Inter-temporal Labour Supply of Married Australian Women

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{This version on 12/10/15}

Abstract

Using the first 13 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey, this study investigates the determinants of the labour supply of married Australian women, with a focus on whether and to what extent there is state dependence in the labour supply. It is found that both observed and unobserved individual heterogeneity contributes to observed inter-temporal persistence of the labour supply of married Australian women, but the persistence remains even after controlling for these factors. It is also found that non-labour income, age, education, health and the number and age of young children have significant effects on married Australian women's labour supply.

Key words: Labour supply; Dynamic models; State dependence; Unobserved heterogeneity

Acknowledgement: The paper uses the data in the confidentialised unit record file from the Department of Social Services' (DSS) Household, Income and Labour Dynamics in Australia (HILDA) Survey, which is managed by the Melbourne Institute of Applied Economic and Social Research. The findings and views reported in the paper, however, are of the author's and should not be attributed to DSS, Melbourne Institute, the Department of Employment or the Australian Government.

I Introduction

Like most other industrialized countries, Australia faces an ageing population. Over the coming decade, the baby boomers will be reaching their retirement age and leaving the labour force. Unless some counter measures are taken, population ageing will lead to a significant slowdown in labour force growth and present challenges to the sustainability of economic growth and the standard of living of future Australians.

One of the broad counter measures recommended by the OECD (2003) is to increase the supply of labour by groups that are 'under-represented' in the labour market. 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. The OECD (2010) notes that not only the labour force participation rate of Australian women lags behind the OECD best performers such as Denmark, Norway and Sweden, the part-time employment rate of Australian women is the second highest among the OECD countries. Developing sound policies to lift female workforce engagement, including both participation and working hours, requires a good understanding of the factors that affect the labour supply decisions of Australian women. However, after a comprehensive review of the literature on the labour supply of Australian women, Birch (2005) points out that there remains much to be studied on the topic. This study is aimed at further enhancing our understanding of this issue.

A salient feature of female labour market activity — the focus of this study — is the high degree of 'inter-temporal persistence' (Nakamura and Nakamura 1985; Eckstein and Wolpin 1989; Shaw 1994; Hyslop 1999). In exploring the reasons for 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).

State dependence refers to the situation where an individual's current labour supply depends on his or her past labour supply. Positive state dependence may arise if working leads to accumulation of human capital 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 of labour supply for individuals who are not employed, relative to those who are already employed.

Unobserved individual heterogeneity, which is persistent over time, may explain persistent labour market behaviour. Unobserved individual heterogeneity may include preferences between work and leisure, motivation and ability. They are often not observable to researchers, although individuals themselves may have certain knowledge of them.

In addition, transitory shocks to labour market decisions that are serially correlated, but unobservable or not measured in data, may also lead to observed persistence of labour market behaviour. For example, deterioration in an individual'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 source of labour market persistence has important policy implications. For example, if there is positive state dependence in unemployment, policies aimed at preventing people from becoming unemployed would be more effective in reducing unemployment than retraining the unemployed. Positive state dependence of labour supply also means that policies that enhance labour supply will have a long-lasting effect. In addition, in the presence of positive state dependence, policy interventions targeted at those already unemployed need to be tailor-designed according to the duration of unemployment. On the other hand, if persistence can be explained by observed and unobserved factors that affect labour supply, unemployment duration is less relevant for designing intervention policy; and any policy effects will be short lived.

This study examines the influence of different sources of observed persistence in the labour supply of married Australian women, using the first 13 waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The paper focuses on married women in Australia as they make up the vast majority of women of working age, and have historically a lower rate of labour force engagement (i.e. low labour force participation rates and higher part-time employment rates) than single women. Meanwhile, the study also investigates the effects of various observed factors, such as education, age, health and the number of children of different ages, on the labour supply of married Australian women. A number of previous Australian studies have also examined these factors, but have used cross-sectional data, which can neither easily capture unobserved individual heterogeneity, nor account for serially correlated unobserved transitory shocks, and so may result in biased estimates.

While the vast majority of the earlier studies examine persistence of labour supply as measured by a binary variable of labour force participation or employment status, this study investigates this issue by examining both labour force participation and hours worked. Positive state dependence in labour supply of married Australian women is found for both the measures after controlling for observed and unobserved individual heterogeneity. The results also suggest that employment status and working hours among those who work appear to be determined by different mechanisms.

The rest of this paper is structured as follows: Section II provides a brief overview of the literature, particularly the studies that examine the dynamic feature of women's labour supply. Section III describes the econometric models and estimation strategies. Section IV describes the data and the model specification. Section V reports the model estimation results, with conclusion drawn in Section VI.

II Literature review

The labour supply of women has been the subject of extensive study both in Australia and overseas. The literature is huge; a detailed review of the literature is out of the scope of this study. Interested readers are referred to Killingsworth (1983), Killingsworth and Heckman (1986) and Heckman (1993) for extensive surveys of the international literature. To save space, this brief literature review only covers those studies that examine the inter-temporal labour supply behaviour of women. [1]

Despite the large literature on women's labour supply, only a few international and Australian studies have examined the inter-temporal labour supply behaviour of women; and this remains a less understood area of labour supply research (Hyslop 1999). However, study in this area is growing rapidly due to the increasing availability of panel data, improved computing power, and advanced modelling techniques.

Shaw (1994) used the Panel Study of Income Dynamics (PSID) over the period 1967-1987 to examine persistence in (annual) working hours of white women in the United States. She found evidence of (statistically) significant persistence in women'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 individual heterogeneity played an important role in the persistence. However, the study did not examine whether the persistence also resulted from unobserved transitory shocks that might be serially correlated.

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

[1] 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.

were also found to have a significant negative effect on the labour force participation decisions of married women in the US.

Inter-temporal persistence in women's labour supply was also examined by Lee and Tae (2005) for Korea, using the first four waves (1998-2001) of the Korean Labour and Income Panel Study. Without considering serial correlation of unobserved transitory shocks, the authors found that both state dependence and unobserved individual heterogeneity were important in explaining inter-temporal persistence in the labour force participation of Korean 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 inter-temporal 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 males and females was analysed separately, with each group being further divided into high and low education groups. High education was defined as completion of secondary school; with low education defined as having a highest qualification that is below secondary school. Only two labour force states were examined — employed or not employed (i.e., a 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 an 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 unobserved transitory shocks.

Some studies have examined the effect of serially correlated unobserved transitory shocks on inter-temporal persistence of labour supply. Michaud and Tatsiramos (2011), 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 on employment status (i.e., a binary dependent variable). Positive state dependence of employment was found for women in all the countries examined after controlling for observed and unobserved individual heterogeneity and serially correlated unobserved transitory shocks. The magnitude of state dependence, as measured by average partial effects, was very similar across all the countries studied, with the probability of a woman being employed being 31 to 49 percentage points higher if she was employed than if she was not employed in the previous year. Like Hyslop (1999), Michaud and Tatsiramos (2011) also found that unobserved transitory shocks are negatively correlated over time for all the countries, and only in 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 for Denmark and the UK, where the effect was positive. For the Netherlands and Italy, women's transitory non-labour income was also found to reduce labour supply.

Much of the existing literature on inter-temporal labour supply has focused on a binary dependent variable measured as labour force participation or employment status. Recently Chang (2011) examined inter-temporal labour supply, as measured by working hours, of married American women using the PSID data between 1984 and 1992. He estimates two types of models: (a) a conventional dynamic Tobit model, where the choice between working and not working and the choice of working hours conditional on working are determined by the same mechanism; and (b) a two-tiered dynamic Tobit model, where the two choices are governed by different mechanisms. Unobserved heterogeneity and serially correlated unobserved transitory shocks are controlled for in both of the models. Chang (2011) finds from both models that unobserved transitory shocks are positively correlated over time and there is negative state dependence of working hours after observed and unobserved individual heterogeneity and serially correlated unobserved transitory shocks are controlled for. However, Xun and Lubrano (2015) show that this result of Chang's (2011) was caused by a misspecification of the dynamic model. With a modified specification, Xun and Lubrano (2015) find that the signs of the estimates on state dependence of labour supply and on the correlation of unobserved transitory shocks are reversed from that of Chang's (2011).

This study uses both labour force participation and working hours as a measure of labour supply. For the measure of labour force participation, the model and estimation method follow Hyslop (1999) in estimating a dynamic Probit model; for the measure of working hours, the model and estimation method follow Chang (2011) and Xun and Lubrano (2015) in estimating both conventional and two-tiered dynamic Tobit models. It is rare in the literature to examine both the measures of labour supply in one study in the context of dynamic labour supply. There are no other Australian studies that have examined both the effects of unobserved individual heterogeneity and serially correlated unobserved transitory shocks on inter-temporal labour supply. Despite this, studies of labour force participation of 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.

III Econometric model and estimation strategy

This study examines labour supply as measured by both labour force participation and hours worked. For labour force participation, a dynamic Probit model is used that incorporates the effects of lagged dependent variables, unobserved individual heterogeneity and serially correlated unobserved transitory shocks on labour supply. 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 modes fits the censored nature of the dependent variable well, it has some limitations. Particularly, in the conventional Tobit model the decision to work and the choice of working hours conditional on working are determined by the same mechanism.[2] To relax this restriction, this study also estimates a two-tiered Tobit model, which is initially proposed by Cragg (1971) and allows the parameters which characterise the decision to work and the parameters which govern the choice of working hours to be different. Take advantage of the panel feature of the data, this study augments both the conventional and two-tiered Tobit models by including (one-year) lagged employment status and lagged working hours (conditional on employment) as explanatory variables, leading to a dynamic labour supply model. Like the dynamic Probit model, the two types of dynamic Tobit models further account for unobserved individual heterogeneity and serially correlated unobserved transitory shocks.

(i) Dynamic Probit and Tobit models

Probit and Tobit models for modelling labour supply can be derived from standard economics theory where an individual makes choice on consumption of goods and leisure time (and consequently working time) to maximize his or her utility subject to a budget constraint (Killingsworth 1983). For a Probit model, the person is observed to be in the labour force when the utility of participating in the labour force is greater than non-participation.

For a Tobit model, when the person chooses to work some positive hours, her marginal rate of substitution of leisure time for goods consumption equals real wages offered by the market. However, for some individuals their wages offered by the market could be lower than their reservation wages. As a result, they would like to consume more leisure time than the total time available to them. In other words, these individuals' preferred working hours are negative. Since in reality they cannot choose negative working hours, their observed working hours are censored at zero

[2] Another limitation of Tobit models is that 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. Such an assumption is commonly made in estimating a two-step wage equation with Heckman selection correction.

and their preferred working hours are latent from a researcher's perspective. For a sample of workers, such as women, where a substantial proportion of them do not work, applying a liner model to observed working hours would produce biased estimates. Tobit models can account for the censored feature of observed working hours naturally.

For an individual *i* at time *t* the dynamic Probit model can be expressed as

$$y_{i,t}^{*} = \alpha y_{i,t-1} + x_{i,t}'\beta + \nu_{i,t}, \text{ for } t=1,\ldots,T;\ i=1,\ldots,N, \text{ with} \tag{1}$$

$$y_{i,t} = \begin{cases} 1 & if\ y_{i,t}^{*} > 0 \\ 0 & if\ y_{i,t}^{*} \leq 0 \end{cases}.$$

The dynamic conventional Tobit model can be expressed as

$$y_{i,t}^{*} = \alpha_1 y_{i,t-1} I\big(y_{i,t-1} > 0\big) + \alpha_2 I\big(y_{i,t-1} > 0\big) + x_{i,t}'\beta + \nu_{i,t}, \text{ with} \tag{2}$$

$$y_{i,t} = \begin{cases} y_{i,t}^{*} & if\ y_{i,t}^{*} > 0 \\ 0 & if\ y_{i,t}^{*} \leq 0 \end{cases}.$$

Where $y_{i,t}^{*}$ and $y_{i,t}$ are the latent and observed labour supply of individual *i* at time *t* respectively; $x_{i,t}$ is a vector of observed variables that are expected to affect labour supply of individual *i* directly, or indirectly through affecting wages; and $\nu_{i,t}$ is an error term, capturing the unobserved factors that affect labour supply decisions, including unmeasured human capital, preferences and motivation. *I(.)* is an indicator function, equal to one when the condition in the bracket is satisfied, and zero otherwise.

The lagged dependent variable $y_{i,t-1}$ is included in the right hand side of equations (1) and (2) to capture the dynamics of labour supply, in the sense that current labour supply may, all other things being equal, depends on past labour supply. This dependence can be due to things like accumulation of skills resulting from past work.[3] In general state-dependence in the Tobit model may be specified in the same way as in the Probit model – that is only observed lagged working hours are included in the right-hand side of the models; and this is indeed the approach taken by Chang (2011). However, Xun and Lubrano (2015) argue that since employment status and working hours are both observed, the lag of both should be included in the dynamic model. They also show that including only the lagged observed working hours leads to counterintuitive estimation results. This current study follows Xun and Lubrano (2015) in specifying the dynamic Tobit model as shown in equation (2).

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3 In developing a theoretical framework for analysing dynamic labour force participation, Hyslop (1999) attributes state dependence of labour force participation to differential searching costs associated with participation and non-participation.

With the assumption that $\nu_{i,t}$ follows a normal distribution with mean zero and variance σ_ν^2 ($\sigma_\nu^2=1$ in the Probit model) and is independent across individuals and over time for the same individual, equations (1) and (2) represent a conventional Probit and Tobit model respectively and can be estimated consistently by pooling the panel data to form an enlarged dataset.

However, the assumption that $\nu_{i,t}$ is independent over time for the same individual is violated if labour supply is affected by unobserved individual heterogeneity that does not vary over time, such as preferences, inherent ability and motivation. In this situation, failing to control for unobserved individual heterogeneity would lead to the estimate for state dependence being biased upwards because those with a strong preference to work or high ability will always be observed to participate in the labour force and/or work more.

An advantage of panel data is that it provides a way to control for unobserved individual heterogeneity through decomposing $\nu_{i,t}$into

$$\nu_{i,t} = \eta_i + \varepsilon_{i,t}, \tag{3}$$

where η_i represents unobserved time invariant individual heterogeneity (e.g., preferences and ability); $\varepsilon_{i,t}$ represents unobserved time variant determinants or shocks to labour supply, and is independent of the observed variables and η_i . Examples of $\varepsilon_{i,t}$ could include transitory wage variation and/or illness of family members, particularly dependent children. In the estimation $\varepsilon_{i,t}$ is assumed to be $\varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2)$.

The unobserved individual effects η_i can be assumed to be either random or fixed in a general modelling framework. However, since the dependent variable in the Tobit model is censored and the Tobit model is a non-linear model, it is not technically feasible to use the fixed effects estimator (Hsiao 2003).[4] As a compromise, we use Mundlak's (1978) approach that allows the unobserved time invariant individual effects to be correlated with observed variables through a linear form. Further, this approach conveniently allows adopting Wooldridge's (2002) approach to addressing the initial condition problem arising from the lagged dependent variable, by specifying [5]

$$\eta_i = \bar{x}_i'\pi + \lambda y_{i,0} + z_0'\gamma + \mu_i, \text{ for the Probit model; and} \tag{4}$$

[4] For modelling labour force participation a fixed Logit model may be used to account for unobserved heterogeneity, but serial correlation of unobserved transitory shocks to labour supply cannot be handled in this modelling framework.

[5] Alternatively Heckman (1981c) proposes approximating the endogenous initial conditions (i.e. labour supply in the first wave) with a static equation that utilises information from the first wave of the data, and then jointly estimates the dynamic model with the initial condition equation. But the specification of the state-dependence in the dynamic Tobit model here does not allow the Heckman approach (Xun and Lubrano 2015).

$$\eta_i = \bar{x}_i'\pi + \lambda_1 y_{i,0} I(y_{i,0} > 0) + \lambda_2 I(y_{i,0} > 0) + z_0'\gamma + \mu_i, \text{ for the Tobit model.} \quad (5)$$

Where $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$ and $\mu_i \sim N(0, \sigma_\mu^2)$ and is uncorrelated with any observed variables and the transitory error $\varepsilon_{i,t}$.[6] z_0 refers to the variables that explain labour supply in the first year of the survey. Only one variable, the proportion of life time in employment, is included in z_0 . Note that in the Probit model, since $\sigma_u^2 + \sigma_\varepsilon^2$ is normalised to one for identification purposes, $\sigma_\varepsilon^2 = 1 - \sigma_u^2$. The models with such a specification for the unobserved time invariant individual effects are known as correlated random effects models (Wooldridge 2002).

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 are positively correlated over time. To control for this source of persistence, an autoregressive relationship between two adjacent unobserved transitory shocks can be specified as

$$\varepsilon_{i,t} = \rho\varepsilon_{i,t-1} + \zeta_{i,t}, \quad (6)$$

where $\zeta_{i,t} \sim N(0, \sigma_\zeta^2)$ and is independent of μ_i and the observed variables, with $\sigma_\zeta^2 = (1 - \rho^2)\sigma_\varepsilon^2$.

The model controls for both unobserved individual heterogeneity (through correlated random effects) and serial correlation of unobserved transitory shocks and should therefore remove potential bias for the estimate of state dependence. In addition, more restrictive models, such as a model that does not account for unobserved heterogeneity and/or serial correlation of unobserved transitory shocks, have also been estimated. The estimation results reject the more restrictive models because, as shown later, the variance estimate for unobserved individual heterogeneity and the correlation estimate for unobserved transitory shocks are both statistically significant. The hypothesis that there is no unobserved individual heterogeneity or serially correlated unobserved transitory shocks should therefore be rejected.[7]

(ii) Two-tiered dynamic Tobit model

As mentioned earlier, a major limitation of the conventional Tobit model is that the decision to work and the choice of working hours conditional on working are determined by the same mechanism, implying that any variables that increase the probability of working must also increase working hours. This may not be the case, particularly in the presence of fixed costs of working (Heckman

[6] 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 on the number of children by age, and non-labour income in the correlated random effects model.

[7] The estimation results for the more restrictive models can be obtained from the author on request.

1993). Studies by Moffitt (1984) and Mroz (1987) also provide empirical evidence against such a restriction. The two-tiered Tobit model proposed by Cragg (1971) relaxes this restriction.

Following Xun and Lubrano (2015), the two-tiered dynamic Tobit model can be expressed as,

$$y^*_{1,(i,t)} = \alpha_{11} y_{i,t-1} I(y_{i,t-1} > 0) + \alpha_{12} I(y_{i,t-1} > 0) + x'_{i,t}\beta_1 + \bar{x}'_i \pi_1 + \lambda_{11} y_{i,0} I(y_{i,0} > 0)$$
$$+\lambda_{12} I(y_{i,0} > 0) + z'_0\gamma_1 + \mu_i + \rho\varepsilon_{i,t-1} + \zeta_{i,t}, \text{ with } y_{1,(i,t)} = \begin{cases} 1 & \text{if } y^*_{1,(i,t)} > 0 \\ 0 & \text{if } y^*_{1,(i,t)} \leq 0 \end{cases}, \text{ and} \quad (7a)$$

$$y_{2,(i,t)} = \alpha_{21} y_{i,t-1} I(y_{i,t-1} > 0) + \alpha_{22} I(y_{i,t-1} > 0) + x'_{i,t}\beta_2 + \bar{x}'_i \pi_2 + \lambda_{21} y_{i,0} I(y_{i,0} > 0)$$
$$+\lambda_{22} I(y_{i,0} > 0) + z'_0\gamma_2 + \mu_i + \rho\varepsilon_{i,t-1} + \zeta_{i,t}, \text{ if } y^*_{1,(i,t)} > 0 \text{ and } y_{2,(i,t)} > 0. \quad (7b)$$

In the two-tiered Tobit model, the probability of working (or not working) is determined by a Probit model (7a) with the first tier parameters; working hours, conditional on working, are determined by equation (7b) with the second tier parameters.[8] Unobserved individual heterogeneity and serially correlated unobserved transitory shocks are incorporated in the two-tiered Tobit model in the same way as described in the previous subsection. The conventional Tobit model can be viewed as a special case of the two-tiered Tobit model, with the coefficient parameters being equal between (7a) and (7b).

For ease of exposition, from now on the dynamic Tobit model described in sub-section (i) will be referred to as 'conventional Tobit', while the two-tiered dynamic Tobit model discussed in this sub-section is referred to as 'two-tiered Tobit'.

(iv) Estimation strategy

Both Probit and Tobit models are estimated using the maximum likelihood estimator. However, in the dynamic model, the presence of μ_i and serially correlated unobserved transitory shocks means that the composite unobserved determinants (i.e., $\mu_i+\varepsilon_{i,t}$) of labour supply are correlated over time for the same individual. As a result, for individuals who experience several periods of not working, their likelihood functions involve evaluating multiple dimensional integrals. This renders the conventional maximum likelihood estimator infeasible. Instead, maximum simulated likelihood (MSL) estimators are used to estimate the models.

Let the composite unobserved determinants of labour supply be denoted by $e_{i,t}$. The assumptions on μ_i and ε_{it} above imply $e_i \sim N(0, \Sigma_{\mu+\varepsilon})$, where $e_i = (e_{i0}, \dots, e_{iT})'$. Let $\Sigma_{\mu+\varepsilon} = A'A$, where A is a lower-triangular matrix representing the Cholesky decomposition of $\Sigma_{\mu+\varepsilon}$.[9] Then we can write

[8] An alternative to the two-tiered model is the Heckman (1979) type of sample selection models. The identification of such models requires some variables that affect the selection equation (i.e. the participation equation in our case) but not the other equation (i.e. the working hour equation). Since both participation and working hours measure labour supply, it would be difficult, if not impossible, to find such a variable.

[9] For the Probit model the variance of the composite errors is normalised to be one.

$e_i = A\eta_i$, where $\eta_i = (\eta_{i,0}, \dots, \eta_{i,T})'$ and $\eta_i \sim N(0, I)$. This decomposition of e_i forms the basis for the MSL estimator (Hajivassiliou et al. 1996).

The MSL estimator has been implemented in Hyslop (1999) to estimate a dynamic Probit model and in Chang (2011) and Xun and Lubrano (2015) to estimate dynamic Tobit models.

Following Hyslop (1999), for the dynamic Probit model the likelihood function for individual *i* can be simulated as,

$$\widehat{L_{P,i}} = \frac{1}{R}\sum_{r=1}^{R}\prod_{t=0}^{T}\left[\Phi(\Delta_{i,t}^{\prime,(r)}/A_{t,t})\right]^{I(y_{i,t}=1)}\left[\Phi(-\Delta_{i,t}^{\prime,(r)}/A_{t,t})\right]^{I(y_{i,t}=0)}; \quad (8)$$

where $\Phi(.)$ refers to the standard normal cumulative distribution function; $\Delta_{i,t}^{\prime,(r)} = \alpha y_{i,t-1} + x_{i,t}'\beta + \bar{x}_i'\pi + \lambda y_{i,0} + z_0'\gamma + \sum_{k=1}^{t-1} A_{t,k}\eta_{i,k}^{(r)}$; $A_{t,k}$ is the element in the t^{th} row and k^{th} column of A; and $\eta_{i,t}^{(r)}$ is simulated as,

$$\eta_{i,t}^{(r)} = \begin{cases} \Phi^{-1}(\xi_{i,t}^{(r)}\Phi\left(-\Delta_{i,t}^{\prime,(r)}/A_{t,t}\right)) & if \quad y_{i,t} = 0 \\ \Phi^{-1}(\xi_{i,t}^{(r)}\Phi\left(\Delta_{i,t}^{\prime,(r)}/A_{tt}\right)) & if \quad y_{i,t} = 1 \end{cases}, \quad (9)$$

where $\xi_{i,t}^{(r)}$ are the r^{th} random draws from the uniform distribution.

For the conventional Tobit model the likelihood function for individual *i* can be simulated as,

$$\widehat{L_{T,i}} = \frac{1}{R}\sum_{r=1}^{R}\prod_{t=0}^{T}\left[\phi(\frac{y_{i,t}-\Delta_{i,t}^{(r)}}{A_{t,t}})/A_{t,t}\right]^{I(y_{i,t}>0)}\left[\Phi(-\Delta_{i,t}^{(r)}/A_{t,t})\right]^{I(y_{i,t}=0)}, \quad (10)$$

where $\phi(.)$ refers to the standard normal density function; $\Delta_{i,t}^{(r)} = \alpha_1 y_{i,t-1} I(y_{i,t-1} > 0) + \alpha_2 I(y_{i,t-1} > 0) + x_{i,t}'\beta + \bar{x}_i'\pi + \lambda_1 y_{i,0} I(y_{i,0} > 0) + \lambda_2 I(y_{i,0} > 0) + z_0'\gamma + \sum_{k=1}^{t-1} A_{t,k}\eta_{i,k}^{(r)}$; $A_{t,k}$ is the element in the t^{th} row and k^{th} column of A; and $\eta_{i,t}^{(r)}$ is simulated or calculated by

$$\eta_{i,t}^{(r)} = \begin{cases} \Phi^{-1}(\xi_{i,t}^{(r)}\Phi\left(-\Delta_{i,t}^{(r)}/A_{t,t}\right)) & if \quad y_{i,t} = 0 \\ (y_{i,t} - \Delta_{i,t}^{(r)})/A_{t,t} & if \quad y_{i,t} > 0 \end{cases}. \quad (11)$$

For the two-tiered Tobit model, the likelihood function for individual *i* is simulated as

$$\widehat{L_{TT,i}} = \frac{1}{R}\sum_{r=1}^{R}\prod_{t=0}^{T}\left[\frac{\Phi\left(\Delta_{i,t}^{1,(r)}/A_{t,t}\right)}{\Phi\left(\Delta_{i,t}^{2,(r)}/A_{t,t}\right)}\phi(\frac{y_{i,t}-\Delta_{i,t}^{(r)}}{A_{t,t}})/A_{t,t}\right]^{I(y_{i,t}>0)}\left[\Phi(-\Delta_{i,t}^{2,(r)}/A_{t,t})\right]^{I(y_{i,t}=0)}, \quad (12)$$

where $\Delta_{i,t}^{1,(r)} = \alpha_{11} y_{i,t-1} I(y_{i,t-1} > 0) + \alpha_{12} I(y_{i,t-1} > 0) + x_{i,t}'\beta_1 + \bar{x}_i'\pi_1 + \lambda_{11} y_{i,0} I(y_{i,0} > 0) + {} + \lambda_{12} I(y_{i,0} > 0) + z_0'\gamma_1 + \sum_{k=1}^{t-1} A_{t,k}\eta_{i,k}^{(r)}$, $\Delta_{i,t}^{2,(r)} = \alpha_{21} y_{i,t-1} I(y_{i,t-1} > 0) + \alpha_{22} I(y_{i,t-1} > 0) + x_{i,t}'\beta_2 + \bar{x}_i'\pi_2 + \lambda_{21} y_{i,0} I(y_{i,0} > 0) + {} + \lambda_{22} I(y_{i,0} > 0) + z_0'\gamma_2 + \sum_{k=1}^{t-1} A_{t,k}\eta_{i,k}^{(r)}$, and $\eta_{i,t}^{(r)}$ is simulated or calculated as

$$\eta_{i,t}^{(r)} = \begin{cases} \Phi^{-1}(\xi_{i,t}^{(r)}\Phi\left(-\Delta_{i,t}^{1,(r)}/A_{t,t}\right)) & if \quad y_{i,t} = 0 \\ (y_{i,t} - \Delta_{i,t}^{2,(r)})/A_{t,t} & if \quad y_{i,t} > 0 \end{cases}. \tag{13}$$

The parameters are estimated by maximising the sum of the simulated individual log-likelihood functions over the sample. Fifty Halton sequence draws are used to simulate the likelihood function in this study. Train (2003) shows that Halton sequence draws perform much better than simple random draws in terms of approximating the objective function.

IV Data source, model specification and descriptive statistics

(i) The HILDA survey

The data used in this study are drawn from the first 13 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)).

Working hours refer to total hours usually worked per week in all paid employment. This is a more appropriate measure of labour supply than hours worked per week in an individual's main job, particularly for married women who may be more likely to have multiple part-time jobs than single women or men.

As married women are the focus of the study, the sample included only women aged 20 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, so were those with missing working hours in any wave of the survey. Since this study is about labour supply, self-employed women are included in the sample (about 5 per cent of the sample).

Respondents of the survey could get married or divorced during the 13 year data period, or leave the survey over the period (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 the 13 waves of the survey available at the time of writing this paper. 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. Longitudinal weights provided with the data have been used in both the descriptive analysis and model estimation, which should mitigate the effect of panel attrition since these weights are adjusted for panel attrition (Summerfield 2010). However, the assumption that staying married is independent of labour supply decisions might be violated, and therefore caution should be exercised when generalizing the results to the general population of married Australian women.[10]

(ii) Model specification

The model specified in this study is a reduced form labour supply model since wages are excluded from the explanatory variables. The reduced form specification is estimated for two reasons. First, wages are not observable for those who are not employed. Second, even if wages were all observable, they might be endogenous to labour supply in the sense that an individual's wages might be affected by her working hours and/or both working hours and wages could be determined by some correlated or common unobserved factors. It seems common in the literature on dynamic labour supply to estimate a reduced form labour supply model, where wages are excluded from the model, but the determinants of wages are included (e.g., Hyslop 1999; Knight, Harris, and Loundes 2002; Lee and Tae 2005; and Michaud and Tatsiramos 2011).

A woman's non-labour income, which is used as an explanatory variable in the model, 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 welfare payments are means tested and thus affected by labour supply.

Other variables included the model are: education qualification (five dummies, indicating the highest qualification obtained), age and its square; health status (a dummy variable, 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; immigration status (two dummies, indicating immigrants from an English speaking country (ESC) and immigrants from a non-English speaking country (NESC)); and whether a person live in a capital city (a dummy variable). These are standard variables for modelling labour supply (Birch 2005). In addition, year (or wave) dummies are included to account for the year effects on the labour supply of married women. As mentioned earlier, initial labour supply and the proportion of life-time being employed are included to address the initial condition problem.

(iii) Descriptive statistics

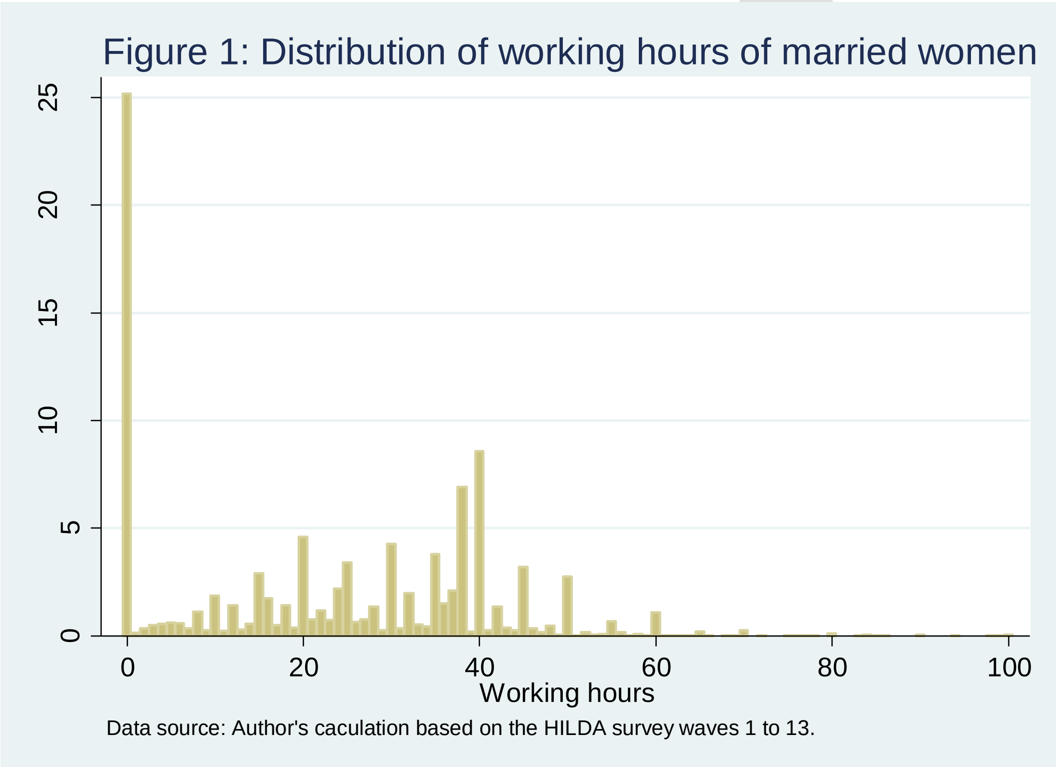
The summary statistics of the sample are presented in Table 1, with the first data column being calculated from all the 13 waves. The summary statistics in the last three columns are calculated from waves 1, 6 and 11 respectively to show variations across waves of the variables. Overall over three quarters of the women were labour force participants. The average working hours of the

[10] The HILDA Statistical Report shows that more than 90 per cent of the couples in the survey remain together from one year to the next; and over 70 per cent of the couples remain together from wave one to wave 6 (Wilkins et. al. 2009).

women (including those who were not employed) in the sample was just over 23 hours per week. Both labour force participation and hours worked increase over the observed period.

Figure 1 shows the distribution of working hours. About 25 per cent of women did not work at the time of the survey. The next largest group consists of women who worked 40 hours a week, accounting for about nine per cent of the sample. About five 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), 40 per cent of the women in the sample worked part-time, and around 36 per cent worked full-time.

Figure 1: Distribution of working hours of married Australian women



Examining observed transitions in labour force or employment status provides an indication of inter-temporal persistence of labour supply. For women in the sample transitions in labour force participation status are shown in Table 2, and transitions in employment status are shown in Table 3. Panel (a) in the two tables show the transitions on a year-on-year basis, while panels (b) and (c) present the transitions over five and 10 years, respectively.

The numbers along the diagonal are the proportion of women who did not change labour force or employment status over time, which gives an indication of persistence in labour supply. Irrespective of the time window examined, labour force and employment status of the women in the sample exhibited substantial persistence. As expected, short-term persistence (panel (a)) is higher than longer term persistence (panels (b) and (c)). For example, on a year-on-year basis, about 80 per cent of the women stayed in the same labour force or employment state. Over five years the proportion of the women staying in non-participation or non-employment was close to 60 per cent, while the proportion remaining in the labour force was close to 90 per cent; and the proportion remaining in each of the employment states was close to 70 per cent. Over 10 years still near half of the non-participants or not-employed stayed in the same labour force or employment state; the proportion remaining in the labour force was still 86 per cent, and the proportion remaining in each of the employment states was close to 60 per cent.

Table 1: Summary statistics

Variables [b]	Waves 1-13	Wave 1	Wave 6	Wave 11
Labour force participants	0.766 [a]	0.731	0.778	0.785
Working hours	23.166	22.276	23.369	24.006
st.d.	17.929 [c]	18.992	17.471	17.239
Degree	0.293	0.283	0.292	0.300
Diploma	0.110	0.107	0.108	0.111
Certificate	0.136	0.087	0.131	0.169
Year 12	0.156	0.179	0.161	0.141
Year 11 or lower	0.305	0.344	0.308	0.279
Age	43.207	37.256	42.216	47.174
st.d.	8.127	7.212	7.223	7.221
Health	0.188	0.132	0.177	0.227
ESC	0.088	0.088	0.088	0.088
NESC	0.131	0.131	0.131	0.131
OZ born	0.781	0.781	0.781	0.781
Children 0-2	0.135	0.255	0.154	0.053
st.d.	0.398	0.516	0.412	0.283
Children 3-5	0.191	0.265	0.228	0.108
st.d.	0.458	0.494	0.503	0.334
Children 6-17	1.025	0.998	1.093	0.961
st.d.	1.070	1.072	1.089	1.060
Capital city	0.579	0.597	0.582	0.570
Non-labour income ($100 000)	0.828	0.555	0.780	1.000
st.d.	0.805	0.406	0.791	0.990
Number of observations	14,053	1,081	1,081	1,081

[a] Summary statistics are weighted using longitudinal weights. [b] For the continuous variables their standard deviation is also presented. For other variables, the summary statistics refer to proportions. [c] This is the standard deviation of observed working hours. The standard deviation of latent working hours is unknown but is expected to be larger since observed working hours are censored at zero.

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

Initial status	Status transiting to: Non-participation	Status transiting to: Participation	Number of observations
	(a). Year-on-year		
Non-participation	**77.97**	22.03	1,981
Participation	6.35	**93.65**	6,667
All	23.13	76.87	8,648
	(b). Five years		
Non-participation	**56.25**	43.75	1,981
Participation	10.54	**89.46**	6,667
All	21.64	78.36	8,648
	(c). Ten years		
Non-participation	**44.98**	55.02	831
Participation	13.56	**86.44**	2,412
All	22.21	77.79	3,243

[a] Statistics are weighted using longitudinal weights.

Table 3: Employment status transition (row per cent)

Initial status	Status transiting to: Not-employed	Status transiting to: Part-time	Status transiting to: Full-time	Number of observations
	(a). Year-on-year			
Not-employed	**78.90**	17.26	3.84	3,061
Part-time	8.26	**79.57**	12.17	5,456
Full-time	4.83	11.32	**83.85**	4,455
All	24.82	39.63	35.55	12,972
	(b). Five year			
Not-employed	**56.94**	32.52	10.54	2,130
Part-time	12.29	**65.32**	22.39	3,577
Full-time	10.19	21.09	**68.72**	2,941
All	23.19	40.91	35.90	8,648
	(b). Ten year			
Not-employed	**45.67**	37.66	16.67	902
Part-time	14.86	**55.96**	29.18	1,268
Full-time	14.62	27.84	**57.54**	1,073
All	23.98	40.51	35.52	3,243

[a] Statistics are weighted using longitudinal weights.

V Model estimation results

Both the Probit and Tobit models are formulated based on latent labour supply y^*. For the Probit model on labour force participation, it is often more intuitive to look at the impact of an explanatory variable on the probability of labour force participation than the impact on the latent dependent variable. Therefore, for the labour force participation model the paper reports both the coefficient estimates and the estimates of the marginal effects on the probability of labour force participation.

For the Tobit models, the marginal effects of observed variables on alternative outcomes of interest can be examined (Wooldridge 2002). Table 4 summarises these alternative outcomes for both the conventional Tobit model and the two-tiered Tobit model.

Row (a) in Table 4 measures the probability of being employed; (b) the expected value of observed working hours (including both zero and positive hours); and (c) the expected working hours of those who are employed. 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.

Table 4: Alternative outcomes for examining marginal effects of Tobit models

	Conventional Tobit	Two-tiered Tobit
(a) $Prob(y^* > 0 \mid X) =$	$\Phi\left(\frac{X'\theta}{\sigma_e}\right)$	$\Phi\left(\frac{X'\theta_1}{\sigma_e}\right)$
(b) $(y \mid X) =$	$\Phi\left(\frac{X'\theta}{\sigma_e}\right)(X'\theta) + \sigma_e\phi\left(\frac{X'\theta}{\sigma_e}\right)$	$\Phi\left(\frac{X'\theta_1}{\sigma_e}\right)[X'\theta_2 + \sigma_e\phi\left(\frac{X'\theta_2}{\sigma_e}\right)/\Phi\left(\frac{X'\theta_2}{\sigma_e}\right)]$
(c) $E(y \mid X, Y > 0) =$	$X'\theta + \sigma_e\phi\left(\frac{X'\theta}{\sigma_e}\right)/\Phi\left(\frac{X'\theta}{\sigma_e}\right)$	$X'\theta_2 + \sigma_e\phi\left(\frac{X'\theta_2}{\sigma_e}\right)/\Phi\left(\frac{X'\theta_2}{\sigma_e}\right)$

Note: X is a vector representing all explanatory variables; θ represents all coefficient estimates.

To preserve space, the marginal effect estimates on the outcomes in rows (a) and (c) in Table 4, along with the coefficient estimates, are presented in this section. The marginal effects on (a) may be regarded as measuring the effect on the extensive margin of labour supply, while the marginal effects on (c) measure the effects on the intensive margin of labour supply.

Instead of calculating the marginal effects at the mean of the observed variables, we calculate the marginal effects for each observation in the sample and then take the mean over the sample. The resulting marginal effects are often called mean marginal effects (MME).[11] Tables 5 and 6 present the results for the Probit and Tobit models respectively.

(i) Estimates on labour supply persistence

Table 5 shows that other thing being equal, past labour force participation increases current labour force participation. The MME estimate indicates that participating in the labour force in the previous year raises the probability of current participation by about 37 percentage points relative to those who did not participate in the previous year.

[11] 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.

Table 5: Dynamic Probit model estimates

Covariates [a]	Coe.	s.e.	MME on Pr(y=1) [b]
Lagged LFP	1.372***	0.061	0.369
Non-labour income: deviation	-0.054**	0.022	-0.009
Non-labour income: mean	-0.151***	0.039	-0.026
Degree	0.390***	0.069	0.068
Diploma	0.110	0.079	0.021
Certificate	0.295***	0.062	0.053
Year 12	0.256***	0.068	0.047
Age	0.334***	0.060	-0.025
Age squared	-0.051***	0.006	
Health	-0.264***	0.040	-0.047
ESC	0.043	0.094	0.007
NESC	-0.219***	0.058	-0.039
Children 0-2	-0.568***	0.044	-0.112
Children 3-5	-0.222***	0.039	-0.040
Children 6-17	-0.047	0.030	-0.008
Capital city	0.094**	0.045	0.016
Children 0-2: mean	-0.384	0.263	-0.065
Children 3-5: mean	-0.238	0.215	-0.041
Children 6-17: mean	0.159***	0.045	0.027
Constant	-1.370***	0.164	
σ_u	0.573***	0.023	
ρ	-0.274***	0.031	
Number of observations	1081		
Log-likelihood	-3423.74		

Note: *** Significant at 1%; ** 5%; and *10%, respectively.

[a] The estimates on the wave dummies and the initial condition variables are not reported in the table, but can be obtained from the author on request.

[b] Standard errors were also calculated for the MME estimates using the Delta method to assess the significance of the MMEs, but were not reported in the table to preserve space. The significance of the MME estimates is generally consistent with that of the coefficient estimates.

Table 6: Dynamic Tobit model estimates

	Conventional dynamic Tobit model				Two-tiered dynamic Tobit model					
					First tier		Second tier			
Covariate [a]	Coe.	s.e.	MME on Pr(y*>0)[b]	MME on E(y|y>0)	Coe.	s.e.	Coe.	s.e.	MME on Pr(y*>0)	MME on E(y|y>0)
Lagged employment	7.981***	0.356	0.108	5.733	14.973***	0.399	-10.130***	0.341	0.488	-9.530
Lagged hours | employed	0.565***	0.010	0.006	0.420	0.019	0.014	0.641***	0.009	0.000	0.593
Non-labour income: deviation	-0.689***	0.145	-0.008	-0.512	-0.435*	0.228	-0.417***	0.118	-0.008	-0.386
Non-labour income: mean	-1.377***	0.315	-0.016	-1.023	-1.081***	0.230	-1.062***	0.164	-0.019	-0.983
Degree	3.208***	0.526	0.036	2.387	2.347***	0.406	1.272***	0.310	0.043	1.216
Diploma	1.339**	0.596	0.016	0.981	0.696	0.472	0.352	0.394	0.013	0.335
Certificate	2.296***	0.390	0.026	1.695	1.911***	0.402	0.705**	0.294	0.036	0.673
Year 12	1.355***	0.489	0.016	0.993	1.351***	0.400	0.173	0.323	0.026	0.165
Age	1.846***	0.408	-0.015	-1.076	2.858***	0.457	-0.278	0.326	-0.017	-3.797
Age squared	-0.343***	0.042			-0.402***	0.048	-0.045	0.034		
Health	-2.149***	0.293	-0.025	-1.580	-2.746***	0.314	-0.441*	0.252	-0.053	-0.421
ESC	1.087*	0.650	0.012	0.816	0.388	0.548	1.262***	0.358	0.007	1.210
NESC	-1.707***	0.452	-0.020	-1.252	-1.903***	0.358	0.292	0.363	-0.036	0.279
Children 0-2	-7.048***	0.296	-0.086	-5.001	-4.671***	0.460	-3.791***	0.267	-0.097	-3.575
Children 3-5	-2.644***	0.270	-0.031	-1.939	-1.309***	0.415	-1.872***	0.242	-0.024	-1.781
Children 6-17	-0.979***	0.180	-0.011	-0.734	-0.110	0.304	-0.568***	0.143	-0.002	-0.544
Capital city	0.835**	0.359	0.009	0.620	0.630**	0.291	0.030	0.230	0.011	0.028
Children 0-2: mean	-2.098	2.347	-0.024	-1.559	-1.733	1.634	0.234	1.417	-0.031	0.217
Children 3-5: mean	-3.312*	1.885	-0.037	-2.461	-0.912	1.407	-3.253***	1.141	-0.016	-3.011
Children 6-17: mean	1.867***	0.330	0.021	1.387	0.772**	0.355	1.160***	0.242	0.014	1.074
Constant	-7.761***	1.141			-12.920***	1.138	21.134***	0.893		
σ_u	5.796***	0.159			3.184***	0.109				
σ_ε	10.900***	0.041			7.979***	0.032				
ρ	-0.198***	0.010			-0.193***	0.011				
Number of observations	1081				1081					
Log-likelihood	-40331.570				-37998.123					

Note: *** Significant at 1%; ** 5%; and *10%, respectively.

[a] The estimates on the wave dummies and the initial condition variables are not reported in the table, but can be obtained from the author on request.

[b] Standard errors were also calculated for the MME estimates using the Delta method to assess the significance of the MMEs, but were not reported in the table to preserve space. The significance of the MME estimates is generally consistent with that of the coefficient estimates.

Table 6 shows that when the impact on the probability of being employed is considered, the estimates for lagged employment in the two Tobit models are qualitatively similar to that in the Probit model. That is, being employed in the previous year is found to increase the probability of being employed in the current year, although the estimated marginal effects differ between the two Tobit models (11 percentage points in the conventional Tobit model vs 48 percentage points in the two tiered Tobit model). However, while lagged employment is found to increase current working hours of those who work by 5.7 hours for each hour worked in the previous year from the conventional Tobit model, it is found to reduce current working hours by 9.6 hours for each hour worked in the previous year from the two-tiered Tobit model.

The estimates for lagged working hours appear to be similar between the two Tobit models – lagged working hours increase current working hours of those who work, but the impact of lagged working hours on the probability of being employed is negligible. The negative estimate for lagged employment and the positive estimate for lagged working hours in the two tiered Tobit model indicate that low working hours (i.e., less than 16 hours a week) in the previous year reduce current working hours of those who work, but working more than 16 hours in the previous year increases current working hours of those who work. In other words, from the two tiered Tobit model, there is still positive state dependence in working hours if working hours are sufficiently large.

For both Tobit models the correlation of unobserved transitory shocks is estimated to be negative, suggesting that failing to control for this correlation would underestimate positive state dependence of labour supply.

In addition to the models reported in Tables 5 and 6 that control for correlated random effects and serially correlated unobserved transitory shocks. Three more restrictive models have also been estimated: (a) a simple dynamic model on pooled data, with the lagged dependent variable and a constant only, without random effects and serially correlated unobserved transitory shocks; (b) a simple dynamic model on pooled data, with all the explanatory variables, but without random effects and serially correlated unobserved transitory shocks; and (c) dynamic models with correlated random effects but without serially correlated unobserved transitory shocks. These models were estimated for both the Probit and Tobit. To save space, only the estimates for lagged dependent variables are presented in Tables 7 and 8.

Table 7 shows the estimates of the more restrictive Probit models. While observed individual heterogeneity plays a role in observed persistence of labour force participation (i.e., model (a) compared with model (b) in the table), it is correlated random effects that reduce the observed persistence the most (i.e., from model (b) to model (c)). Comparing the estimates in model (c) with that in Table 6 suggests that failing to control for serial correlated unobserved transitory shocks would underestimate state dependence of labour force participation.

Table 7: Alternative Probit models

	Coe.	s.e.	MME on Pr(y=1)
(a). Pooled data, with lagged dependent and constant only			
Lagged participation[(a)]	2.297***	0.027	0.721
(b). Pooled data, with all explanatory variables			
Lagged participation	2.139***	0.029	0.648
(c). Dynamic model, with correlated RE, but without serial correlation			
Lagged participation	0.995***	0.072	0.252

Note: *** Significant at 1%; ** 5%; *10%.

(a) Only estimates on the lagged dependent variables are reported here in the table. The estimates for other variables can be obtained from the author on request.

Table 8 presents the estimates of the more restrictive Tobit models. The patterns of the results are very much similar to that in Table 7. That is, in general unobserved heterogeneity appears to account for more of observed labour supply persistence; and failing to control for serial correlated unobserved heterogeneity tends to underestimate state dependence of labour supply.

(ii) Estimates for other variables

The estimates for the other explanatory variables are generally as expected and are briefly summarised as follows.

The effects of non-labour income – both permanent and transitory non-labour income – are estimated to reduce married women's labour supply. As expected, permanent non-labour income has a larger impact than transitory non-labour income.

Education is found to have a significant impact on a married woman's labour supply. The impact of education on hours worked of those who work (i.e. the intensive margin of labour supply) tends to be larger in the conventional Tobit model than in the two tiered Tobit model.

Age is estimated to increase labour supply but at a decreasing rate. The mean marginal effect estimates are negative on both the intensive and extensive margins of labour supply. The two tiered Tobit model results show that the effect of age is largely on the extensive margin rather than on the intensive margin. The impact of age on the intensive margin is much larger in the two tiered Tobit model than in the traditional Tobit model.

Having a health condition is found to reduce labour supply relative to those without a health condition; again the effect is largely on the extensive margin.

Table 8: Alternative Tobit models

	Conventional dynamic Tobit model[(a)]				Two-tiered dynamic Tobit model					
			MME	MME	First tier		Second tier		MME	MME
	Coe.	s.e.	On Pr(y*>0)	on E(y|y>0)	Coe.	s.e.	Coe.	s.e.	On Pr(y*>0)	on E(y|y>0)
a. Pooled data, with lagged dependent and constant only										
Lagged employed	10.766***	0.365	0.156	7.466	16.293***	0.373	-13.362***	0.265	0.587	-12.471
Lagged hours | employed	0.791***	0.009	0.009	0.575	0.133***	0.009	0.807***	0.005	0.003	0.750
b. Pooled data, with all explanatory variables										
Lagged employed	9.441***	0.359	0.132	6.620	15.544***	0.391	-13.536***	0.272	0.536	-12.608
Lagged hours | employed	0.762***	0.008	0.009	0.556	0.115***	0.010	0.787***	0.005	0.002	0.728
c. Dynamic model, with correlated RE, but without serial correlation										
Lagged employed	6.454***	0.357	0.084	4.610	15.949***	0.389	-8.854***	0.351	0.505	-8.401
Lagged hours | employed	0.434***	0.011	0.005	0.319	-0.102***	0.014	0.507***	0.010	-0.002	0.473

Note: *** Significant at 1%; ** 5%; *10%.

(a) Only estimates on the lagged dependent variables are reported here in the table. The estimates for other variables can be obtained from the author on request.

Compared to native born Australians, immigrants from an English speaking country have a higher labour supply; and this effect is largely on the intensive margin. But immigrants from a non-English speaking country have a lower labour supply relative to the native born; and this effect is largely on the extensive margin.

Having dependent children reduces labour supply. The younger the age of the children, the larger is the negative impact.

Living in a capital city is estimated to increase labour supply relative to living in other areas; and the impact is largely on the extensive margin.

VI Conclusion

Using the first 13 waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey, this study examined the labour supply of married Australian women, with a focus on whether and to what extent state dependence occurs in their labour supply. The model estimation results showed that while observed and unobserved individual heterogeneity contributes to observed persistence of labour supply of married Australian women, there exists genuine state dependence in the labour supply of married Australian women after these factors are controlled for, implying that policy intervention that increases married women's labour supply would have a long-lasting effect. It is also found that failing to control for serially correlated unobserved transitory shocks would lead to underestimation of genuine state dependence of labour supply, a result similar to other international studies (although in a different modelling framework).

The results from this study also show that individual characteristics of married women are important drivers of labour supply as well. This suggests that 'one-size-fits-all' policies aimed at increasing labour supply of all married women may not work; instead, tailored policies which take into account of individual characteristics and circumstances would have a better chance of being effective.

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 have a significant effect on the labour supply 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 help increase the labour supply of married women with young children.

The lower labour supply of married women from non-English speaking background than the native born 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 identifying the exact causes.

Finally, the differences in the estimated effects between the conventional Tobit model and the two-tiered Tobit model indicate that workforce participation decisions of married women may be determined by a different mechanism from the decision on how many hours to work conditional on they choose to work.

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