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National Centre for Social and Economic Modelling

• University of Canberra •

Modelling the workers of tomorrow: the APPSIM dynamic microsimulation model

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About NATSEM

The National Centre for Social and Economic Modelling was established on 1 January 1993, and supports its activities through research grants, commissioned research and longer term contracts for model maintenance and development with the federal departments of Family and Community Services, Employment and Workplace Relations, Treasury, and Education, Science and Training.

NATSEM aims to be a key contributor to social and economic policy debate and analysis by developing models of the highest quality, undertaking independent and impartial research, and supplying valued consultancy services.

Policy changes often have to be made without sufficient information about either the current environment or the consequences of change. NATSEM specialises in analysing data and producing models so that decision makers have the best possible quantitative information on which to base their decisions.

NATSEM has an international reputation as a centre of excellence for analysing microdata and constructing microsimulation models. Such data and models commence with the records of real (but unidentifiable) Australians. Analysis typically begins by looking at either the characteristics or the impact of a policy change on an individual household, building up to the bigger picture by looking at many individual cases through the use of large datasets.

It must be emphasised that NATSEM does not have views on policy. All opinions are the authors' own and are not necessarily shared by NATSEM.

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Abstract

As the recently released *Intergenerational Report 2007* makes clear, population ageing is expected to create severe fiscal pressures for governments. With 13 Commonwealth agencies as research partners, NATSEM is currently constructing the Australian Population and Policy Simulation Model (APPSIM), to simulate our likely social and economic futures and the future distributional impact of policy changes. The APPSIM model takes the 2001 Census one per cent sample file as its base data and then ages the individuals within the sample, year by year, to about 2050.

This paper provides an overview of APPSIM and then describes in more detail the labour force participation module for APPSIM and the methodology and data sources being used to develop it. The purpose of the labour force module within APPSIM is to project the distribution of labour force participation for the next 50 years.

The primary source of data for the module is HILDA, the Household, Income and Labour Dynamics in Australia Survey. The five waves of HILDA are used to determine the likelihood that individuals within APPSIM will change their labour force status from one year to the next, given such characteristics as their age, sex, education, marital status, children, health and working history. Since the previous year's labour force status is one of the strongest predictors of the current year's labour force status, the longitudinal nature of HILDA is invaluable to the development of this model.

The paper contains a brief summary of patterns and projections of Australian labour force participation. It then discusses the methodology used in the development of the equations to predict labour force participation. It goes on to describe how the module projects the four possible labour force statuses of full-time work, part-time work, unemployed and not in the labour force. Finally, the paper discusses the alignment of the model to user-definable aggregate projections of labour force participation.

Author note

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General caveat

NATSEM research findings are generally based on estimated characteristics of the population. Such estimates are usually derived from the application of microsimulation modelling techniques to microdata based on sample surveys.

These estimates may be different from the actual characteristics of the population because of sampling and nonsampling errors in the microdata and because of the assumptions underlying the modelling techniques.

The microdata do not contain any information that enables identification of the individuals or families to which they refer.

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1 Introduction

1.1 Why dynamic microsimulation?

The Australian Treasury and the Productivity Commission have undertaken large modelling projects to estimate the likely fiscal and social impacts of the ageing population (Treasury 2002 and 2007, Productivity Commission 2005). These reports have found that, over the next 50 years:

- the proportion of retired people in the population will increase,
- the average age of the population will increase;
- the ratio of people in the labour force to the overall population will decrease, resulting in fewer workers supporting a larger number of non-workers; and
- as a result of these factors and assuming current policy remains unchanged, a 'fiscal gap' in the Federal Government's budget will develop, due to the increase in expenditures on pensions and healthcare and slowing growth in taxation revenue due to relatively fewer people in the labour market.

The social and fiscal difficulties likely to face Australia over the next 40-50 years are already well known, so why is there the need for yet another model? The answer to this lies in the fact that the *distributional* impact of these changes is not well understood. If changes to government policy in regards to the tax-transfer system are being proposed it is important to know the impact on different groups within society as well as the aggregate impact. Who will be the winners and losers under the proposed policy change? Dynamic microsimulation modelling (DMSM) is a tool well suited to examining this distributional impact.

DMSM has become a popular methodological tool for governments and academics. It was pioneered by Guy Orcutt (1957), who proposed a model of interacting individuals to address some of the shortcomings of macroeconomic models. Its use has increased as Western nations face ageing populations and declining birthrates, as it allows modellers to predict the likely future distributional impacts of social and fiscal policies, such as future pensions and healthcare costs (Harding and Gupta 2007). The focus of DMSM is on how fiscal and social policies affect the future distributional outcomes of individuals, which can then be aggregated to determine overall economic effects, rather than simply focusing on aggregate data. The major benefit of DMSM over conventional modelling is that it can demonstrate the heterogeneity of future populations and the distributional impact of policy, economic and social changes (Klevmarken 2005). In other words, DMSM can measure the impact of changes on specific groups in a population, such as the poor, single parents, the retired etc.

DMSM involves using statistical data on a country's population to develop a model subset of individuals and households and their characteristics, such as age, education, employment status, marital status and health. The lives of this subset of individuals are updated as time passes in the model. Moving from one characteristic to another is called an event, and events can include commencing or finishing education, becoming unemployed, finding a new job, getting married or divorced, having a child, moving out of the parental home or retiring. Using existing datasets, modellers can estimate the probability that an individual or household will change one of their characteristics in a certain period of time (Bourguignon and Spadaro 2006). A DMSM can then model the lives of hundreds of thousands of individuals over decades into the future as they gain an education, start work, earn and save money, marry, have children, divorce, become unemployed, retire and die (O'Donoghue 2001).

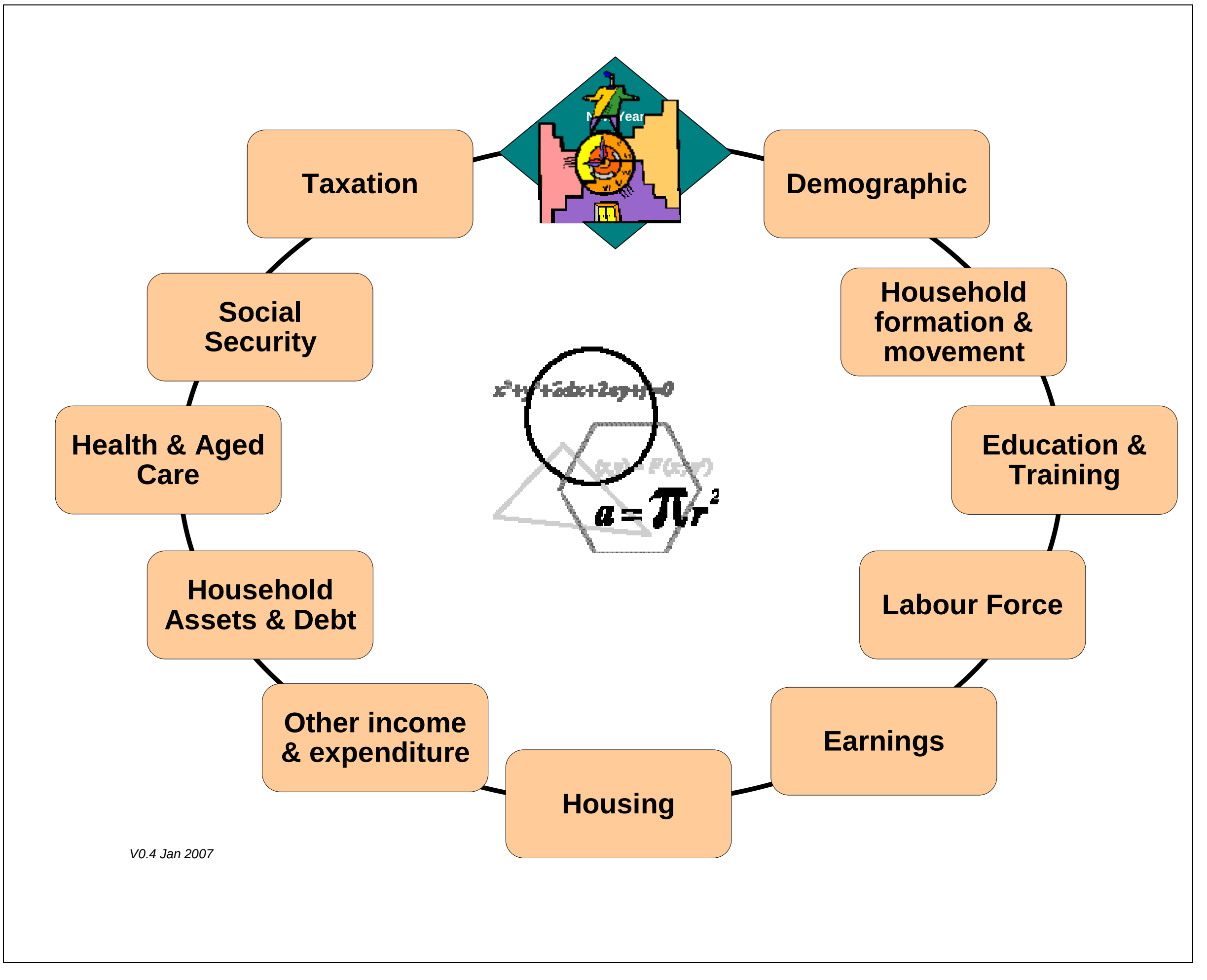
1.2 APPSIM

The ageing of the population and the availability of HILDA, a reasonably-sized longitudinal dataset, has prompted NATSEM to commence building a dynamic microsimulation model for Australia. Under an Australian Research Council Linkage Grant (LP0562493), NATSEM is collaborating with 13 government agencies in developing the Australian Population and Policy Simulation Model (APPSIM), a model of the Australian population until 2050, to be used in evaluating the impact of future social and fiscal policies. Because the main development driver of the model is to provide a decision support tool for policy makers which allows them to develop policy that will minimise the costs and maximise the benefits of the ageing population, it must be tailored to represent the particular concerns that arise from the ageing population.

The starting point for APPSIM is the one percent sample of the 2001 Census. Onto these 188 000 records, extra characteristics are added and some more detailed information is imputed to form the initial APPSIM population – the *base data*. NATSEM modellers are using HILDA and other datasets to generate transition probabilities for events within the model; that is, the likelihood a person will move from one state (eg full-time employment, married, good health) to another (eg unemployed, separated, disabled). The modelling will also include the probabilities of childbirth, overseas migration and death, allowing the simulated population to change over time. The transition probabilities will be applied to every person in the initial APPSIM population to update the population's characteristics for each year in the model. For example, one transition probability might give 32 year old married women with certain characteristics a 25 percent chance of having a baby in the following year. APPSIM will then apply this transition probability to all such women in its dataset. When APPSIM's 'clock' ticks over to the next year, around a quarter of these women will have had a baby.

APPSIM is a modular DMSM; that is, its primary functions are broken down into groupings. Figure 1 shows the flow of modules in APPSIM. The demographic module models births, deaths and migration. The household formation and movement module models couple formation and separation and children leaving home. These modules create a basis of people and their relationships to each other, upon which estimation of education, labour force participation and the other modules can be based (Kelly 2007).

Figure 1 **The modules in APPSIM**



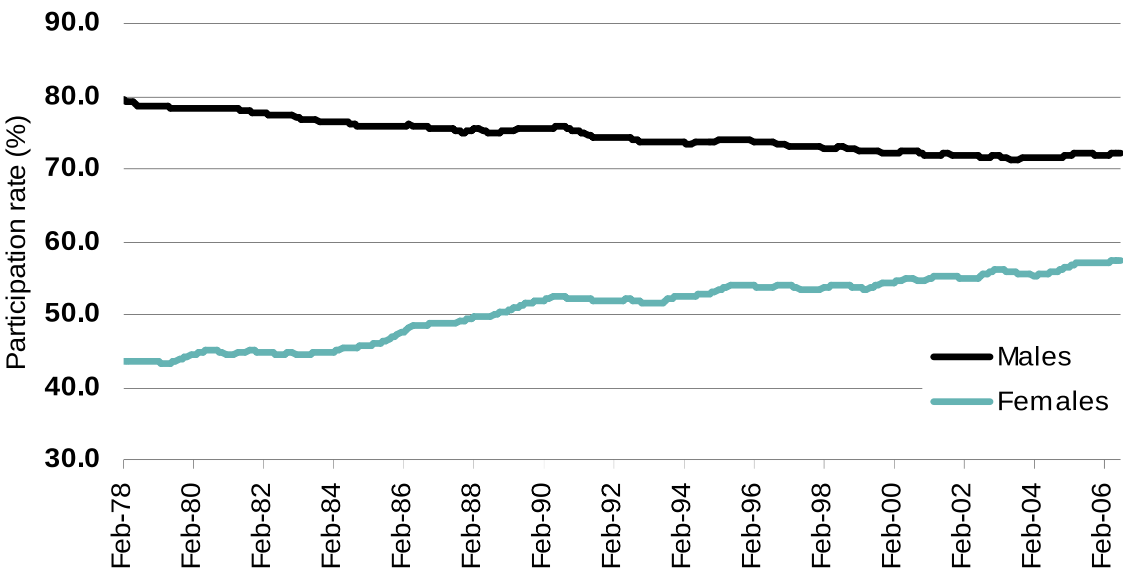
This paper focuses on the development of the labour force module within APPSIM. This module is expected to be highly significant for policy purposes as it represents one of the three Ps that influence output per capita – participation (Productivity Commission 2005). Increasing rates of labour force participation will increase GDP per capita and thus may be valuable in mitigating the expected budgetary deficits caused by the ageing of the population. A model that estimates the labour force participation of individuals is thus a very important part of APPSIM.

2 Labour force participation in Australia

2.1 Current labour force participation patterns

One of the most notable trends in labour force participation is the increasing participation rates among women and declining participation rates among men, which can be seen in Figure 2. In 1978, nearly 80 percent of men and only 43 percent of women of working age participated in the labour market. Since then, men's labour force participation has followed a steady downward trend while women's participation has increased. However, participation rates for men are still much higher than those for women. In 2006, 72 percent of men and 58 percent of women participated in the labour market (ABS 2007).

Figure 2 **Labour force participation by rates by sex**



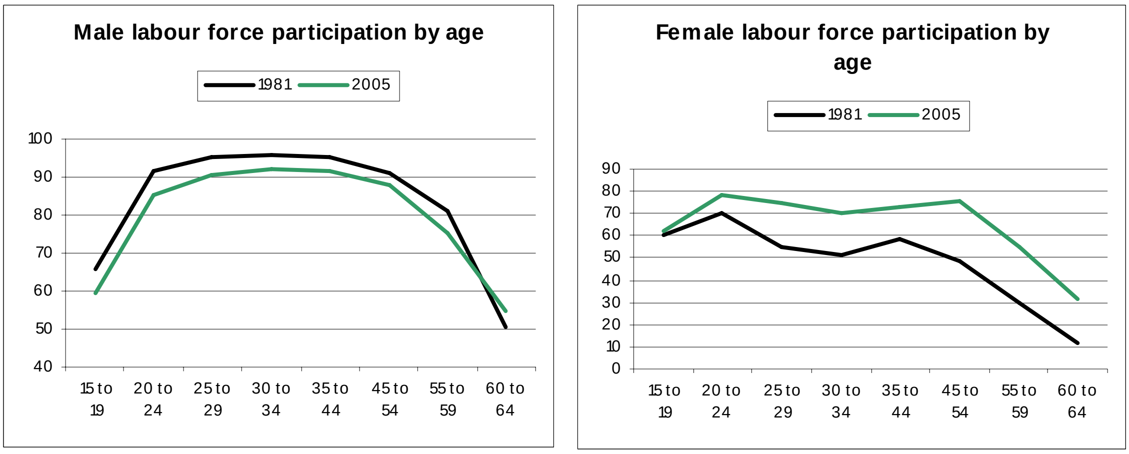
Note: Based on the civilian labour force aged 15 and over.
Data source: (ABS 2007)

The reasons for these changing patterns are numerous. More time spent in full-time study discourages employment, particularly full-time employment, among under-

25s. Improved pay and opportunities for women, maternity leave policies, part-time work and greater availability of white-collar jobs which men and women can do equally well has encouraged more women to not only enter the labour force, but remain in the labour force when they have children.

The declining participation rate of men since 1981 can be seen across all ages except for the 60-64 age group (although there is a higher degree of variance in the participation rates of these men over time than most other age groups, suggesting that the participation of this group is more vulnerable to economic conditions.) The increase in women's participation can be seen in all age groups except ages 15-19, where it remains relatively static. The 'nappy valley' – the dip in women's labour force participation during peak childrearing years - has become shallower, and while it still impacts 30-34 year olds the most, its impact on the 25-29 age group has lessened (OECD 2007) – see Figure 3.

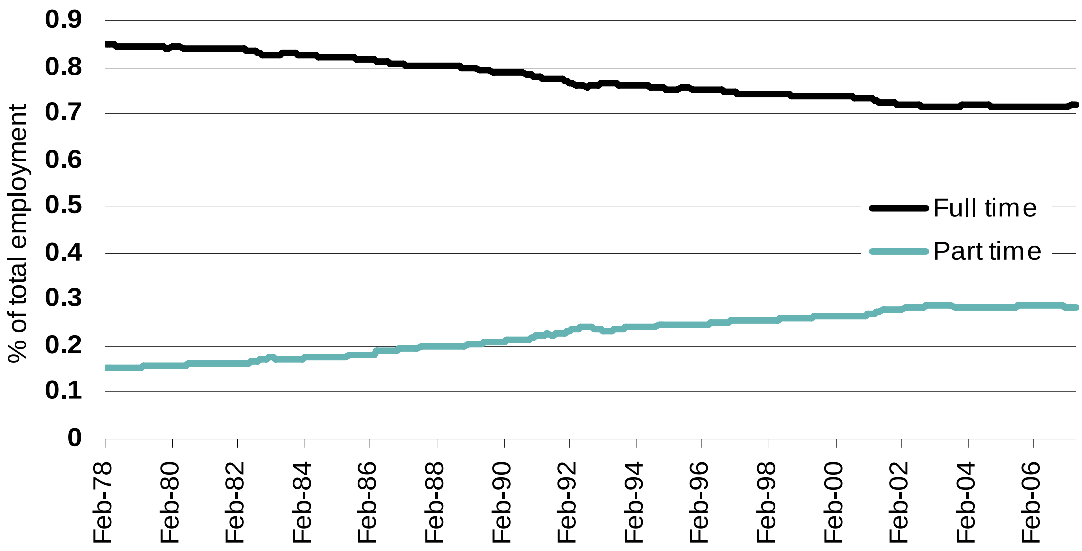
Figure 3 **Labour force participation rates by age and sex**



Data source: (OECD 2007)

Another notable trend that has appeared over the last few decades is the move away from traditional permanent, full-time employment towards more part-time, casual and contract work. The reasons for this are both supply- and demand-based: some people such as full-time students, mothers with primary child care duties and the semi-retired often prefer to work less than full-time hours, and some employers prefer the flexibility that is offered by these forms of employment (Productivity Commission 2006). Figure 4 shows the increase in part-time employment from 15 percent in 1978 to 29 percent in 2007.

Figure 4 **Part-time employment as a proportion of total employment**



Data source: (ABS 2007)

2.2 Projections of future labour force participation

As the population ages, it is expected that some of the features of the labour force will change. Compared to the workforce of today, the workforce in 20-40 years time is expected to be older, healthier, more educated and a smaller percentage of the total population (Productivity Commission 2005).

Labour force participation levels of persons aged over 15 are projected to fall to 57 percent by 2046-47 as persons aged 65 and over make up a greater proportion of the population (Treasury 2007). It is expected that the participation rate of prime-aged workers – those between 15 and 64 – will increase from 76 percent in 2006-07 to 78 percent by 2046-47, as a result of higher participation rates among older workers aged 55-64. However, projections show increasing labour force participation among women and a flattening-out of the declining labour force participation of men. It is also expected that men aged over 65 will increase their labour force participation.

The decline in average hours worked due to the increasing prevalence of part-time work is likely to continue, with average hours worked expected to decline from 35.8 in 1997 to 34.5 in 2046-47. This is due to the increasing proportions of women and older people in the labour force, who are more likely to work part-time (Treasury 2007).

3 Methodology used in the development of the labour force module

The purpose of APPSIM's labour force module is to enable the prediction of an individual's labour force status based on certain characteristics. The module will be used to predict the annual labour force states of a subset of the Australian population each year between 2001 and 2050.

Labour force status is classified within the model as full-time (35+ hours per week), part-time (less than 35 hours per week), unemployed and not in the labour force. Hours worked will be allocated by a separate process.

The estimation of the equations used in the labour force module is based on all five available waves of the HILDA survey, plus 'wave zero'; that is, people's responses in wave 1 regarding their activities in the previous year. Regressions were only estimated for waves 2-5; this is because a person's current labour force status was found to be dependent on their labour force status over the previous two years. Thus data from waves 0 and 1 were necessary to estimate these variables for wave 2. A total of 39 087 observations were used to estimate the equations.

When estimating regressions using longitudinal data, it is important to consider the effect of the time unit in which each wave of data is collected. Events external to the data will have an impact on the data. For example, the probability that an individual will move from unemployment to full-time work will be very different in a recession year than in a growth year. In theory, this should mean the effect of the year on the likelihood an individual will take a particular labour force status should be considered.

However, during the five years in which HILDA has been collected, there have not been any significant shocks that might make transition probabilities substantially different between years. Economic growth has been steady and positive, the mining boom has been running for the years under consideration and unemployment has been steadily declining. Earlier versions of the regressions were run with dummy variables for the waves of the survey, and none of the parameters were statistically significant. For this reason, wave-specific effects have not been modelled.

Broadly speaking, the model estimates the probability that a person will be working full-time, part-time, unemployed or not in the labour force based on the following multinomial logit model:

$$\mathbf{P}_{\mathbf{FT,\ PT,\ UE,\ NILF}} = \frac{\mathbf{1}}{\mathbf{1 + e^{-(education,\ marital\ status,\ children,\ health,\ lfprev)}}}.$$

where *lfprev*=labour force status in previous periods. Separate equations are estimated for sex and age groups.

Several other independent variables were tested for their effect on labour force status and were found not to have statistically significant effects. These include one's region classification, spouse's labour force status, spouse's weekly income from wages, salary and government benefits and whether a person owned their own business in the previous period.

Age

Labour force participation will be calculated for all persons aged 15 to 74. Of the HILDA observations of people aged 75 and over, only 2.7 percent remained in the labour force either full-time or part-time. Seventy-five has been used as a mandatory retirement age in short-term projections in APPSIM.

Separate equations will be estimated for people aged 15-24, aged 25-54, aged 55-64 and aged 65-74. This is because each of these age groups face different life events that affect labour force participation. The first face full-time study and finding a first job; in the second group, children and career peaks; in the third, retirement is an option and risk of disability increases; in the fourth, one becomes eligible for the pension. Age and age-squared were both tested as independent variables for inclusion in the equations and were found not to be significant.

An age-specific dummy variable for people aged 60 and over has been included in the equation for 55-64 year olds.

Extremely few HILDA respondents reported being unemployed after the age of 64. Out of all the observations for persons aged 65 and over, only nine were unemployed. Such a small number of observations were insufficient to generate reasonable transition probabilities into and out of unemployment. To account for this data limitation, the labour force category of unemployed has been merged with not in the labour force for over-65s.

Sex

Separate equations are estimated for males and females. This is because the independent variables in the model affect men and women differently, most notably children. For example, while having a baby has significant effects on the labour force participation of both mothers and fathers, the presence of a preschool child only has statistically significant effects on mothers.

Education

For this module, education has been classified into four levels: university, trade or diploma, Year 12 only or less than Year 12.

The labour force activities of full-time students will be modelled separately, possibly as part of the education module.

Marital status

HILDA classifies individuals according to six marital states: married, de facto, separated, divorced, widowed and single.

There are no significant differences between labour force statuses of the unpartnered, that is, those who are separated, divorced, widowed and single. Partnered persons, however, were found to have significantly different participation patterns than the unpartnered. No significant differences were found between the labour force participation patterns of married or defacto people. Marital status is therefore classified as either partnered or unpartnered.

Children

Several methods of modelling the impact of children have been tested, including a variable for the age of the youngest child, a variable for the total number of children, and dummy variables for children of different ages. The method that produced the most significant results was dummy variables for the age group of the youngest child. These dummies are *baby* (for a child aged 0), *toddler* (child aged 1-2) and *preschool* (child aged (3-5). Children aged 6 and older do not have statistically significant effects on their parents' labour force participation.

The dummy variables for children only apply to persons in the 15-24 and 25-54 age groups, because the demographic module in APPSIM limits childbirth to women under 50. Preschool children and toddlers do not appear to have a significant impact on men's labour force participation, so this dummy was excluded from the men's equations. Babies did not appear to have a significant impact on the labour force participation of men aged 15-24, so this dummy was excluded.

Health

The main variable used to estimate the impact of a person's health or disability on their labour force participation was a question that asked individuals to rate the effect their poor health or disability had on their ability to work on a scale of 0 to 10, where 0=no effect, 10= total effect (ie cannot work).

The modular nature of APPSIM, as shown in Figure 1, requires the modules to be calculated in a specific order. For example, demographics – births, deaths and migration – are usually placed at the start of the simulation cycle, so that the total population and its age distribution are clear before the other transitions are estimated. However, some compromises must be made with the order of modules. One such compromise relates to the effect of health on labour force participation. Since the health module comes after the labour force module, a person's health status is updated after their labour force status in the APPSIM simulation cycle. As a result, a change in a person's health in period t cannot affect a person's labour force status in period t – it can only affect their labour force status in t+1. For this reason, a lagged health variable was used as an explanatory variable.

At present it is uncertain whether a health variable will be used in the short term to predict labour force participation. It is not expected that a health module for APPSIM will be developed for at least another year and, without a health module, there is no means of projecting health status. Without an indicator of future health status of individuals, a health variable in the labour force module will not be helpful. Two options will therefore be considered in the short term – to remove the severely disabled from the labour force and otherwise not consider the effect of health on labour force participation; or to generate some very basic health projections that can be replaced when the health module is developed. Health has been included as a variable in the modelling for this paper to gauge the impact of health on labour force participation.

Previous labour force status

The most likely scenario is that a person will not change their labour force status from year to year. That is, if a person is a full-time employee in a given year, it is very likely they will still be working full-time in the following year. The only exception was for unemployment; a person looking for a job is more likely to find one or drop out of the labour force than remain searching for work. Tables 1 and 2 show the labour market transitions for males and females of all the HILDA observations used in the model.

Table 1 **Transitions between employment states for males aged 15-74**

	FT in year t	PT in year t	UE in year t	NILF in year t	% with same LF status over both periods
FT in t-1	12,275	445	186	290	91%
PT in t-1	631	1,101	68	236	57%
UE in t-1	265	151	271	145	40%
NILF in t-1	255	220	148	3,542	84%

Note: This table is generated from weighted data. Excludes full-time students.

Source: Author’s calculations using HILDA waves 1-5

Table 2 **Transitions between employment states for females aged 15-74**

	FT in year t	PT in year t	UE in year t	NILF in year t	% with same LF status over both periods
FT in t-1	5,170	678	77	314	81%
PT in t-1	868	3,991	98	636	72%
UE in t-1	128	174	165	208	29%
NILF in t-1	217	727	228	6,647	85%

Note: This table is generated from weighted data. Excludes full-time students.

Source: Author’s calculations using HILDA waves 1-5

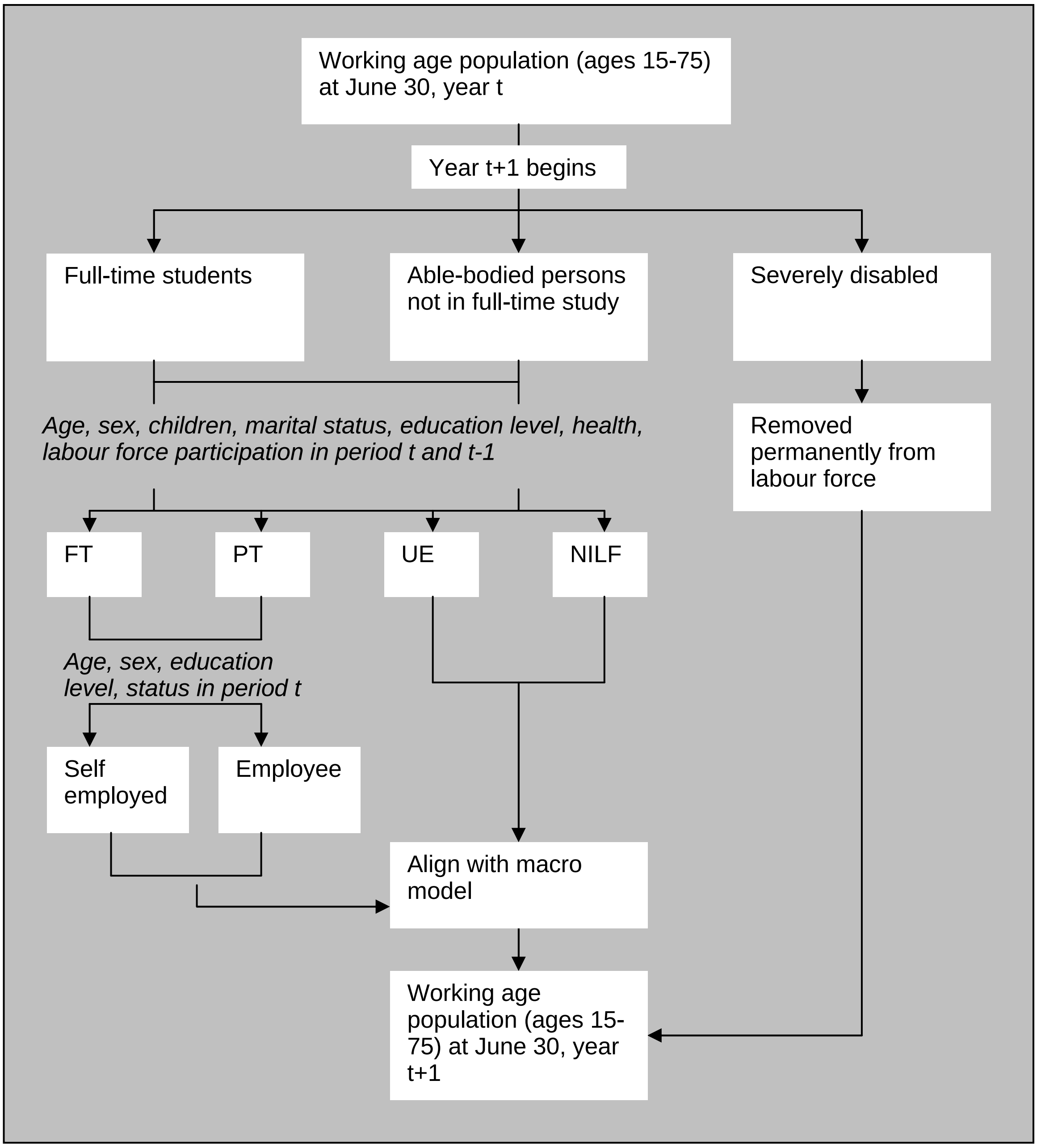
The model includes a variable for a person’s labour force status in the previous year (*lfprev*), and for the year before that (*lfprev2*). For example, for HILDA’s 2002 respondents, the variable *lfprev* would represent their labour force status in the 2001 survey, and the variable *lfprev2* would represent their labour force status in 2000, as reported in the 2001 survey.

In deciding whether to include the variable *lfprev2* in the equations, the costs and benefits of both options had to be considered. It is beneficial to include this variable because stability of employment is a factor in predicting future labour force status: a person who is unemployed in 2001 and employed in 2002 is more likely to become unemployed in 2003 than a person who was employed in both 2001 and 2002. Thus the use of *lfprev2* improves the predictive ability of the model. However, it requires the elimination of a year’s worth of data in estimating the model – since wave 1 of HILDA in 2001 did not report on labour force participation in 2000 and 1999, it cannot be used in estimating 2001 labour force participation based on *lfprev* and *lfprev2*. Preliminary analysis shows that the improvement in prediction accuracy from using *lfprev2* outweighs the effect of losing a year’s worth of data; that is, the model produces more accurate results including *lfprev2* using 2002-05 data than removing *lfprev2* and using 2001-2005 data.

4 Projection of labour force states

Figure 5 shows how the labour force module in APPSIM will predict the labour force status of individuals at June 30 each year. At the start of a model year, after demographics, family formation and education have been simulated, full-time students and possibly the severely disabled will be removed from the main pool. All other persons will have their labour force status estimated based on their age, sex, children, marital status, education, health and previous labour force participation. Those in employment will be classified as self employed or employees. Total labour force outcomes will be then be aligned with a macro model.

Figure 5 **Operation of the labour force module**



This chapter focuses on modelling the labour force states of able-bodied persons not in full time study, and the alignment with macro outcomes. It is expected that self-employed/employee states will be allocated using a similar process to that used to allocate labour force states.

4.1 Outputs of the regression equations

The coefficients, standard errors and t-statistics from the multinomial logit regressions of HILDA data are presented in Tables 6, 7, 8 and 9 in the Appendix. The coefficients will be used to generate transition probabilities for the APPSIM population.

The output of the multinomial logit model is a series of four probabilities per observation that represent the likelihood that the person will be full-time, part-time, unemployed or not in the labour force as at June 30 each year, based on their characteristics. For example, the model might estimate that a 19 year old single female who has not previously been in the labour force has a 40 percent probability of working full-time, a 20 percent probability of working part-time, a 10 percent probability of becoming unemployed and a 30 percent probability of remaining out of the labour force.

The model was tested for accuracy by comparing an individual's labour force state reported in HILDA with the labour force state that the regression model predicted was most likely. On average, the model is able to predict the labour force states of women with 76 percent accuracy and men with 85 percent accuracy. Prediction accuracy varies widely across age ranges, with persons aged 15-24 being the least predictable (prediction accuracy 69% for males and 59% for females). Table 3 shows the accuracy rates for each age/sex regression.

Table 3 **Prediction accuracy of base regression equations**

	15-24	25-54	55-64	65+
	%	%	%	%
Males	69	89	82	89
Females	59	75	82	92

Note: Accuracy of the model was tested by comparing actual labour force status with the labour force state predicted most likely by the model. Based on unweighted observations.

Source: HILDA waves 1-5, author's calculations

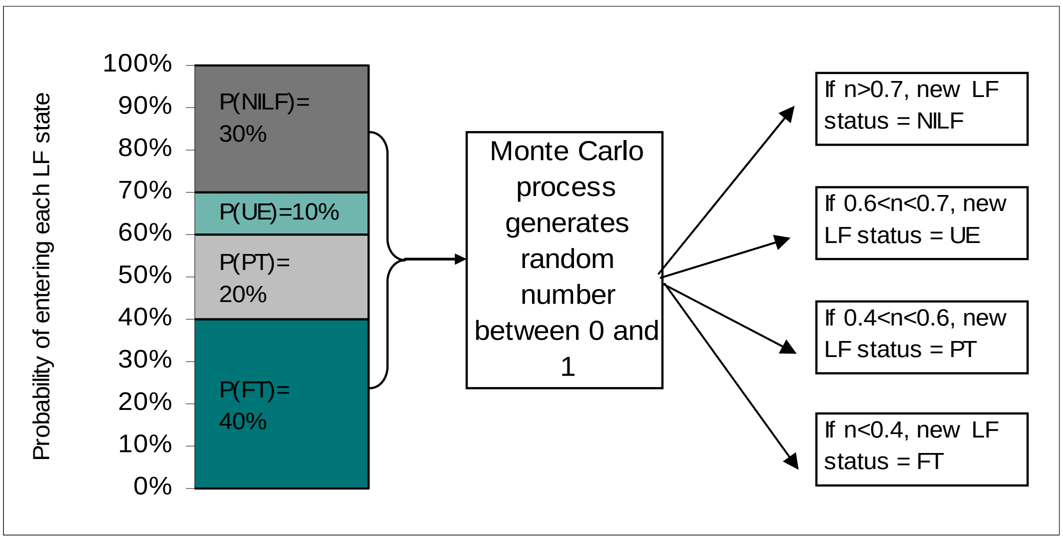
4.2 The Monte Carlo process

Once the probabilities of being in each labour force state have been generated for every individual in the model, the Monte Carlo process will be used to allocate labour force states according to the probabilities.

Monte Carlo processes are commonly used in dynamic microsimulation to allocate changes to a person's state once probabilities of the change have been calculated. In a simplified example, suppose that a model estimates that women with toddlers have a 70 percent chance of having a job and a 30 percent chance of not having a job. The Monte Carlo process generates a random number between 0 and 1 for each woman. If this number is less than 0.7, she is deemed to have a job. If the random number is greater than 0.7, she is deemed to not have a job. Using Monte Carlo processes to allocate jobs to one thousand such women would result in, on average, 700 women having jobs (van Imhoff and Post 1998). However, in any one simulation there may be either more or less than 700 women having jobs, due to Monte Carlo variation.

When the individual faces four possible labour force outcomes instead of two, the cumulative probabilities of each labour force state must be calculated. Taking the example of the 19 year old woman above, this would mean that 0.0-0.4 represents her probability of working full-time, 0.4-0.6 represents the probability she will work part-time, 0.6-0.7 represents unemployment and 0.7-1.0 represents remaining out of the labour force. A random number between 0 and 1 is generated. Whatever probability is associated with the random number becomes her labour force state for that year. This process is applied to every individual in the model. Figure 6 demonstrates the use of the Monte Carlo process to estimate labour force states.

Figure 6 **The Monte Carlo process of allocating labour force states**



The reason why the Monte Carlo process will be used to allocate labour force states, rather than simply allocating the most likely labour force state to an individual, is that in a population of 180 000, the base population of APPSIM, some unlikely labour force transitions will happen. Using a Monte Carlo process allows a small amount of unlikely transitions to occur, while allocating only likely labour force states prohibits them entirely.

Let us consider what would happen to the distribution of labour force states of married, university educated men aged 35-45 under a Monte Carlo process and a 'most likely state' process. The model predicts that such men have a very high likelihood of working full-time, say 95%. Thus of 1000 such men, we would expect 950 to be full-time employed and 50 to be either part-time, unemployed or not in the labour force. The 'most likely state' process would result in all of these men being full-time employed, while the Monte Carlo process would result in 950 being full-time employed. Not using the Monte Carlo method may thus introduce bias in the labour force status totals and eliminate some of the diversity apparent in the real world.

Using the Monte Carlo process instead of the 'most likely state' method does lower prediction accuracy, if one is testing how accurately the model predicts each person's actual labour force state. The reason why can be illustrated by reference to the men described in the previous paragraph. The 'most likely state' method would predict all 1000 men to be full-time employed when only 950 actually are, so it is 95 percent accurate. The Monte Carlo process will predict 950 men to be full-time employed and 50 men to be in another labour force status – but it will mostly predict the wrong 50 men and therefore will have a prediction accuracy of around 90%.

This can be seen in Tables 4 and 5 below. These tables compare the actual labour force states of men and women aged 25-54 with the labour force states predicted by the labour force module, using a Monte Carlo process. The prediction accuracy rate is lower using than the 'most likely state' method used in Table 3, with the prediction accuracies of 84 percent for men and 66 percent for women. These numbers may change slightly in repeat simulations due to Monte Carlo variation.

Table 4 **Actual and predicted labour force states for men aged 25-54**

	Predicted labour force state				
Actual labour force state	FT	PT	UE	NILF	Total
FT	8,973	396	151	172	9,692
PT	411	289	57	73	830
UE	151	45	49	70	315
NILF	166	103	62	538	869
Total	9,701	833	319	853	11,706

Note: This table is generated from unweighted data.

Source: Author's calculations based on HILDA waves 1-5

Table 5 **Actual and predicted labour force states for women aged 25-54**

	Predicted labour force state				
Actual labour force state	FT	PT	UE	NILF	Total
FT	3,744	899	81	275	4,999
PT	926	2,695	108	732	4,461
UE	66	104	37	152	359
NILF	250	729	133	2,198	3,310
Total	4,986	4,427	359	3,357	13,129

Note: This table is generated from unweighted data.
Source: Author's calculations based on HILDA waves 1-5

4.3 Findings of the model

No projections of future distributions of labour force states have been undertaken at this stage. The labour force module described and modelled above is one part of an integrated dynamic microsimulation model. Because the demographic and household formation modules of APPSIM are not yet complete, projections undertaken at this stage would be meaningless. An alternative could be to undertake labour force projections based on the 2005 HILDA population, but as we have no way of knowing how the population's health, children, education and marital status will change in the future, they would not be very useful.

Instead, this paper will show some of the model's predictions of labour force status, and some of the more interesting findings from the research surrounding the model.

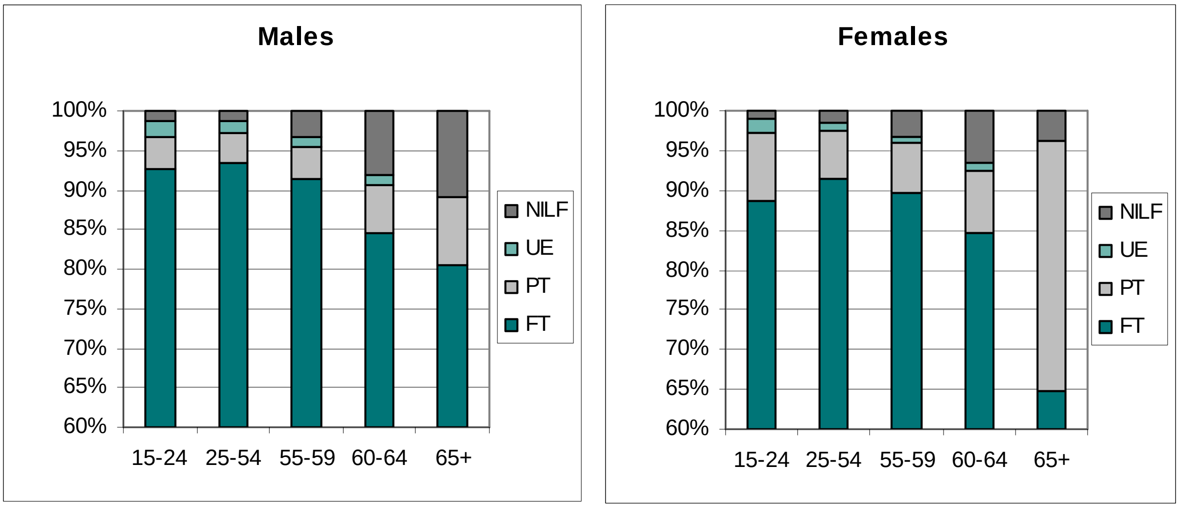
The effect of age and labour force history on current labour force status

It was noted earlier in the paper that a person's previous labour force state is an important predictor of their current labour force state, since most people do not change their labour force state from one year to the next.

To compare the estimated probabilities of being in each labour force state by age and sex, it was necessary to select a subset of people with similar education, health, family characteristics and employment history. It was decided to compare healthy, able people who were unpartnered, had no children under the age of six and had Year 12 education only, and to compare the predicted labour force probabilities of people who had been full time employed in the previous two periods with those who had been out of the labour force in the previous two periods.

Figure 7 shows the probability that such a person will be in each of the four labour force states, given that they were full time employed in the previous two periods. Probabilities are broken down by age group and sex. Figure 8 shows a similar distribution of probabilities for people who were not in the labour force in the two previous periods.

Figure 7 **Probability of entering each labour force state, given previous FT status**

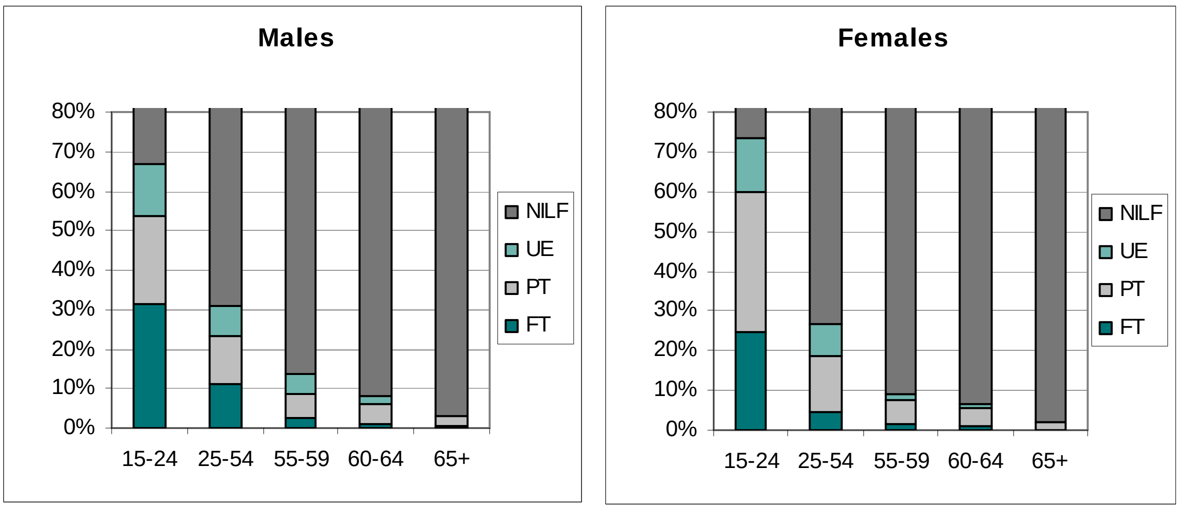


[a] Estimates for women aged 65+ may not be accurate due to the small number of women of this age in HILDA who were full-time employed in the previous two years.

Note: Estimates are for unpartnered men and women with Year 12 only education, in good health with no children under six who were full-time employed in the previous two years.

Data source: Outputs of APPSIM labour market module

Figure 8 **Probability of entering each labour force state, given previous NILF status**



Note: Estimates are for unpartnered men and women with Year 12 only education, in good health with no children under six who were not in the labour force in the previous two years.

Data source: Outputs of APPSIM labour market module

These two figures show that, all other things being equal, a 25-54 year old man has a 1% chance of being out of the labour force in a given year if he was full-time employed in the previous years, compared with a 69% chance if he was out of the labour force in the previous two years (these figures were very similar for women in the same circumstances). However, no matter what a person's previous labour force state, the propensity to find oneself out of the labour force increases with age, while the likelihood one will be full-time employed decreases with age.

Men and babies

Having a baby increases the likelihood that a man aged 25-54 will not be in the labour force by a small but statistically significant amount. At first this appears at odds with earlier findings from HILDA data that children increase men's participation in the labour force (Breunig, et al. 2005). There are two reasons for this apparent discrepancy. First, the current model separates the impact of babies, toddlers and preschool children on labour force participation, while Breunig et al did not. Secondly, Breunig et al considered the impact of children on total hours worked, rather than which of four classes of labour force states a man would be in.

It should be pointed out that the impact of a baby on its father's labour force status is much less than the impact on its mother's. The labour force module estimates that a healthy, partnered, Year 12-educated man aged 25-54 who was full-time employed in the previous two periods, has a 1.6 percent chance of being not in the labour force if he has a baby, compared with an 0.9 percent chance if he does not. A woman with the same characteristics has a 34.4% chance of being out of the labour force if she has a baby, compared to a 1.9% chance if she does not.

Age of mothers and labour force status

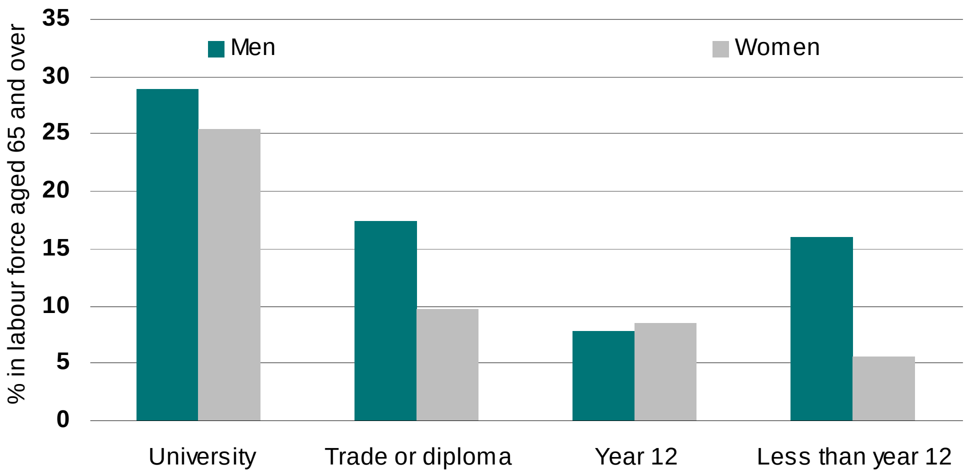
Women aged 15-24 who have children drop out of the labour force at higher rates than women aged 25-54 who have children, and tend to stay out of the labour force for longer. Two years prior to the survey in which they had a baby, the younger group and the older group had roughly the same participation rates (68% and 67%, excluding full time students), although younger women were more likely to be unemployed. By the time these women had their babies, the labour force participation rate of young mothers was 20% lower than that of older mothers (21% and 42%). By the time the child was aged two, labour force participation rates had increased for mothers in both age groups, but the younger women still had participation rates 16% lower than the older women.

There are several possible reasons for this. It may partially be a reflection of discouraged jobseekers among young mothers, who tended to have very high unemployment rates before their babies were born. It may also be the case that because younger mothers have less education and work experience and thus have lower earning potential than older mothers, income support for parents or relying on one's spouse for financial support are relatively more attractive options for younger mothers than older mothers. Alternatively, some women may have children at a younger age because of disinterest in pursuing a career.

Older workers and education levels

The higher a person's education level, the greater the likelihood that they will work past the age of 65. This effect is particularly strong for the university educated, and is far more apparent for women than men. Figure 9 shows the percentage of men and women who still participate in the labour force after the age of 65.

Figure 9 **Education and participation among persons aged 65 and over**



Data source: Author's calculations using waves 2-5 of HILDA

The implication this has for long term modelling of the labour force is that when the young of today, who have higher education levels than their seniors, are aged 65 and over, they may be more likely to participate in the labour force than today's over-65s. Thus labour force participation among older workers, particularly those past pension age, is likely to be higher in the future than it is now. This estimation is in agreement with the assumptions and underlying projections undertaken by the Productivity Commission (2005) and Treasury (2007).

4.4 Incorporation of the labour force module into APPSIM

It is expected that the labour force module will be inserted into APPSIM in the latter half of 2007, with the ability to estimate the number of hours worked during the year. Once APPSIM has calculated demographics, family formation and educational participation, it will estimate the transitions in labour force status from one year to the next.

5 Alignment and validation of model outcomes

A model that is well specified and estimated should be able to track historical aggregates, such as total labour force participation levels or unemployment rates, and be able to project these aggregates into the future, as well as providing insight into distributional outcomes.

A dynamic microsimulation model as described is not sufficient to provide reasonably accurate estimates of the distribution of labour force states for decades into the future (Bacon and Pennec 2007). There are several reasons for this:

- HILDA data only covers a limited time period, characterised by robust economic growth and a very specific set of government policies, social practices etc. Thus the transition probabilities applicable to Australians now will not necessarily be applicable in the future, when we will have different policies, perhaps slower or negative growth, changing social attitudes and behaviour etc.
- The small sample size of HILDA makes it difficult to accurately estimate all the factors that influence people’s labour force participation; in fact HILDA’s weighted totals match ABS aggregates only approximately. Thus labour force projections for the whole of Australia’s population based only on transition probabilities drawn from HILDA may result in inaccurate projections.
- Monte Carlo variation may have fairly small effects in one simulation only, but these are magnified greatly when the model uses several Monte Carlo processes in each year of the model.
- Using the model to estimate policy impacts requires certain assumptions about future economic and social conditions. For example, how low do we expect our unemployment levels to go? Do we expect unemployment to increase at some stage in the future, and if so, when? Is it likely that participation patterns will change in the future in response to changes in caring responsibilities; for example, do we expect to see more fathers working part-time to care for children, or more people taking time out from the labour force to care for elderly parents? A microsimulation model needs to be able to test the effects of such changes.

A solution to these issues is alignment of the microsimulation model to a model of aggregate outcomes. In the case of the labour force, alignment might mean that the model ensures five percent of the total labour force is unemployed, or that 65 percent of working age people participate in the labour force. Alignment outcomes can also be further subdivided, to give 'target numbers' by age and sex.

The aggregate outcomes used for alignment are a combination of historical data and macro projections. The macro projections can be estimated by the modeller, but it is common to use official government projections (Klevmarken 2005). It is intended that the labour force module in APPSIM will initially be aligned to the projections estimated by Treasury for the second Intergenerational Report. The projections used will be total labour force participation by age group and sex, and unemployment rates by age group and sex.

5.1 The alignment process

Alignment essentially involves 'forcing' the model to produce a particular total result.

When the model has finished allocating labour force states for a particular period, it estimates the total number of persons, by age and sex, that it has allocated to be in the labour force and unemployed. For some groups (probably most or all groups) the percentage of people modelled to be in the labour force and unemployed for that year will not exactly match the aggregate macro projections. For every such group, certain individuals will have their labour force status reallocated so that the total participation rate and unemployment rate match the Treasury projections. The individuals who have their status changed will be those who were quite likely to have been in their new labour force state. For example, if the percentage of 15-24 year old males estimated as unemployed by the model is less than that in Treasury projections, the alignment process will select the required number of young men whose labour force status will be changed to unemployed. This selection process will focus on young men who had a reasonably high risk of becoming unemployed; that is, men who faced a 30% chance of becoming unemployed will be selected rather than men who had a 5% chance of becoming unemployed.

Once this process is completed for all age and sex groups, the labour force states for the financial year will be finalised.

5.2 Potential uses of the alignment process

One of the main uses for the alignment process is to stabilise the outcomes of the model in a baseline modelling scenario. Monte Carlo variation over a large number of time periods can result in unrealistic projections, or at least projections that are different to those of a macro model.

Alternatively, it can be used to correct biased outcomes that may be produced by the microsimulation module (due, for example, to small sample size or the lack of availability of many years of longitudinal data). It should be noted that this is a last-resort option to fix biased outcomes – it is far better to correct the micro model.

An intended use for alignment in this model is to test the impact of policy or situation change over the long term. If a policy or situation is likely to change participation rates, then alignment can force the model to produce outcomes consistent with policy change. For example, if a policy is expected to increase labour force participation by 5% among a particular age/sex group, the alignment process can force the model to increase the participation rate to the required level. Then the long term effects of this increase in participation can be modelled – such as effects on retirement savings, asset accumulation etc.

6 Conclusion

The labour force module and the associated alignment process are expected to provide reasonably accurate estimates of the distribution of labour force states among the population. The transition probabilities calculated using multinomial logit regression equations will be incorporated into the greater APPSIM model. They will then be used to calculate the labour force state of each person aged 15-74 within APPSIM, from 2002-2050.

APPSIM can then be used to estimate the impact of current and future policy on future labour force participation, and thus on earnings, accumulation of assets, superannuation, etc. It is expected that APPSIM will prove to be a valuable policy analysis tool as the population ages, due to its ability to assess the distributional consequences of policy.

It is possible that the transition probabilities may be updated at some time in the future as new waves of HILDA become available. This will allow the impact of changing economic conditions and social behaviours to be estimated and incorporated into future projections.

A Appendix

Table 6 **Transition probabilities: ages 15-24**

	Males			Females		
	Coefficient	Standard error	t-statistic	Coefficient	Standard error	t-statistic
Lfstatus=PT						
Lfprev=PT	2.14	0.20	10.77	2.22	0.19	11.48
Lfprev=UE	1.85	0.26	7.13	1.80	0.26	6.89
Lfprev=NILF	1.71	0.28	6.16	1.49	0.25	6.07
Lfprev2=PT	1.04	0.21	5.04	0.73	0.20	3.60
Lfprev2=UE	1.08	0.27	3.97	0.83	0.28	3.01
Lfprev2=NILF	1.12	0.25	4.49	1.18	0.23	5.04
Education= trade/diploma	0.54	0.29	1.85	0.30	0.22	1.38
Education= Year 12	0.53	0.27	1.97	0.54	0.21	2.59
Education= <Yr12	0.58	0.26	2.24	0.74	0.23	3.27
Partner	-0.52	0.24	-2.16	-0.12	0.15	-0.77
Baby				2.13	0.59	3.60
Toddler				0.56	0.40	1.40
Preschool				1.12	0.58	1.92
Health	0.06	0.07	0.94	0.03	0.05	0.51
Constant	-3.66	0.31	-11.82	-2.86	0.25	-11.63
Lfstatus = UE						
Lfprev=PT	0.66	0.31	2.10	1.07	0.31	3.47
Lfprev=UE	2.60	0.28	9.27	2.39	0.35	6.82
Lfprev=NILF	2.09	0.30	6.95	1.82	0.36	5.09
Lfprev2=PT	0.75	0.28	2.66	0.69	0.33	2.11
Lfprev2=UE	1.44	0.32	4.53	1.95	0.38	5.07
Lfprev2=NILF	0.77	0.29	2.64	1.41	0.36	3.89
Education= trade/diploma	0.94	0.41	2.28	0.64	0.45	1.42
Education= Year 12	0.88	0.39	2.25	1.04	0.44	2.36
Education= <Yr12	1.60	0.37	4.32	1.73	0.44	3.96
Partner	-0.17	0.26	-0.64	-0.17	0.24	-0.70
Baby				2.75	0.62	4.46
Toddler				0.87	0.47	1.85
Preschool				1.74	0.61	2.85

Health	0.07	0.07	0.94	0.15	0.06	2.43
Constant	-4.59	0.42	-10.81	-4.86	0.51	-9.48
Lfstatus = NILF						
Lfprev=PT	1.62	0.40	4.03	1.83	0.30	6.00
Lfprev=UE	2.01	0.44	4.58	2.34	0.34	6.79
Lfprev=NILF	3.03	0.41	7.42	2.87	0.30	9.44
Lfprev2=PT	0.44	0.41	1.07	0.66	0.30	2.19
Lfprev2=UE	1.00	0.48	2.06	1.47	0.36	4.04
Lfprev2=NILF	1.37	0.42	3.24	1.58	0.32	4.90
Education= trade/diploma	0.12	0.46	0.26	-0.04	0.34	-0.11
Education= Year 12	0.51	0.37	1.40	0.43	0.33	1.29
Education= <Yr12	0.53	0.35	1.51	1.07	0.32	3.30
Partner	-0.57	0.33	-1.71	0.04	0.21	0.20
Baby				4.90	0.55	8.87
Toddler				2.22	0.37	5.93
Preschool				2.34	0.55	4.28
Health	0.34	0.05	6.73	0.11	0.06	1.73
Constant	-4.79	0.46	-10.44	-4.69	0.39	-11.91

Source: Author's calculations from HILDA waves 1-5

Table 7 **Transition probabilities: ages 25-54**

	Males			Females		
	Coefficient	Standard error	t-statistic	Coefficient	Standard error	t-statistic
Lfstatus=PT						
Lfprev=PT	3.02	0.13	24.09	2.80	0.08	35.80
Lfprev=UE	2.20	0.19	11.67	1.72	0.17	9.96
Lfprev=NILF	2.11	0.22	9.69	2.39	0.13	18.16
Lfprev2=PT	1.41	0.13	10.95	1.38	0.08	18.00
Lfprev2=UE	0.95	0.21	4.63	1.01	0.19	5.38
Lfprev2=NILF	1.06	0.21	5.18	1.47	0.13	11.50
Education= trade/diploma	-0.18	0.12	-1.45	0.08	0.08	1.06
Education= Year 12	0.46	0.15	3.02	0.16	0.09	1.79
Education= <Yr12	0.12	0.13	0.92	0.35	0.08	4.41
Partner	-0.19	0.10	-1.77	0.29	0.07	4.17
Baby	0.13	0.19	0.68	2.05	0.16	12.90
Toddler				0.61	0.12	5.11
Preschool				0.30	0.09	3.36
Health	0.18	0.02	7.91	0.06	0.02	2.59

Constant	-3.66	0.14	-26.99	-2.84	0.09	-32.63
Lfstatus = UE						
Lfprev=PT	1.42	0.24	5.85	1.45	0.23	6.40
Lfprev=UE	3.03	0.18	16.70	3.24	0.23	14.02
Lfprev=NILF	2.39	0.25	9.36	3.07	0.23	13.27
Lfprev2=PT	1.02	0.22	4.64	1.12	0.22	5.18
Lfprev2=UE	2.07	0.20	10.40	2.41	0.27	8.85
Lfprev2=NILF	1.42	0.26	5.36	2.09	0.23	9.01
Education= trade/diploma	0.25	0.18	1.34	0.51	0.18	2.82
Education= Year 12	0.23	0.25	0.93	0.49	0.22	2.26
Education= <Yr12	0.55	0.19	2.93	0.67	0.18	3.72
Partner	-0.79	0.13	-6.32	-0.53	0.13	-4.08
Baby	0.18	0.28	0.64	2.06	0.33	6.30
Toddler				-0.18	0.28	-0.63
Preschool				0.44	0.16	2.70
Health	0.13	0.03	4.28	0.13	0.03	3.84
Constant	-4.31	0.19	-22.27	-4.98	0.22	-23.10
Lfstatus = NILF						
Lfprev=PT	1.87	0.21	8.72	1.84	0.13	14.58
Lfprev=UE	2.50	0.21	11.74	2.40	0.20	12.07
Lfprev=NILF	3.92	0.18	22.32	4.06	0.14	29.25
Lfprev2=PT	0.68	0.19	3.55	1.17	0.12	9.80
Lfprev2=UE	1.41	0.21	6.55	1.63	0.20	7.98
Lfprev2=NILF	2.19	0.17	12.68	2.75	0.14	19.81
Education= trade/diploma	0.48	0.16	2.93	0.45	0.11	4.23
Education= Year 12	0.68	0.21	3.29	0.66	0.12	5.59
Education= <Yr12	0.85	0.17	5.02	1.10	0.10	10.83
Partner	-0.52	0.12	-4.32	0.15	0.09	1.72
Baby	0.51	0.21	2.40	3.71	0.17	21.36
Toddler				0.60	0.14	4.35
Preschool				0.26	0.11	2.31
Health	0.27	0.02	11.66	0.21	0.03	8.27
Constant	-4.76	0.18	-26.76	-4.57	0.13	-35.21

Source: Author’s calculations from HILDA waves 1-5

Table 8 **Transition probabilities: ages 55-64**

	Males			Females		
	Coefficient	Standard	t-statistic	Coefficient	Standard	t-statistic

		error			error	
Lfstatus=PT						
Lfprev=PT	3.09	0.22	14.28	3.16	0.24	13.24
Lfprev=UE	2.24	0.45	5.02	2.96	0.80	3.72
Lfprev=NILF	2.71	0.34	7.95	2.81	0.35	7.98
Lfprev2=PT	1.32	0.22	6.14	1.42	0.20	7.17
Lfprev2=UE	0.85	0.63	1.36	1.07	0.60	1.78
Lfprev2=NILF	1.23	0.37	3.28	1.32	0.37	3.61
Education= trade/diploma	-0.74	0.20	-3.75	-0.03	0.24	-0.12
Education= Year 12	-0.76	0.28	-2.74	-0.06	0.33	-0.17
Education= <Yr12	-0.53	0.20	-2.66	0.21	0.21	1.00
Partner	-0.16	0.21	-0.75	0.44	0.18	2.48
Age 60+	0.62	0.16	3.89	0.38	0.18	2.11
Health	0.07	0.04	1.81	0.03	0.05	0.54
Constant	-2.30	0.24	-9.47	-2.67	0.23	-11.51
Lfstatus = UE						
Lfprev=PT	1.27	0.55	2.30	0.51	0.74	0.69
Lfprev=UE	4.20	0.53	7.91	4.31	1.07	4.03
Lfprev=NILF	3.78	0.51	7.45	2.96	0.79	3.76
Lfprev2=PT	1.21	0.45	2.67	1.30	0.56	2.32
Lfprev2=UE	2.14	0.64	3.34	2.75	0.97	2.84
Lfprev2=NILF	1.39	0.51	2.72	1.69	0.85	1.99
Education= trade/diploma	-0.52	0.34	-1.56	-1.28	0.71	-1.79
Education= Year 12	-0.83	0.48	-1.75	-0.22	0.76	-0.29
Education= <Yr12	-0.71	0.37	-1.95	-0.27	0.45	-0.61
Partner	-0.94	0.30	-3.18	0.11	0.42	0.26
Age 60+	-0.22	0.32	-0.69	0.32	0.38	0.83
Health	0.05	0.05	0.84	0.18	0.07	2.56
Constant	-3.32	0.39	-8.46	-4.58	0.50	-9.13
Lfstatus = NILF						
Lfprev=PT	1.81	0.23	7.79	2.07	0.26	7.97
Lfprev=UE	2.42	0.41	5.94	3.24	0.83	3.89
Lfprev=NILF	4.33	0.27	16.23	4.81	0.35	13.67
Lfprev2=PT	0.75	0.23	3.23	1.04	0.22	4.84
Lfprev2=UE	1.52	0.52	2.93	1.57	0.67	2.35
Lfprev2=NILF	2.37	0.32	7.48	2.76	0.36	7.60
Education= trade/diploma	-0.12	0.22	-0.53	0.35	0.27	1.31
Education= Year 12	-0.27	0.29	-0.90	0.25	0.38	0.64
Education= <Yr12	-0.09	0.23	-0.40	0.74	0.24	3.09
Partner	-0.36	0.19	-1.91	0.57	0.19	2.99

Age 60+	0.89	0.16	5.57	0.66	0.19	3.54
Health	0.24	0.03	7.04	0.07	0.05	1.44
Constant	-2.81	0.26	-10.94	-3.51	0.27	-13.06

Source: Author's calculations from HILDA waves 1-5

Table 9 **Transition probabilities: ages 65-74**

	Males			Females		
	Coefficient	Standard error	t-statistic	Coefficient	Standard error	t-statistic
Lfstatus=PT						
Lfprev=PT	2.41	0.47	5.12	2.50	0.53	4.72
Lfprev=NILF	2.23	0.53	4.21	2.17	0.86	2.51
Lfprev2=PT	2.71	0.46	5.88	1.44	0.66	2.19
Lfprev2=NILF	1.63	0.52	3.15	1.25	0.49	2.54
Education= trade/diploma	-0.66	0.38	-1.74	-1.56	0.67	-2.34
Education= Year 12	-0.53	0.77	-0.69	-0.05	0.86	-0.06
Education= <Yr12	-1.01	0.40	-2.49	0.24	0.50	0.48
Partner	0.16	0.39	0.40	0.45	0.48	0.93
Health	0.18	0.10	1.82	-0.15	0.12	-1.25
Constant	-1.70	0.51	-3.34	-0.73	0.55	-1.34
Lfstatus = NILF						
Lfprev=PT	1.99	0.40	4.98	3.28	0.72	4.55
Lfprev=NILF	4.64	0.39	11.86	6.18	0.82	7.52
Lfprev2=PT	1.52	0.43	3.51	1.60	0.69	2.32
Lfprev2=NILF	2.65	0.44	6.01	3.53	0.57	6.23
Education= trade/diploma	-0.29	0.41	-0.70	-0.42	0.71	-0.59
Education= Year 12	-0.15	0.71	-0.21	0.42	0.85	0.50
Education= <Yr12	-0.64	0.42	-1.53	1.29	0.56	2.28
Partner	0.35	0.40	0.89	0.30	0.49	0.62
Health	0.30	0.09	3.25	-0.03	0.11	-0.29
Constant	-1.85	0.55	-3.35	-3.63	1.17	-3.11

Source: Author's calculations from HILDA waves 1-5

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