0.9421	0.0119	0.7116**
s.e.	*0.711*	*0.0096*	*0.4411*	*0.6209*	*0.0083*	*0.3764*	*0.6245*	*0.0082*	*0.3764*	*0.6288*	*0.0079*	*0.3481*
Constant	-0.6745	-0.0091	-0.5178	11.5814***	0.1553***	9.1397***	16.3183***	0.2155***	12.7703***	25.6379***	0.3252***	19.2826***
s.e.	*1.6118*	*0.0218*	*1.2372*	*1.8742*	*0.0248*	*1.4950*	*2.0410*	*0.0261*	*1.6177*	*2.4724*	*0.0300*	*1.9067*
Variance of time variant error	2.6484***			2.4893***			2.4856***			2.5153***		
s.e.	*0.0064*			*0.0051*			*0.0052*			*0.0082*		
Ln(variance of random effects)				5.2689			5.2238			5.8371		
s.e.				*0.0629*			*0.0618*			*0.0723*		
Correlation of transitory error										0.2940		
s.e.										*0.0260*		
Mean log-likelihood	-15.4969			-18.5846			-18.5465			-18.5195		

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

The effect of permanent non-labour income (as measured by the mean of non-labour income) on a married woman's labour supply is significant and negative. Transitory change in non-labour income (as measured by the deviation from mean of non-labour income), while having an expected negative sign, is not significant. These estimates suggest that permanent non-labour income, rather than the transitory non-labour income, has the greatest effect on labour supply.[13] The MME estimates from the preferred model (Model IV) indicate that a $10 000 increase in a woman's permanent non-labour income would reduce the probability of her being employed by 0.75 percentage point and reduce working hours by 0.45 hour. To put these estimates in context, the mean non-labour income of the women in the sample is about $58 000. Therefore, a woman who has permanent non-labour income at the sample mean would have a probability of being employed that is about 4.4 percentage points lower and working hours that are 2.6 hours less, compared with a woman without any non-labour income.

Evaluated at the sample mean, the elasticity of working hours with respect to permanent non-labour income is -0.12, and the elasticity of the probability of being employed is -0.06.[14] Comparing the estimates from the other three models, we see that the MME estimates from Model I for both working hours and the probability of being employed are less than a third of those estimated from Model IV. The estimates from Models II and III fall in between those of Models I and IV. That is, failure to adjust for unobserved heterogeneity leads to an underestimation of the importance of non-labour income on labour supply of married women.

Age also appears to influence the labour supply of married women. Note that the reference age group refers to those aged 26-35 years. While the coefficient estimates on the different age cohorts are not all individually statistically significant, they are jointly significant at the 1 per cent level in all the four models. The estimates from the preferred model indicate that, all else equal, older women tend to supply less labour than younger ones. For

[13] The insignificance of transitory non-labour income may also be due to measurement errors in non-labour income. Measurement error leads to the estimate to be biased towards zeros. If non-labour income is measured with errors, the errors are more likely to be reflected in the deviation from mean than the mean itself.

example, the MME estimates of the probability of being employed show that compared with women aged 26-35 years, those aged 46-55 years have a probability of being employed that is 2.5 percentage points lower, with the probability of being employed for those aged 56 and over 11.2 percentage points lower. For observed working hours, compared to the 26-35 years age group, the MME estimates show that those aged 46-55 years are expected to work 1.5 hours less and those aged 56 and over 6 hours less. The estimates from Model III are qualitatively similar to those from Model IV, but the MME estimates are slightly smaller. The estimate on the age dummy aged 36-45 in Model I has an opposite sign to that from Model IV, and it is significant at the 10 per cent level. For the two older age groups, the MME estimates in Model I are also much smaller than those in Model IV, indicating that the pooled model might have provided misleading inferences regarding the effect of age alone on a woman's labour supply.

As with other models of labour supply, education is found to have a significant effect (all variables in all models significant at the 1 per cent level). For the education variables, the reference group is those who did not complete year 12. In general the higher the education level, the greater is the labour supply. Focusing on the preferred model, the probability of being employed for those married women who completed year 12 is 10.1 percentage points higher compared to those who did not complete year 12. For other education levels the effect is also significant, with the probability of being employed 8.9 percentage points higher for those with a certificate; 14.3 percentage points higher for those with a diploma; and 20.7 percentage points higher for those with a degree compared to those married women who did not complete year 12.

As with the probability of being employed, increases education levels increase working hours. Those married women who completed year 12 are expected to work 5.1 hours more per week than those who did not, those with a certificate 4.4 hours more, diploma 7.7 hours more and degree 12.9 hours more. The corresponding MME estimates from the pooled model (Model I) are much smaller than those from Model IV. For example, the MME estimate for the degree variable on observed working hours in Model I is less than one

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[14] The sample mean of non-labour income is $58 000; the sample mean of working hours is 21.61; and the sample mean of the probability of employment is 0.71.

fourth of that from Model IV. The MME estimates between Models II and III are similar, but both slightly smaller than those from Model IV.

The specification of the health variables differed in Models III and IV compared with models I and II and thus may not be directly comparable. Despite this, the coefficient estimates in all the four models are significant and have the same sign. As expected, the results indicate that having a health condition reduces a married woman's labour supply.

In models III and IV, both the mean of health (over the six-year data period for an individual) and its actual value are used, with only the actual value used in Models I and II. The estimate on mean health conditions can be interpreted as the effect of a woman's permanent health status on labour supply, while the estimate on the actual value can be seen as the effect of temporary health changes. The results of the preferred model indicate that a 'temporary' health deterioration (that is, a change from no condition to having a conditions) reduces the probability of being employed by 1.4 percentage points, and reduces working hours by 0.8.[15]

As with other studies of labour supply, the impact of children, particularly young children, is found to be significant. Similar to the approach used to measure the effect of health status, the variables used to measure the influence of children vary between Models I and II and Models III and IV. The mean of the child variables were included in Models III and IV to account for correlation of observed variables and unobserved individual effects. Consequently, the MME estimates on these variables from Models III and IV cannot be compared with those from Models I and II.

Despite lack of comparability in results across the models, the coefficient estimates from all the four models show that children, particularly younger ones, have a negative effect on labour supply of married women. In all the four models, the estimates on the variables 'child 0-2' and 'child 3-5' are strongly significant. The MME estimates from the preferred model show that an additional child under two years would reduce the probability of being

[15] For the mean health variable, the MMEs was calculated by treating it as a continuous variable. While this may not be appropriate since the health condition variable is a dummy variable, there are no better options for calculating the MME for the mean variable. Without emphasis on the

employed by 16.3 percentage points and reduce expected working hours by 9.7. An additional child aged 3-5 reduces the probability of being employed by 6.6 percentage points and reduces working hours by 3.9. Having an additional child aged 6-17 is also found to have a negative effect in the preferred model, but the estimate is statistically insignificant.

All the models indicate that labour supply of overseas born women is lower than those born in Australia, but only the estimate for immigrants from non-English speaking countries is significantly lower (the omitted group for this variable refers to those women born in Australia). The MME estimates from the preferred model show that compared with Australian born women, the probability of those who immigrated from non-English speaking countries being employed is 7.4 percentage points lower, and working hours are expected to be 4 hours less. While this may be due to differences in cultural preferences, language difficulty is another possible explanation. It could also be caused by discrimination in employment and/or wages. The MME estimates from the other models are smaller than those from Model IV. In particular, the MME estimates from Model I are the smallest among all the four models, suggesting that standard estimation approaches may significantly underestimate this effect.

Living in a capital city is not found to have a significant effect on labour supply in any of the four models. Local unemployment has a positive sign, but it is also insignificant in all of the models.[16]

The estimates on the wave/year dummies indicate that women appear to supply more labour in the later years than in the earlier years, perhaps reflecting the booming of the

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MME estimate of the mean health variable, the coefficient does suggest that permanent health might have a much larger impact on labour supply than temporary health deterioration.

[16] In theory the effect of the unemployment rate on married women's labour supply is ambiguous. On the one hand increases in the unemployment rate may reduce married women's labour supply through, for example, reducing wage offers. On the other hand, worsening labour market conditions may increase labour supply of married women as higher unemployment rates increase uncertainty of family income, an 'added worker' effect. This may explain why the unemployment rate variable is insignificant in the model. In addition, the unemployment rate is a measure at the ABS major statistical region level. As such, it may not reflect the labour market conditions an individual actually faces. This may be another reason for the insignificance.

economy during the period examined, and the general increasing trend of female labour supply.

Structural form estimation

The estimation results for the structural form specification are presented in Table 4. As for the reduced form specification, both unobserved heterogeneity and serial correlation of transitory error were found to have a significant effect, leading to the conclusion that Model IV was once again the preferred model.

The results for state dependence are also as observed for the reduced form specification — there is no evidence of state dependence of labour supply once observed and unobserved heterogeneity and serially correlated transitory shocks to labour supply are controlled for. The MME estimates of the lagged working hour variable on both the probability of being employed and observed working hours are very similar in the reduced form and structural specifications.

The structural form specification included a woman's own wage in two forms — a mean measure to represent permanent earnings capacity, and a deviation from the mean to measure transitory wage changes. The measure of a woman's permanent earning capacity is found to be significant in the preferred model (Model IV). The sign indicates that an increase in the mean of a woman's wages increases her labour supply. That is, for married Australian women the substitution effect of permanent wages dominates the income effect. The MME estimates show that a $10 increase in a woman's mean (hourly) wage raises the probability of her being employed by 6.5 percentage points, and raises her expected working week by 3.8 hours.

Evaluated at the sample mean, the estimates for mean wages imply an elasticity of a woman's working hours with respect to her mean wages of 0.29, and an elasticity of the probability of being employed of 0.15.[17] The other three models suggest that these elasticities are smaller. In particular, the MME estimate from Model I is less than half the estimate from Model IV. For the other three models, the estimate on the deviation of wages

[17] The sample mean of women's wages is $16.54; the sample mean of working hours is 21.61; and the sample proportion employed 71.08 per cent.

is also significant and positive, but the size of the effect of transitory wages is much smaller than that of mean wages.

Looking at the wages of a woman's partner, the results show that both the mean and the deviation of his wages are significant and negative. This indicates that both permanent and transitory earning capacities of a woman's partner have a negative effect on her labour supply. The MME estimates from our preferred model indicate that a $10 increase in a partner's permanent wages reduces the probability of the woman being employed by 2.9 percentage points, and reduces her working hours by 1.7. Evaluated at the sample mean, the cross-elasticity of working hours of a woman with respect to her partner's permanent wages is -0.18, and the elasticity of the probability of the woman being employed is -0.09. The effects of transitory wages of the partner are statistically significant but much smaller in size than a partner's permanent wages. The estimated effects from the pooled model (Model I) are much smaller than those from our preferred model, particularly for the partner's mean wage variable. The estimates from Models II and III fall in between those of Model I and Model IV.

Along with examining the effect of a partner's income, the effect of his working hours was also examined to see whether there was any complementarity in a couple's labour supply. A partner's working hours, measured as working hours divided by 10, and its square (to capture possible non-linear effects) were added to all models. The results indicate some complementarity in labour supply, however, the square of working hours is only significant in the pooled model (Model 1) and is found insignificant when unobserved heterogeneity is controlled (Models II to IV), suggesting the relationship is linear. The MME estimates from the preferred model (Model IV) show that a 10 hour increase in a partner's working hours raises the probability of a woman being employed by 1.4 percentage points, and raises their expected working hours by 0.83. The estimated effects from the other three models are larger than that from Model IV. The MME estimate from Model I is the largest.

Table 4: Coefficient and MME estimates of the structural specification

	Model I: Pooled simple			Model II: RE			Model III: Cor. RE			AR.Cor.RE		
	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)
Lagged hours	0.8810***	0.0115***	0.6724***	0.3442***	0.0045***	0.2697***	0.3394***	0.0044***	0.2642***	0.0446	0.0006	0.0336
s.e.	*0.0098*	*0.0001*	*0.0069*	*0.0137*	*0.0002*	*0.0107*	*0.0137*	*0.0002*	*0.0106*	*0.0316*	*0.0004*	*0.0239*
Own wages: deviation	0.0311***	0.0004***	0.0237***	0.0180**	0.0002**	0.0141**	0.0175**	0.0002**	0.0136**	0.0110	0.0001	0.0083
s.e.	*0.0100*	*0.0001*	*0.0077*	*0.0084*	*0.0001*	*0.0066*	*0.0085*	*0.0001*	*0.0066*	*0.0083*	*0.0001*	*0.0063*
Own wages: mean	0.1951***	0.0026***	0.1489***	0.4301***	0.0057***	0.3370***	0.4014***	0.0052***	0.3125***	0.5083***	0.0065***	0.3834***
s.e.	*0.0129*	*0.0002*	*0.0099*	*0.0296*	*0.0004*	*0.0232*	*0.0312*	*0.0004*	*0.0242*	*0.0415*	*0.0005*	*0.0313*
Family non-labour income: deviation	-0.0099	-0.0001	-0.0076	0.0025	0.0000	0.0020	0.0014	0.0000	0.0011	-0.0045	-0.0001	-0.0034
s.e.	*0.0472*	*0.0006*	*0.0360*	*0.0391*	*0.0005*	*0.0306*	*0.0391*	*0.0005*	*0.0304*	*0.0377*	*0.0005*	*0.0284*
Family non-labour income: mean	-0.2461***	-0.0032***	-0.1879***	-0.5239***	-0.0069***	-0.4105***	-0.5194***	-0.0068***	-0.4043***	-0.6688***	-0.0085***	-0.5044***
s.e.	*0.0769*	*0.0010*	*0.0586*	*0.1598*	*0.0021*	*0.1252*	*0.1529*	*0.002*	*0.1190*	*0.1956*	*0.0025*	*0.1475*
Partner's wages: deviation	-0.0197	-0.0003	-0.0150	-0.0400**	-0.0005**	-0.0313**	-0.0420**	-0.0005**	-0.0327**	-0.0342**	-0.0004**	-0.0258**
s.e.	*0.0186*	*0.0002*	*0.0142*	*0.0178*	*0.0002*	*0.0139*	*0.0179*	*0.0002*	*0.0139*	*0.0149*	*0.0002*	*0.0112*
Partner's wages: mean	-0.0657***	-0.0009***	-0.0502***	-0.1755***	-0.0023***	-0.1375***	-0.1726***	-0.0022***	-0.1343***	-0.2300***	-0.0029***	-0.1735***
s.e.	*0.008*	*0.0001*	*0.0061*	*0.0252*	*0.0003*	*0.0198*	*0.0255*	*0.0003*	*0.0199*	*0.0333*	*0.0004*	*0.0252*
Partner's working hours	1.5517***	0.0203***	1.1843***	1.3611***	0.0180***	1.0665***	1.2722***	0.0166***	0.9904***	1.1391***	0.0145***	0.8591***
s.e.	*0.2324*	*0.0030*	*0.1775*	*0.2784*	*0.0036*	*0.2188*	*0.2774*	*0.0036*	*0.2166*	*0.2903*	*0.0037*	*0.2199*
Partner's working hours squared	-0.1208***	-0.0016***	-0.0922***	-0.0527	-0.0007	-0.0413	-0.0485	-0.0006	-0.0378	-0.0160	-0.0002	-0.0121
s.e.	*0.0320*	*0.0004*	*0.0244*	*0.0361*	*0.0005*	*0.0283*	*0.0361*	*0.0005*	*0.0281*	*0.0371*	*0.0005*	*0.0280*
Aged 18-25	2.2446	0.0288	1.7580	2.6263	0.0319	2.1340*	2.8489	0.0330	2.3282*	2.4427	0.0280	1.9364
s.e.	*1.6310*	*0.0204*	*1.0829*	*1.8315*	*0.0211*	*1.2098*	*1.8742*	*0.0205*	*1.2636*	*2.2679*	*0.0249*	*1.4097*
Aged 36-45	0.6198	0.0081	0.4790	-0.2734	-0.0035	-0.2173	-0.8834	-0.011	-0.7023	-1.1971	-0.0146	-0.9233**
s.e.	*0.5274*	*0.0069*	*0.3306*	*0.6780*	*0.0087*	*0.4198*	*0.7088*	*0.0087*	*0.4416*	*0.8006*	*0.0096*	*0.4661*
Aged 46-55	-0.4320	-0.0057	-0.3309	-0.9001	-0.0117	-0.7115	-2.2254**	-0.0283**	-1.7501***	-2.3442**	-0.0291**	-1.7914***
s.e.	*0.6202*	*0.0082*	*0.3838*	*0.9344*	*0.0121*	*0.5735*	*1.0065*	*0.0127*	*0.6153*	*1.1737*	*0.0144*	*0.6701*

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Table 4: (Continued)

	Model I: Pooled simple			Model II: RE			Model III: Cor. RE			AR.Cor.RE		
	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)
Aged 56 plus	-4.2788***	-0.0583***	-3.1659***	-5.4445***	-0.0765***	-4.1332***	-7.3422***	-0.1015***	-5.5180***	-8.3392***	-0.1120***	-6.0416***
s.e.	*0.7209*	*0.0098*	*0.4160*	*1.1435*	*0.0163*	*0.6465*	*1.2299*	*0.0170*	*0.6864*	*1.4812*	*0.0199*	*0.7618*
Degree	2.1298***	0.0280***	1.6271***	8.2190***	0.1090***	6.4915***	8.3345***	0.1088***	6.5455***	11.3104***	0.1441***	8.6048***
s.e.	*0.4849*	*0.0064*	*0.3024*	*1.0680*	*0.0134*	*0.6772*	*1.0667*	*0.0132*	*0.6731*	*1.3743*	*0.0165*	*0.8154*
Diploma	1.6671***	0.0221***	1.2686***	6.0177***	0.0831***	4.6672***	5.6970***	0.0779***	4.3778***	7.7092***	0.1037***	5.6917***
s.e.	*0.5674*	*0.0074*	*0.3528*	*1.3511*	*0.0174*	*0.8428*	*1.3333*	*0.0171*	*0.8201*	*1.7186*	*0.0215*	*0.9861*
Certificate	1.7210***	0.0228***	1.3102***	4.7647***	0.0673***	3.6550***	4.6297***	0.0645***	3.5245***	6.1154***	0.0842***	4.4507***
s.e.	*0.5548*	*0.0073*	*0.3453*	*0.9715*	*0.0132*	*0.5834*	*0.9702*	*0.013*	*0.5769*	*1.1961*	*0.0158*	*0.6543*
Year 12	1.4383***	0.0191***	1.0923***	4.3824***	0.0623***	3.3501***	4.3943***	0.0615***	3.3383***	5.8324***	0.0806***	4.2337***
s.e.	*0.5228*	*0.0069*	*0.3225*	*1.0831*	*0.0149*	*0.6406*	*1.0826*	*0.0147*	*0.6366*	*1.3494*	*0.018*	*0.727*
Health	-3.1564***	-0.0424***	-2.3721***	-2.7175***	-0.0370***	-2.1005***	-1.2068*	-0.0159*	-0.9343**	-1.1201*	-0.0144*	-0.8403**
s.e.	*0.4324*	*0.0059*	*0.2499*	*0.5544*	*0.0078*	*0.3193*	*0.6918*	*0.0093*	*0.4057*	*0.629*	*0.0082*	*0.3444*
Child 0-2	-6.4097***	-0.0838***	-4.8922***	-10.5732***	-0.1396***	-8.2850***	-9.6229***	-0.1253***	-7.4910***	-12.5954***	-0.1603***	-9.4991***
s.e.	*0.4738*	*0.006*	*0.3610*	*0.4502*	*0.0061*	*0.3563*	*0.5222*	*0.0070*	*0.4099*	*0.5402*	*0.0074*	*0.4171*
Child 3-5	-1.0221**	-0.0134**	-0.7801**	-3.9057***	-0.0516***	-3.0604***	-3.0417***	-0.0396***	-2.3679***	-5.0039***	-0.0637***	-3.7738***
s.e.	*0.452*	*0.0059*	*0.345*	*0.5060*	*0.0067*	*0.3975*	*0.6363*	*0.0083*	*0.4958*	*0.6839*	*0.0088*	*0.5177*
Child 6-17	-0.2632	-0.0034	-0.2009	-0.9639***	-0.0127***	-0.7553***	-0.4279	-0.0056	-0.3331	-0.5674	-0.0072	-0.428
s.e.	*0.1829*	*0.0024*	*0.1396*	*0.3021*	*0.0040*	*0.2366*	*0.4706*	*0.0061*	*0.3662*	*0.4706*	*0.006*	*0.3547*
Capital city	-0.3430	-0.0045	-0.2619	-0.8161	-0.0108	-0.6401*	-0.3535	-0.0046	-0.2753	-1.1490	-0.0146	-0.8679
s.e.	*0.3747*	*0.0049*	*0.2315*	*0.6409*	*0.0084*	*0.3866*	*1.2870*	*0.0167*	*0.7699*	*1.2291*	*0.0156*	*0.6862*
ESC	0.0213	0.0003	0.0163	0.2335	0.0030	0.1843	0.0474	0.0006	0.0371	0.1299	0.0016	0.0988
s.e.	*0.5430*	*0.0071*	*0.3368*	*1.3632*	*0.0177*	*0.8312*	*1.336*	*0.0172*	*0.8071*	*1.7357*	*0.0217*	*0.9782*
NESC	-1.2201**	-0.0161**	-0.9238***	-2.5748**	-0.0352**	-1.9831***	-2.8652***	-0.0387**	-2.1890***	-3.6154**	-0.0478**	-2.6618***
s.e.	*0.5148*	*0.0068*	*0.3079*	*1.1043*	*0.0155*	*0.6279*	*1.1059*	*0.0153*	*0.6225*	*1.4300*	*0.0194*	*0.7381*
Unem rate	0.1313	0.0017	0.1002	0.0343	0.0005	0.0269	0.0602	0.0008	0.0469	0.0273	0.0003	0.0206
s.e.	*0.2028*	*0.0027*	*0.1548*	*0.2092*	*0.0028*	*0.1639*	*0.209*	*0.0027*	*0.1627*	*0.2223*	*0.0028*	*0.1676*
Health: mean							-9.8383***	-0.1281***	-7.6587***	-13.4628***	-0.1714***	-10.1532***
s.e.							*1.4144*	*0.0181*	*1.1011*	*1.7688*	*0.022*	*1.3355*

(continued next page)

Table 4: (Continued)

	Model I: Pooled simple			Model II: RE			Model III: Cor. RE			AR.Cor.RE		
	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)	E(y*|x)	Pr(y*>0|x)	E(y|x)
Child 0-2: mean							-3.5508	-0.0462	-2.7641	-2.2207	-0.0283	-1.6748
s.e.							*2.2939*	*0.0298*	*1.7840*	*2.9155*	*0.0371*	*2.1973*
Child 3-5: mean							-5.4673**	-0.0712**	-4.2561**	-8.8641***	-0.1128***	-6.6850***
s.e.							*2.4026*	*0.0312*	*1.8717*	*3.1252*	*0.0396*	*2.3610*
Child 6-17: mean							-1.2406**	-0.0161**	-0.9657**	-1.7737**	-0.0226**	-1.3377**
s.e.							*0.6128*	*0.0079*	*0.4774*	*0.6978*	*0.0088*	*0.5271*
Capital city: mean							-0.7465	-0.0097	-0.5811	-0.3219	-0.0041	-0.2428
s.e.							*1.5289*	*0.0199*	*1.1901*	*1.6327*	*0.0208*	*1.2313*
Wave 3	0.0429	0.0006	0.0322	-0.3043	-0.0041	-0.2359	-0.3256	-0.0043	-0.2504	-0.4335	-0.0056	-0.3237
s.e.	*0.5412*	*0.0072*	*0.324*	*0.5285*	*0.0071*	*0.3124*	*0.5271*	*0.0070*	*0.3082*	*0.482*	*0.0062*	*0.2640*
Wave 4	1.2000**	0.0158**	0.9110**	0.5134	0.0068	0.4009	0.5856	0.0077	0.4538	0.2539	0.0033	0.1907
s.e.	*0.5921*	*0.0078*	*0.3613*	*0.5309*	*0.0071*	*0.3172*	*0.5301*	*0.0070*	*0.3137*	*0.5629*	*0.0072*	*0.3109*
Wave 5	1.4960**	0.0196**	1.1386***	0.8859	0.0117	0.6938**	1.0254*	0.0134*	0.7976**	0.7461	0.0095	0.5627*
s.e.	*0.6604*	*0.0087*	*0.4054*	*0.5732*	*0.0076*	*0.3444*	*0.5706*	*0.0074*	*0.3400*	*0.5902*	*0.0075*	*0.3283*
Wave 6	1.8095**	0.0237**	1.3809***	1.2606**	0.0166**	0.9904***	1.4915**	0.0193**	1.1647***	1.2639**	0.0160**	0.9574***
s.e.	*0.7125*	*0.0093*	*0.4406*	*0.6261*	*0.0082*	*0.3789*	*0.6299*	*0.0081*	*0.3788*	*0.6363*	*0.0080*	*0.3570*
Cons	-6.5165***	-0.0852***	-4.9737***	3.2401*	0.0428*	2.5389	8.1404***	0.1060***	6.3370***	15.4697***	0.1969***	11.6668***
s.e.	*1.6712*	*0.0218*	*1.2741*	*1.9673*	*0.0259*	*1.5452*	*2.1158*	*0.0272*	*1.6554*	*2.5269*	*0.0315*	*1.9298*
Variance of time variant error	2.6440***			2.4862***			2.4832***			2.5056***		
s.e.	*0.0062*			*0.0054*			*0.0056*			*0.0079*		
Ln(variance of random effects)				5.1633***			5.1181***			5.6879***		
s.e.				*0.0618*			*0.0614*			*0.0735*		
Correlation of transitory error										0.2647		
s.e.										0.0261305		
Mean log-likelihood	-15.4305			-18.5024			-18.4721			-18.4498		

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

There are a range of possible reasons to explain the complementarity in a married couple's labour supply. One reason relates to leisure time. Partners may tend to share their leisure time, or they may share similar preferences between work and leisure (due to the 'marriage sorting process' which may lead to individuals with similar preferences being 'paired'). However, the exact explanations warrant further investigation.

In the structural specification, a woman's non-labour income was treated differently to the reduced form specification as it did not include her partner's earnings. Thus non-labour income in the structural specification represents family non-labour income. However, despite this difference the qualitative effect on labour supply was found to be similar. Permanent family non-labour income is found to have a significant negative effect on the labour supply of married women. For example, estimates from the preferred model (Model IV) show that a \$10 000 increase in permanent family non-labour income reduces the probability of a woman being employed by 0.9 percentage points, and reduces her working week by a 0.5 hours. The MME estimates from the other three models are smaller, with those from Model I being the smallest.

The estimates for all other variables in the structural specification are remarkably similar to those estimated from the reduced form specification with the exception of the education variables. The effect of education was found to be much smaller in the structural specification than in the reduced form specification. However, this was expected since education is the most important determinant of wages which are also included in the structural specification. The small change in the estimated effects of the other variables included in both the specifications suggests relatively little indirect effect of those variables on a woman's labour supply through their effect on wages.

6. Conclusion and discussion

Using the first six waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey, this study examined the labour supply behaviour of married Australian women. The focus of the study was on whether, and to what extent, state dependence occurred in the labour supply of married Australian women.

As in other countries, inter-temporal persistence of labour supply for married Australian women was observed in the HILDA data. This persistence was found to remain even after controlling for a range of factors that influence labour supply, including individual-specific unobserved factors (unobserved heterogeneity).

However, when the analysis was expanded to assess the effects of potential unobserved transitory shocks to labour supply, no evidence was found to support state dependence in labour supply. Put differently, the inter-temporal persistence of labour supply of married Australian women in the HILDA survey can be explained by observed and unobserved heterogeneity and unobserved transitory shocks to labour supply decisions, and not state dependence.

The lack of evidence supporting true state dependence of married Australian women has some important implications for the design of policies that attempt to increase the labour force participation of this group. For example, in the absence of state dependence in labour supply, early interventions aimed at preventing people from becoming unemployed will not be more effective in altering employment levels than those interventions which target those who are unemployed.

The results from this study also show that individual characteristics of married women (observed and unobserved heterogeneity) are key drivers of labour supply. This suggests that 'one-size-fits-all' policies aimed at increasing labour supply of all married women may not work, and instead, tailored policies which take account of individual characteristics and circumstances would have a greater chance of being effective.

Wages were also found to be important drivers of the labour supply of Australian women. Improvements in their own permanent wages (when wages were treated as exogenous) increased their labour supply. The positive influence of own wages implies that closing the observed gap between male and female wages — estimated to be over 10 per cent in Australia (Kee 2006) — would lift the labour supply of married Australian women.

The wage of a woman's spouse, however, had the inverse effect on her labour supply. The higher the wage of her partner, the less labour supplied. Despite this, there was also evidence to suggest that the labour supply of a woman was complementary to that of her partner when working hours were examined. Increased hours worked by a woman's partner were also likely to increase her labour supply. However, these results rely on the assumption that wages for both are exogenous.

A range of other factors were also found to influence labour supply. Permanent non-labour income, education, health, and the number and age of young children were all found to have significant effects on the labour supply of married women. Labour supply decreased with permanent non-labour income, deterioration of health, and the number of young children, but increased with education. It was also found that labour supply in general decreased with a woman's age; and women who migrated from a non-English speaking country tended to supply less labour, compared with their counterparts born in Australia or who had migrated from an English speaking country.

The importance of education and health provide supportive evidence for the reforms proposed as part of the human capital stream of COAG's National Reform Agenda (2006). The reform agenda has proposed improvements to health promotion and disease prevention, along with improving education and training in order to increase labour force participation and productivity to meet the challenges of population ageing. In addition to supporting this reform push, the estimates on health and education obtained by this study are useful inputs into models to assess the relative effects of programs aimed at promoting health and education outcomes.

This study, as with others, found that the presence of young children had a significant effect on the workforce engagement of married Australian women. This effect is likely to be tied to a mother's preferences, but may also be linked to the availability, affordability and quality of formal childcare. Improvements in childcare policies may thus still provide one means to increase the labour force participation of married women with young children.

Importantly, this study tested various assumptions typically made when estimating labour supply through the use of four models. The results indicate that assumptions made about the presence and influence of unobserved individual factors, both static and dynamic, can significantly influence the estimates obtained and therefore the policy implications. In this study, it was found that a model with the least restrictive assumptions — which allowed for correlated random effects and unobserved transitory shocks — provided the most robust estimates of drivers of labour supply. Thus, when using such models to inform policy, it is important to test the validity of the assumptions made, or at least, highlight them and their potential effects on the inferences drawn.

Finally, the results in this paper point to directions for future research. For example, the lower labour supply of married women from non-English speaking background may result from cultural differences, particularly attitudes towards working women, but may also be caused by deficiencies in English language skills and/or discrimination in workplaces. To identify policies which may be effective in narrowing the labour supply gap between women from different language/cultural backgrounds requires identification of the exact causes. Similarly the result that labour supply of partners is complementary could be investigated further.

References

Abhayaratna, J. and Lattimore, R. 2006, *Workforce Participation Rates – How Does Australia Compare?*, Productivity Commission Staff Working Paper, Canberra.

Arulampalam, W., Booth, A.L. and Taylor, M.P. 2000, ‘Unemployment Persistence’, *Oxford Economic Papers*, vol. 52, pp. 24-50.

Birch, E.S. 2005, ‘Studies of labour supply of Australian women: what have we learned?’, *Economic Record*, vol. 81, pp. 65-84.

Blau, D.M. and Riphahn, R.T. 1999, ‘Labor force transitions of older married couples in Germany’, *Labour Economics*, vol. 6, pp. 229-51.

Cai, L. 2009, ‘Effects of health on wages of Australian men’, *Economic Record*, vol. 85, pp. 290-303.

COAG (Council of Australian Governments) 2006, *Council of Australian governments Meeting,* 10 February 2006 Communiqué, Canberra. http://www.coag.gov.au/meetings/100206/index.htm.

Eckstein, Z. and Wolpin, K.I. 1989, ‘Dynamic labour force participation of married women and endogenous work experience’, *Review of Economic Studies*, vol. 56, pp. 375-390.

Greene, W.H. 2000, *Econometric Analysis*, 4th Edition, Prentice Hall, Upper Saddle River, New Jersey.

Heckman, J.J. 1978, ‘Simple statistical models for discrete panel data developed and applied to test the hypothesis of true state dependence against the hypothesis of spurious state dependence’, *Annales De l’INSEE*, No. 30-31, pp. 227-269.

—— 1981a, ‘Statistical models for discrete panel data’, in Manski, C. and McFadden, D. (eds), *Structural Analysis of Discrete Data*, MIT Press, Cambridge.

—— 1981b, ‘Heterogeneity and state dependence, in Rosen, S. (ed), *Studies in Labor Markets*, University of Chicago Press, Chicago.

—— 1981c, ‘The incidental parameter problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process’, in Manski, C and McFadden, D. (eds), *Structural Analysis of Discrete Data*, MIT Press, Cambridge.

—— 1993, ‘What has been learnt about labor supply in the past twenty years?’, *American Economic Review*, vol. 83, pp. 116-21.

Heckman, J.J. and Willis, R.J. 1977, ‘A beta-logistic model for the analysis of sequential labor force participation by married women’, *Journal of Political Economy*, vol. 85, pp. 27-58.

Hsiao, C. 2003, *Analysis of Panel Data*, 2nd Edition, Cambridge University Press.

Hyslop, D.R. 1999, ‘State dependence, serial correlation and heterogeneity in intertemporal labor force participation of married women’, *Econometrics*, vol. 67, pp. 1255-94.

Kee, H.J. 2006, ‘Glass ceiling or stick floor? exploring the australian gender pay gap’, *Economic Record*, vol. 82, pp. 408-27.

Killingsworth, M.R. and Heckman, J.J. 1986, ‘Female labor supply: a survey’, in Ashenfelter, O. and Layard, R. (eds), *Handbook of Labor Economics,* vol I, Elsevier Science Publisher.

Knight, S. Harris, M. and Loundes, J. 2002, ‘Dynamic relationship in australian labour market: heterogeneity and state dependence’, *Economic Record*, vol. 78, pp. 284-98.

Laplagne, P., Glover, M. and Shomos, A. 2007, *Effects of Health and Education on Labour Force Participation*, Productivity Commission Staff Working Paper, Canberra.

Lee, M.J. and Tae, Y.H. 2005, ‘Analysis of labour force participation behaviour of korean women with dynamic probit and conditional logit’, *Oxford Bulletin of Economics and Statistics*, vol. 67, pp. 71-91.

Maddala, G.S. (1992) *Introduction to Econometrics*, 2nd ed., New York: Macmillan Pub. Co.

Mühleisen, M. and Zimmermann, K.F. 1994, ‘A panel analysis of job changes and unemployment’, *European Economic Review*, vol. 38, pp. 793-801.

Nakamura, L. and Nakamura, M. 1985, ‘Dynamic model of the labor force behavior of married women which can be estimated using limited amounts of past information’, *Journal of Econometrics*, vol. 27, pp. 273-98.

OECD (Organisation for Economic Co-operation and Development) 2003, *OECD Employment Outlook 2003, Towards More and Better Jobs*, Paris.

Productivity Commission 2005, *Economic Implications of an Ageing Australia*, Productivity Commission Research Report, Canberra.

—— 2006, *Potential Benefits of the National Reform Agenda*, Productivity Commission Research Report, Canberra.

Shaw, K. 1994, 'The persistence of female labor supply', *Journal of Human Resources*, vol. 29, pp. 348-78.

Tatsiramos, K. 2008, *Fertility and Female Employment Dynamics in Europe: The Effect of Using Alternative Econometric Modelling Assumptions*, IZA Discussion Paper No. 3853.

Watson, N. and Wooden, M. 2004, 'The HILDA Survey four years on', *Australian Economic Review*, vol. 37, pp. 343-49.

Wooldridge, J. 2002, *Econometric Analysis of Cross Section and Panel Data*, The MIT Press.

Appendix A: Predicting wages for those who are not employed

The conventional Heckman approach is used to predict wages for those who are not employed in order to include wages as an explanatory variable in the structural dynamic labour supply model. The approach involves three steps, as can be seen from a brief description of the model. Formally, let the wage equation for a person *i*, randomly picked up from the working-age population, be

$$\ln(w_i) = x_i^{'}\beta + \omega_i, \tag{a.1}$$

where $ln(w_i)$ refers to the natural log of wages of individual *i*; x_i is a vector of wage covariates associated with individual *i*; ω_i is an error term with zero mean and variance δ_{ω}^2. The error term ω_i summarizes all unobserved determinants of wages for individual *i*.

However, since wages are not observed for those who are not employed, equation (a.1) cannot be estimated using a sample that comprises both those who are employed and those who are not employed. On the other hand, the parameters β in equation (a.1) will be estimated with bias if the equation is estimated only on those who are employed, since unobserved determinants of wages (ω) are likely to be systematically different between those who are employed and those who are not employed (Greene 2000). In other words, ω_i is likely to be correlated with the unobserved determinants of employment status of person *i*. Let the determination of employment status of individual *i* be described as

$$E_i^* = z_i^{'}\varphi + \psi_i, \text{ with } E_i = \begin{cases} = 1 & (employed) \quad if\ E_i^* > 0 \\ = 0 & (not\ employed) \quad f\ E_i^* \le 0 \end{cases}, \tag{a.2}$$

Where E_i^* denotes the propensity of employment of individual *i*; E_i refers to observed employment status. z_i is a vector of observed variables that affect individual employment status; ψ_i is an error term, summarising unobserved determinants of employment status. If ω_i and ψ_i are correlated with a correlation coefficient ρ, and ψ_i is assumed to follow the normal distribution with mean zero and normalised variance of unity, then it can be shown that for those who are employed, their expected log-wage can be written as (Greene 2000):

$$\ln(w \mid E=1) = x'\beta + \rho\delta_{\omega} \cdot \lambda_1, \text{ with } \lambda_1 = \frac{\phi(z'\varphi)}{\Phi(z'\varphi)}; \tag{a.3}$$

And for those who are not employed, their expected log-wage can be written as

$$\ln(w \mid E=0) = x'\beta + \rho\delta_{\omega} \cdot \lambda_0, \text{ with } \lambda_0 = -\frac{\phi(z'\varphi)}{1-\Phi(z'\varphi)}, \tag{a.4}$$

where $\phi(.)$ refers to the standard normal density function, and $\Phi(.)$ the standard normal cumulative probability function.

Therefore, the first step for predicting wages is to estimate the employment status equation (a.2), and then to use the resulting parameters $\hat{\varphi}$ to compute $\hat{\lambda}_1$, known as the inverse Mills' ratio, for those who are employed, and $\hat{\lambda}_0$ for those who are not employed. In the second step, the wage equation (a.3) is estimated for those who are employed. Note that in the second step $\hat{\lambda}_1$ is included in the wage equation as one of the explanatory variables.[18] In the third step, wages for those who are not employed are predicted using equation (a.4) with the parameter estimates from the second step and $\hat{\lambda}_0$ from the first step.

Predicted wages for women and their partner were done separately. The employment and wage equations for women are reported in table A1; the corresponding wage and employment status models for the partner are presented in table A2. Note that for identification purposes, in the employment status equation estimated using a Probit model, the variables for the number and age of young children and non-labour income are included. These variables are excluded from the wage equation.

[18] Note that $\rho\delta_{\omega}$ is estimated as one coefficient parameter on $\hat{\lambda}_1$ in the second step. But if one wishes, ρ and δ_{ω} can be calculated using the formulas described in Greene (2000).

Table A1: Employment and wage equation for predicting wages - Women

	Wage equation		Employment equation	
	Coef.	S.E.	Coef.	S.E.
Degree	0.5181	0.0293	0.9348	0.0442
Diploma	0.2539	0.0296	0.5459	0.0533
Certificate	0.0698	0.0266	0.3601	0.0484
Year 12	0.1500	0.0265	0.4059	0.0467
Tenure	0.0130	0.0029		
Tenure squared	-0.0003	0.0001		
Work experience	0.0323	0.0055	0.1227	0.0061
Work experience square	-0.0006	0.0001	-0.0020	0.0002
NESC	0.0069	0.0255	-0.1726	0.0515
ESC	-0.1129	0.0255	-0.2720	0.0482
Health	-0.1728	0.0264	-0.5735	0.0388
VIC	-0.0227	0.0204	-0.0942	0.0418
QLD	-0.0394	0.0221	-0.1081	0.0445
SA	-0.1043	0.0279	-0.1018	0.0567
WA/NT	-0.0934	0.0286	-0.2087	0.0536
TAS	0.0500	0.0460	-0.0197	0.0969
Capital city	0.1290	0.0167	-0.1501	0.0334
Wave 2	-0.0242	0.0263	-0.0702	0.0530
Wave 3	-0.0510	0.0266	-0.1127	0.0528
Wave 4	-0.0416	0.0265	-0.1111	0.0530
Wave 5	-0.0166	0.0264	-0.0885	0.0535
Wave 6	0.0216	0.0265	-0.1111	0.0537
Child 0-2			-0.4531	0.0351
Child 3-5			-0.1776	0.0353
Child 6-17			0.0800	0.0153
Non-labour income ($10000)			-0.0145	0.0025
Lambda (λ_1)	0.3185	0.0633		
Constant	2.0269	0.0854	-0.6001	0.0748

Table A2: Employment and wage equation for predicting wages - Men

	Wage equation		Employment equation	
	Coef.	S.E.	Coef.	S.E.
Degree	0.4456	0.0338	0.7285	0.0639
Diploma	0.2719	0.0337	0.3323	0.0730
Certificate	0.0155	0.0273	0.3782	0.0511
Year 12	0.1286	0.0395	0.6849	0.0896
Tenure	0.0033	0.0026		
Tenure squared	-0.0002	0.0001		
Work experience	0.0111	0.0048	0.0581	0.0091
Work experience square	-0.0002	0.0001	-0.0011	0.0002
NESC	-0.0717	0.0246	0.0512	0.0660
ESC	-0.1778	0.0343	-0.6309	0.0613
Health	-0.0545	0.0580	-1.1600	0.0422
VIC	-0.0308	0.0215	0.0109	0.0569
QLD	-0.0209	0.0234	-0.0602	0.0591
SA	-0.2467	0.0295	-0.0390	0.0744
WA/NT	-0.0906	0.0285	0.0580	0.0762
TAS	0.0883	0.0519	-0.2030	0.1094
Capital city	0.2658	0.0177	0.0738	0.0452
Wave 2	-0.0239	0.0276	-0.0662	0.0726
Wave 3	-0.0314	0.0276	0.0558	0.0734
Wave 4	-0.0060	0.0276	-0.0090	0.0725
Wave 5	0.0219	0.0278	-0.0449	0.0716
Wave 6	0.0388	0.0283	-0.1352	0.0708
Child 0-2			0.1123	0.0562
Child 3-5			0.1704	0.0589
Child 6-17			0.1428	0.0231
Non-labour income ($10000)			-0.0052	0.0041
Lambda (λ_1)	-0.1153	0.1475		
Constant	2.4909	0.0773	0.6329	0.1322

Appendix B: Initial condition equation estimation

Table B1: Coefficient estimates of the initial condition equation in the reduced form specification

	Model II: RE		Model III: Cor. RE		Model IV: AR. Cor. RE	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Non-labour income: deviation	-0.1914	0.0951	-0.1782	0.0953	-0.124	0.0966
Non-labour income: mean	-0.3541	0.1134	-0.3639	0.1121	-0.3543	0.1139
Aged 18-25	-1.7494	2.0618	-1.9025	2.1227	-1.9688	2.0971
Aged 36-45	-3.6249	1.0398	-3.9428	1.1231	-3.1692	1.1072
Aged 46-55	-1.5964	1.3572	-2.5801	1.5249	-1.8823	1.4684
Aged 56 plus	-4.9603	2.0893	-6.1894	2.2344	-5.2325	2.1267
Degree	16.1513	1.5445	15.8835	1.5264	15.5419	1.4831
Diploma	11.4967	2.0143	11.0916	2.0002	10.8226	1.957
Certificate	6.6051	1.4714	6.1116	1.4453	5.9173	1.4262
Year 12	5.2922	1.4989	4.8785	1.5012	5.1655	1.4915
Health	-1.3058	0.996	-0.6086	1.3795	0.1286	1.383
Child 0-2	-16.8487	0.9732	-9.9918	1.6613	-10.8552	1.5497
Child 3-5	-6.4527	0.8397	-0.3724	1.5168	-2.0045	1.4648
Child 6-17	-2.0637	0.4973	-1.522	1.0823	-1.8146	1.0542
Capital city	-1.884	1.0691	1.5995	2.4374	0.1831	2.3047
ESC	-1.3181	1.9294	-1.6318	1.8838	-1.872	1.857
NESC	-3.3731	1.5987	-3.5506	1.576	-3.3413	1.5682
Unem rate	0.1363	0.3891	0.1019	0.3921	0.2522	0.3911
Health: mean			-11.9606	2.133	-13.3365	2.1543
Child 0-2: mean			5.2957	3.2458	4.1802	3.1993
Child 3-5: mean			-27.0014	4.6227	-22.4303	4.4513
Child 6-17: mean			-1.3053	1.2227	-0.6995	1.1894
Capital city: mean			-3.8213	2.6198	-1.7579	2.502
Mother white collar	-0.222	1.1073	-0.0624	1.1356	0.1004	1.1159
Mother blue collar	-0.4982	1.2307	-0.386	1.2514	-0.181	1.2238
Mother's occupation unknown	1.2791	1.2017	1.5049	1.2437	1.2485	1.2011
Proportion of life employed	15.435	1.7865	15.4235	1.7777	11.7882	1.7571
Proportion of life unemployed	-15.4928	5.9341	-14.3904	5.9566	-16.3167	5.3557
Constant	10.917	4.0379	15.7999	4.2169	16.3327	4.2511
Coefficient on random effects	1.1743	0.0442	1.1615	0.0445	0.8696	0.0358

Table B2: Coefficient estimates of the initial condition equations in the structural specification

	Model II: RE		Model III: Cor. RE		Model IV: AR. Cor. RE	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Own wages: deviation	0.0473	0.025	0.0509	0.0246	0.0509	0.027
Own wages: mean	0.4803	0.0517	0.4509	0.0534	0.4551	0.053
Family non-labour income: deviation	-0.1318	0.2527	-0.112	0.2516	-0.1192	0.2461
Family non-labour income: mean	-0.3562	0.2026	-0.3554	0.1979	-0.3804	0.189
Spouse wages: deviation	-0.1014	0.0482	-0.1023	0.0479	-0.0764	0.0484
Spouse wages: mean	-0.1909	0.0227	-0.1888	0.023	-0.1983	0.0236
Spouse working hours	0.2975	0.5605	0.2529	0.5635	0.242	0.5584
Spouse working hours squared	0.1817	0.0646	0.1833	0.0643	0.1638	0.064
Aged 18-25	-2.4883	2.003	-2.6843	2.0562	-2.6687	2.0382
Aged 36-45	-3.8772	1.0401	-4.4641	1.1256	-3.5706	1.1102
Aged 46-55	-1.9877	1.3748	-3.5649	1.5503	-2.6564	1.4921
Aged 56 plus	-5.2296	2.0988	-7.333	2.2455	-6.0655	2.1559
Degree	11.0943	1.5224	11.0134	1.5336	10.902	1.52
Diploma	8.7586	1.8933	8.1371	1.8714	8.0352	1.8578
Certificate	6.0619	1.4951	5.809	1.4667	5.8118	1.4493
Year 12	3.9443	1.5438	3.6956	1.5406	4.0782	1.5462
Health	-1.3251	0.9971	-1.0239	1.383	-0.2306	1.391
Child 0-2	-17.2859	0.965	-10.0247	1.6579	-10.7966	1.571
Child 3-5	-6.8976	0.8409	-0.5583	1.5128	-1.9258	1.4712
Child 6-17	-2.3058	0.4934	-1.4212	1.0899	-1.6767	1.0716
Capital city	-1.7877	1.0679	2.9158	2.5774	1.3243	2.4294
ESC	-0.7383	1.9573	-0.8952	1.9265	-1.151	1.9103
NESC	-1.7591	1.5765	-1.7345	1.554	-1.68	1.56
Unem rate	0.1805	0.3885	0.1066	0.394	0.2756	0.3914
Health: mean			-8.7381	2.1425	-10.1032	2.1652
Child 0-2: mean			4.128	3.1876	3.7211	3.1526
Child 3-5: mean			-26.002	4.5766	-22.096	4.4392
Child 6-17: mean			-1.984	1.222	-1.4137	1.1988
Capital city: mean			-5.2408	2.7016	-3.0429	2.5887
Mother white collar	-0.4252	1.1203	-0.2352	1.1535	-0.0591	1.1333
Mother blue collar	-0.937	1.2381	-0.8331	1.2554	-0.5958	1.2317
Mother's occupation unknown	0.8125	1.2113	1.0643	1.2561	0.9183	1.2208
Proportion of life employed	15.5895	1.8071	15.5442	1.7985	12.344	1.7812

(continued next page)

Table B2: (continued)

	Model II: RE		Model III: Cor. RE		Model IV: AR. Cor. RE	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Proportion of life unemployed	-11.1743	6.0392	-10.8919	6.0886	-13.1993	5.5243
Constant	2.3348	4.147	7.9861	4.3589	8.4277	4.3968
Coefficient on random effects	1.1603	0.0474	1.1449	0.0475	0.8785	0.0378