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Effects of Health and Education on Labour Force Participation

Staff Working Paper

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The views expressed in this paper are those of the staff involved and do not necessarily reflect those of the Productivity Commission

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Contents

BOXES

FIGURES

TABLES

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Abbreviations and explanations

Abbreviations

ABS	Australian Bureau of Statistics
AIC	Akaike’s Information Criterion
BIC	Bayesian Information Criterion
COAG	Council of Australian Governments
HILDA	Household, Income and Labour Dynamics in Australia (survey)
IES	Institute of Education Sciences
IIA	Independence of irrelevant alternatives (assumption)
FIML	Full information maximum likelihood (method)
MNL	Multinomial logit (model)
NCP	National Competition Policy
NESB	Non-English speaking background
NRA	National Reform Agenda
OECD	Organisation for Economic Co-operation and Development
PMNL	Panel multinomial logit (model)
SEM	Simultaneous equations model
SMNL	Standard multinomial logit (model)

Explanations

ppt	Percentage point

Glossary

Cross-section data	One-off snapshot of the characteristics of a group of individuals
Endogeneity bias	The bias affecting the coefficients of an estimated equation in which one (or more) of the explanatory variables is correlated with the error term
Fixed effects	Refers to a method for modelling unobserved heterogeneity using panel data, whereby it is assumed that some characteristics are individual specific and time invariant
Labour force participation	A participant in the labour force is a person aged 15 years or over, and who is either employed or unemployed
LR test	Likelihood ratio test of the goodness of fit of a model
Marginal effect	For a binary variable: the effect on the dependent variable of the binary variable changing from 0 to 1. For a continuous variable: the effect on the dependent variable of a one-unit change in the continuous variable
Objective health condition	In HILDA, the self-reported occurrence of a specific health condition, diagnosed or not, evaluated against a pre-determined scale of the effect of that condition on the person
Panel data	Repeated observations over time on the characteristics of the same individuals
Pooled cross-sections data	A collated series of snapshots of the characteristics of different individuals over time
Random effects	A method for modelling unobserved heterogeneity using panel data, whereby individual values of some characteristics are assumed to be drawn randomly from a known statistical distribution

Rationalisation endogeneity	The endogeneity that occurs when people use their self-assessed level of health as justification for not working
SE model	Simultaneous equations model, based on Cai and Kalb (2006)
Self-assessed health	A summary measure of a person's overall health status, as determined and reported by that person
Simultaneity	A situation arising when two variables being modelled influence each other
Simultaneous equations model	An econometric model consisting of two (or more) equations, to be estimated jointly
Subjective health measure	A summary measure of a person's overall health status, as determined by that person
True health	A summary measure of a person's overall real health status, not determined by that person
Unobserved heterogeneity	Describes the case when unobserved characteristics of a person jointly influence two (or more) of the variables being modelled, including the dependent variable

OVERVIEW

Key points

- This paper provides new estimates of the effects, on the probability of participation in the labour force, of changes in the prevalence of health conditions or changes in educational attainment levels.
- The research confirms that better health and education can result in substantially greater labour force participation for those affected:
  – Of the six health conditions identified, a mental health or nervous condition, when averted, has the largest positive impact on labour force participation.
  – Having a degree or higher qualification has the largest impact on labour force participation, relative to not completing Year 12.
- Measurement of these effects is complicated by possible endogeneity bias due to:
  – unobserved characteristics of individuals — for example, motivation, innate ability or preferences — which may influence health and education as well as the decision to engage in paid work; and
  – the simultaneous determination of health and labour force participation.
- Results suggest that:
  – unobserved characteristics affect decisions to participate in the labour force; and
  – health and labour force participation influence each other simultaneously.
- This paper forms part of a Productivity Commission research program investigating in more detail parameters used in its report *Potential Benefits of the National Reform Agenda*.
- The new parameter estimates:
  – would alter some of the labour market projections contained in the report, but would not affect the thrust of the conclusions; and
  – provide an improved basis for cost–benefit analyses of possible changes in specific health or education policies.

Overview

The National Reform Agenda (NRA) proposed in 2006 by the Council of Australian Governments (COAG) includes a human capital stream of reforms, designed to effect changes in health, education and work incentives. In 2006, the Productivity Commission undertook an assessment of the economic and fiscal impacts that NRA might produce by 2030, including impacts flowing from better health and education (Productivity Commission 2006).

The potential economic benefits of better health and education have been the subject of increasing policy interest in recent times in Australia. This interest has largely been motivated by the projected implications of population ageing in terms of lowered labour force participation and output growth. The observation that Australia lags some comparable countries in terms of labour force participation has signalled one possible avenue for alleviating the economic effects of ageing. Also, claims that skill shortages may be limiting growth in some regions and industries have added to the interest in the potential for greater labour force participation to ease some of the economic bottlenecks Australia may encounter.

Health and education are generally regarded as crucial contributors to a person's stock of 'human capital' — the changing bundle of individual skills, knowledge and capabilities that everyone possesses. Other contributors to human capital are work experience, training and motivation. Human capital is a key determinant of individual labour market outcomes, because it is positively associated with workers' productivity and, hence, with the demand for their labour. Faced with a choice between two same-wage workers with identical characteristics, except for differing levels of productivity, a rational employer will choose the more productive worker. Because high employer demand translates into comparatively high wages, abundant human capital underlies strong incentives for people to engage in paid work. Conversely, a dearth of human capital creates a barrier to employment.

Recognition of the central role of human capital in labour market outcomes has made it the focus of government policies which, like NRA, aim in part to lift labour force participation in response to population ageing. Briefly, the rationale behind this type of policy is that, by endowing people with more human capital, through better illness prevention, detection and treatment, and more education and training, both labour demand and labour supply are stimulated. The result, it is believed, will be a higher rate of labour force participation.

In its 2006 report to COAG on NRA, the Productivity Commission sought to quantify the increase in labour force participation that could be expected from meeting certain targets for illness reduction and educational improvements. The methodological approach adopted in the report rests on the use of literature reviews and case studies to obtain quantitative estimates of the key effects. Because of the information gaps inherent in this approach, the Commission also undertook its own exploratory quantitative work designed to benchmark, strengthen and refine estimates from other sources. Part of this work, which continued after the Commission issued its report, is presented in this paper. Another paper (forthcoming) will provide quantitative analyses pertaining to labour productivity and wages.

This paper's main contribution to the understanding of the effects of health and education on labour force participation is twofold:

- Through the use of an integrated model of labour force participation, all relevant effects are estimated simultaneously in a consistent framework, thus making comparisons and interpretation of these effects easier.
- It investigates the possibility that various types of bias may affect the relationships of interest.

The theoretical chain linking health and education with labour force participation is potentially subject to a number of weaknesses. First, health and education are imperfect proxies for the stock of human capital. For example, although educational attainment is widely regarded as a proxy for numeracy, literacy, communication and socialisation skills, this may not be true for all individuals.

Second, some elements of human capital, such as ability and motivation, are typically not observed. If these characteristics jointly influence the educational performance and the labour supply decision of individuals, then estimates of the role of education which ignore them are likely to be biased.

Third, the quality of one's health may be a consequence, as well as a cause, of participation in work. Manual jobs involving high physical demands, or risk of injury, are a prime example of this causal effect.

Fourth, the indicator of health — self-assessed health — used in the analysis may be prone to bias due to measurement error or self-justification by the people surveyed.

These issues complicate policy decisions regarding appropriate investment in improvements in health and education. There is a risk that efforts to raise labour force participation might rely too much (or too little) on health and education. This risk has led to renewed attempts to account for possible sources of bias in measuring the key relationships of interest. Addressing this bias — known technically as ‘endogeneity bias’ — is a central objective of this paper, in which econometric modelling is used to ascertain the existence and severity of the problems set out above.

Modelling approach and data

The approach adopted in this paper is designed to maximise the transparent and systematic nature of the analysis. Three models of labour force participation are estimated with near-identical variables based on the same dataset. One model, termed the ‘standard multinomial logit’ (standard MNL) model, is used as a benchmark for the other two, because it represents one of the most common, but least sophisticated, approaches to modelling labour force participation, in that it cannot account for any form of endogeneity bias.

The second model, called the ‘panel multinomial logit’ (panel MNL), is a variant of the first, designed to account for that form of endogeneity bias which is due to unobserved heterogeneity. This refers to the presence of unobserved individual characteristics which may affect participation, but cannot be explicitly included in the model because they are not observed in practice. This is the case when, for example, both participation and educational attainment are jointly influenced by a third, unobserved, variable such as motivation.

Unlike the first two models, which consist of a single equation, the third and final model has two equations. This model, referred to as the ‘simultaneous equations’ (SE) model, is based on research by Cai and Kalb (2006). Its structure is designed, first, to test whether summary health measures such as self-assessed health status are both influencing, and influenced by, labour force participation. Second, if the presence of such simultaneity is confirmed, then the two-equation system corrects for the endogeneity bias that this would cause in a single equation model. The SE model can also detect (but not correct) a third source of bias: rationalisation endogeneity bias arises when self-assessed health status is used by a survey respondent to justify a prior decision not to engage in work.

The three models are estimated for men and women separately, using identical data from the Household, Income and Labour Dynamics in Australia (HILDA) survey, for 2001–04. That survey is a rich source of repeated annual observations (panel data) on some of the factors that are frequently found to influence participation in work. (One such factor — the existence and nature of diagnosed health conditions — is not covered comprehensively in all years of HILDA data. For that reason, a prerequisite of the estimation was the imputation of detailed health data in years where those data were not available.)

Comparing the models

Econometric results from the models are analysed and compared in several dimensions: marginal effects of health and education; goodness of fit; evidence of unobserved heterogeneity; and evidence of simultaneity and rationalisation endogeneity.

Marginal effects of health and education

In the paper, the marginal effects of a health or education variable measure the change in the probability of labour force participation when, all else being equal:

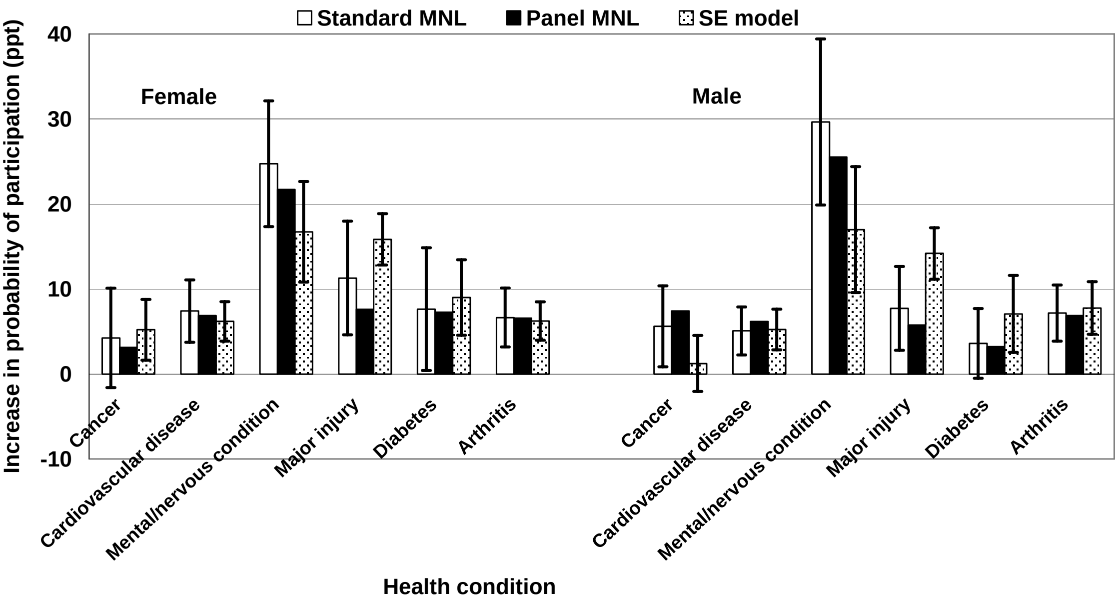
- the onset of one of the following six health conditions is prevented or averted: cancer; cardiovascular disease; mental/nervous condition; major injury; diabetes; and arthritis; or
- a person's level of educational attainment changes from Year 11 or lower to either: Year 12; diploma or certificate; or university degree or higher.

These effects are estimated using data from the 2001–04 period, and their values depend on the population and labour market structures in place during that period. Should those structures change in future, so would the estimated marginal effects.

The effects of preventing each of the six health conditions in turn are summarised in figure 1. Salient features of that summary include differences in marginal effects between health conditions, between models and between men and women. These differences notwithstanding, all three models indicate that mental health or nervous conditions are the pre-eminent health reason for lowered labour force participation, for both genders. Major injury is usually the condition with the second highest estimated effect on labour force participation, followed by the other conditions, the ranking of which varies somewhat across models and between genders.

Overall, the marginal effects presented in figure 1 confirm the positive association, found in the literature, between better health and greater involvement in the labour market.

Figure 1 Marginal effects of preventing selected health conditions on labour force participation, 2001–04



Data source: Figure 5.2.

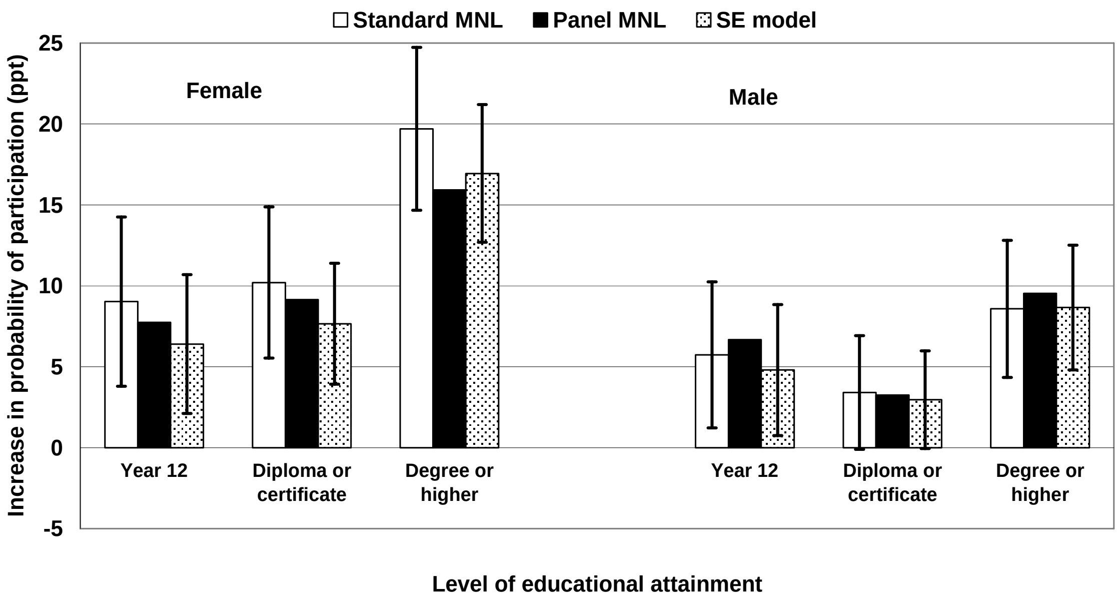
Education marginal effects are shown in figure 2. They point to the importance of education for the decision to participate in the labour force. As in health, one category clearly stands out in terms of education, for both men and women, that of ‘degree or higher’. The impact of university qualifications on participation is especially large in the case of women, for whom it increases the probability of being in the labour force (relative to having completed Year 11 at most) by between 15 and 20 percentage points. As in the case of health, there are inter-model differences in the effects of education, most noticeably for women.

The SE model results detailed in the paper suggest that better education leads to a better overall self-assessed health status, which, in turn, leads to higher labour force participation. This indirect effect of education on participation appears to be more important for males than for females.

Overall, the health and education marginal effects produced by the three models strongly confirm the importance of human capital for participation in paid work.

Figure 2 **Marginal effects of greater educational attainment on labour force participation, 2001–04**

Educational attainment relative to Year 11 or lower



Data source: Figure 5.1.

Goodness of fit

Assessing their respective goodness of fit provides the first formal criterion to distinguish between the three models. Although it does not provide direct evidence of endogeneity bias due to unobserved heterogeneity or to simultaneity, goodness of fit is a useful measure of the overall explanatory power of a model. Because that measure is not amenable to being captured by a single indicator, several are examined here, in accordance with accepted econometric practice (table 1). Overall, these indicators consistently point to the panel multinomial logit model as providing the best fit of the three models benchmarked, followed by the standard multinomial logit model.

Table 1 **Ranking of selected goodness of fit indicators**[a]

	Panel MNL	*Standard MNL*	*SE model*
	Rank	Rank	Rank
Females			
Akaike's Information Criterion	1	2	3
Bayesian Information Criterion	1	2	3
Likelihood ratio test	1	2	3
Males			
Akaike's Information Criterion	1	2	3
Bayesian Information Criterion	1	2	3
Likelihood ratio test	1	2	3

a Numbers in rows indicate each model's ranking according to a particular goodness of fit indicator, from most preferred (1) to least preferred (3).

Source: Table 5.2.

Endogeneity due to simultaneity or rationalisation

As mentioned earlier, regressing one variable against another with which it is jointly determined will result in simultaneity bias in a single equation framework. One way to test whether simultaneity may be affecting the relationship between self-assessed health and labour force participation is to test, in the SE model, the joint significance of:

- the participation coefficient in the health equation; and
- the correlation coefficient between the two equations' error terms.

The test is significant for each of the four separate age and gender variants of the SE model. That is, labour force participation influences self-assessed health status for older, as well as younger, men and women. Unfortunately, it is not possible to state categorically, for some age and gender groups, whether that influence is due to simultaneity between participation and 'true' (unobserved) health, or between participation and self-assessed (observed) health. Only the latter measure of health is available, which creates the potential for rationalisation endogeneity bias. This form of endogeneity arises when people first 'decide' whether to work or not, then choose a level of self-assessed health to justify that decision.

Rationalisation endogeneity hinders somewhat the analysis of the relationship between health and labour force participation, because it can create the impression that simultaneity is present when it is not. Moreover, when both rationalisation endogeneity and simultaneity are present, the effects of the former can obscure those of the latter.

Fortunately, in this paper, rationalisation endogeneity (if present) may have a significant effect for one group only, namely women aged 50 and over. This is consistent with results obtained by other researchers (Cai 2007; Cai and Kalb 2006). For other groups, if there is any rationalisation endogeneity, it appears to be offset by other factors.

Unobserved heterogeneity

Unobserved characteristics that jointly affect the dependent variable and one (or more) explanatory variable(s) in a model will lead to coefficients and marginal effects that are systematically overestimated. For that reason, a comparison of the marginal effects of interest in the panel and standard variants of the multinomial logit model is instructive.

Casual inspection of the results for women in figures 1 and 2 indicates that the marginal effects of the panel multinomial logit are invariably below those of the standard multinomial logit. This is consistent with unobserved characteristics being a significant influence on female labour supply, something which other studies have also found (Cai 2007; Haynes et al. 2005). Based on the existing literature, it is possible to speculate that such characteristics include innate ability or motivation; women who possess high levels of both may be more likely than others to have higher qualifications *and* be drawn into the labour force. Conversely, women whose unobserved characteristics include a preference for unpaid activities such as volunteer work and caring, may be less likely to participate than their observed characteristics would suggest.

For men, a comparison of the relevant marginal effects provides weaker evidence of unobserved heterogeneity, although other indicators presented in the paper suggest that it may also be affecting that group.

Implications for modelling labour force participation

Overall, the results presented in this paper support the hypothesis that the modelling of labour force participation is subject to endogeneity bias arising from several sources. Therefore, to estimate the marginal effects of education and health accurately, for example, as an input into cost–benefit analysis, a modelling framework that explicitly controls for endogeneity is required. Even though unsophisticated models of labour force participation may generally conclude correctly that participation is positively associated with health and education, these models are unlikely to produce accurate marginal effects and labour force participation predictions.

As mentioned above, not allowing for the presence of unobserved heterogeneity results in an overestimate of the influence of human capital on labour market outcomes. In contrast, not correcting for simultaneity can result in an overestimate or an underestimate of the key relationships.

Simultaneity-corrected estimates may themselves be biased, to some extent. If the summary health measure used is self-assessed by survey respondents, then rationalisation endogeneity may bias those estimates downward. Results, however, indicate that this form of endogeneity may only affect (and bias the modelling results for) older women. For the other groups, controlling for simultaneity by using a simultaneous equations approach unequivocally improves the measurement of the key relationships.

Substituting this paper's estimates for those used in the Productivity Commission's NRA report (2006) alters the projected values of some labour market aggregates in 2030. But sensitivity testing indicates that, overall, the new projections obtained following this substitution are not very different from those in the NRA report. Compared to that report, labour force participation is slightly lower in this paper and overall labour productivity slightly higher. These two effects partly offset each other, so that the NRA-induced increase in the economy's effective labour supply is only 5 per cent lower in 2030 than suggested in the NRA report: whereas that report projected an increase of 8 per cent (compared with the baseline projection for that year), the parameter estimates in this paper imply an increase of 7.6 per cent. This small difference is unlikely to alter the broad economic and fiscal impacts of NRA, as assessed by the Productivity Commission.

Conclusion

Economic policy makers and researchers are interested in the potential for greater human capital to meet some of the economic challenges created by population ageing, such as the projected decline in labour force participation.

Modelling results presented in this paper confirm that two major components of human capital — health and education — have the potential to lift the rate of labour force participation, by a substantial amount in some cases. In the health area, the largest impact is obtained through the prevention of a lasting mental health or nervous condition. Results from the two preferred (endogeneity-corrected) models point to the probability of labour force participation, for those affected by these conditions, being up to 22 percentage points (women) or up to 26 percentage points (men) higher than it would have been in the absence of such prevention (figure 1).

With respect to education, a bachelor’s degree or higher boosts the probability of participating in the labour force by up to 17 percentage points for women and up to 9 percentage points for men (figure 2).

The estimates contained in this paper derive from models that are consistent with the human capital framework used in the Productivity Commission’s NRA report. These models integrate aspects of health and education that are important determinants of labour force participation. Subject to the caveat that they measure the effects of human capital pertaining to a particular period, and may not apply in future, the estimates presented here are likely to be adequate for cost–benefit analyses of possible changes to specific health or education policies.

1 Introduction

In 2006, the Productivity Commission reported to the Council of Australian Governments (COAG) on the potential economic and fiscal impacts of the National Reform Agenda (NRA). The Agenda encompasses an ambitious program of competition-related and regulatory reforms, building on similar reforms previously implemented under the National Competition Policy (NCP). In contrast to NCP, NRA also includes a ‘human capital’ stream of reforms covering education and training, health and work incentives (Productivity Commission 2006).

The human capital dimension of NRA reflects a growing policy interest in the potential benefits of raising Australia’s stock of health and education on its supply of labour, and on its productive capacity. Apart from the Productivity Commission’s *Potential Benefits of the National Reform Agenda* report (2006), studies by Dawkins et al. (2004) and the Victorian Department of Treasury and Finance (2005) are recent examples of policy-oriented investigations into the relationship between health and labour force participation (or employment) in Australia. Studies by Kennedy and Hedley (2003) and Access Economics (2005) have similarly explored the links between education and participation or employment.

As in other OECD countries, recent awareness of human capital issues in Australia is largely motivated by the anticipated effects of population ageing on the supply of labour and, hence, on economic growth. The momentum of demographic trends means that population ageing will continue for the foreseeable future. If labour force participation by age group also continues on its current course, it is predicted that the overall labour force participation rate will decline from 64.5 per cent in 2005-06 to 57.1 per cent in 2046-47 (Australian Government Treasury 2007).

While population ageing is less advanced in Australia than in many countries (Productivity Commission 2005), its detrimental implications for labour supply are heightened by the gap between labour force participation in Australia and in some comparable OECD countries. That gap is partly due to inter-country variation in statistical practices. Even after adjusting for differences in statistical practices, however, Australia’s participation rate still lags for: prime aged males; child-bearing aged females; and people nearing retirement (Abhayaratna and Lattimore 2006).

International comparisons suggest that scope exists for Australia to raise its labour force participation rate. This would help alleviate some of the economic and fiscal impacts that a growing population of older and retired Australians is predicted to generate (Australian Government Treasury 2007; Productivity Commission 2005). For example, the outlook for government revenue and expenditure would become more favourable if more older persons were successfully encouraged to remain in (or to rejoin) the labour force.

Encouraging labour force participation of all adults is also seen as a possible remedy to perceived skill shortages in some areas of the workforce. It is argued that, by creating incentives for people to join or return to the labour force, such shortages may be alleviated, where they exist.

Improvements to human capital are viewed by many governments as the key to greater work incentives and increased labour force participation. A stylised finding from the empirical literature on the determinants of labour supply is that workers' characteristics that contribute to their stock of 'human capital' — health, education, training and work experience — are positively associated with the decision to engage in paid work. This decision is a product of factors operating on both the demand and the supply side of the labour market. Because workers' labour productivity increases with their stock of human capital, employers demand relatively more labour from — and offer higher wages to — workers with attributes that reflect high human capital.[1] A lower risk of unemployment and the expectation of higher wages then create financial incentives for workers with these attributes to join the labour force. There are also supply forces at work. For example, people with relatively high educational attainment may derive utility from the social and intellectual stimulation that work provides, thus supplying more labour, at a given wage level, than people with lower levels of education.

1.1 The National Reform Agenda

The human capital stream of COAG's National Reform Agenda comprises a set of policies aimed at promoting higher levels of human capital in the Australian population, by 2030. The strategy to accomplish that goal is to:

- equip people with higher levels of education and training; and

[1] There are competing or complementary explanations for the education – high-wages link. One such explanation is that, through their qualifications, candidates signal to employers that they have the ability to do jobs more productively.

- reduce the amount of human capital lost through illness or injury.[2]

It is hypothesised that both these objectives will remove barriers to participation and, further, create incentives for people to join, rejoin or remain in the labour force. Other factors besides health and education influence barriers and incentives to work. They include the regulatory and tax frameworks (for example, rules governing superannuation and pensions, childcare benefits and disability benefits). While the human capital stream of NRA also envisages reforms to that framework as a way of increasing labour force participation, the effects of such reforms are not the focus of this paper.

In order to project the future economic benefits of the improvements to health and education assumed in NRA, the Productivity Commission (2006) undertook an extensive review of the social, economic and scientific literature. However, the information that could be obtained from this review was unavoidably incomplete, fragmented and speculative. Where possible, exploratory quantitative work was undertaken to fill the gaps. In its NRA report, the Commission indicated its commitment to continue this work, in order to benchmark, strengthen and refine the published parameters it used in its NRA report. This paper is the result of one such follow-up project, focussing on the labour force participation effects of selected health conditions and levels of educational attainment. Another follow-up project (forthcoming) focuses on the importance of those variables for labour productivity and wages.

1.2 Aim of the paper and analytical approach

The aim of this paper is to explore alternative methodologies to obtain estimates of the labour force participation effects of the health and education variables targeted by NRA. Such estimates are important because they influence not only projections of the proportion of the population in work, but also the labour productivity of workers, and their contribution to economic output. Thus, accurate information about these effects is a prerequisite to the ex-ante economic evaluation of policies in the health and education areas, be they as wide-ranging as NRA or more narrowly defined (for example, targeting a reduction in the prevalence of diabetes).

[2] In contrast to a chronic illness, an injury, even a major one, may not permanently lower a person’s stock of health-based human capital. However, time spent out of the labour force, because of injury, reduces a person’s accumulated work experience, which forms a part of that person’s human capital. In addition, enforced ‘time out’ of the labour force may result in skill attrition.

This paper's contribution is twofold:

- It examines the effects of health and education within an integrated modelling framework, something which could not be fully completed in time for the NRA study. In that study, the various effects of interest were obtained from disparate sources using different methodologies, making consistency checks and direct comparisons difficult. By contrast, this paper considers all the relevant effects within a single model and dataset, thus making comparisons and interpretation easier.
- It investigates the suggestion, often encountered in the literature on the effects of health and education on labour market outcomes, that these relationships are more complex than they appear to be at first glance. In particular, measurement of the key effects can be affected by endogeneity bias (box 1.1), which means that some published estimates of these effects are unreliable because they have not accounted for such bias.

These two contributions are related because the impact of any endogeneity bias is best examined within a single, integrated and flexible modelling framework. Accordingly, the investigative approach adopted in this paper involves a systematic comparison of results from three models of labour force participation, estimated using the same dataset and near-identical variables:

1. A conventional multinomial logit model of four labour market states: full-time employment; part-time employment; unemployment; and not in the labour force. Henceforth, this model is referred to as the 'standard multinomial logit' model.
2. A random effects panel data multinomial logit of the four same labour market states listed above. Hereafter, this model is referred to as the 'panel multinomial logit' model.
3. A system of two simultaneous equations of labour force participation and self-assessed health. Below, this model is referred to as the 'simultaneous equations' (SE) model.

The first of these models is designed to provide a benchmark for the other two, as it does not control for any form of endogeneity bias. Nonetheless, it is frequently used in studies of participation and employment decisions. The second model controls for possible unobserved heterogeneity, by fitting random effects to the intercepts of the model, using panel data. However, it cannot control for the possible simultaneity of the participation decision and health status. The third model has the capacity to control for simultaneity. Furthermore, it can help to detect (but not correct) the existence of rationalisation endogeneity when self-assessed health measures are used. That model is a variant of the model originally proposed by Cai and Kalb (2006). This paper extends the Cai and Kalb framework by using pooled annual data, rather than a single cross-section, and by including specific health conditions as determinants of self-assessed health status, rather than the generic long-term condition identifier used in the original model.[3]

Box 1.1 **Human capital and labour force participation: correlation or causation?**

The long-standing caveat that 'correlation does not equal causation' applies to human capital and participation. The examples below illustrate this point:

1. A person's educational attainment and labour force participation decision may be jointly influenced by a third, unobserved characteristic of that individual, creating the erroneous impression that the first two characteristics are causally related. Candidates for such unobserved characteristics which, by their nature, are difficult to measure, include innate ability, motivation and a preference for unpaid work.
2. For a manual worker, a better level of health is likely to be synonymous with higher labour productivity, higher wages and, therefore, a higher probability of being in the labour force. Conversely, poor health may cause this worker to withdraw from the labour force, as the opportunity cost of not working diminishes. In this scenario, good health may be said to 'cause' labour force participation. However, the reverse may also be true. The manual nature of the job may cause the worker's health to deteriorate, either through physical demands or injury. In that sense, labour force participation may be 'causing' ill health.
3. As mentioned in point 2, lower expected earnings for people in poor health reduce the opportunity cost of not working and may explain why many are not in the labour force. An alternative explanation is that some people who choose not to participate, for non-health reasons possibly related to the unobserved characteristics mentioned in point 1, may rationalise that decision by reporting poor health. This behaviour results in a reversal of the conventionally assumed direction of causality between reported health status and labour force status.

The scenarios outlined above typify some of the problems that complicate the study of the relationship between human capital and labour force participation. All scenarios result in what is technically known as 'endogeneity bias'. This bias can arise because of:

- unobserved heterogeneity (unobserved characteristics of individuals), as in point 1;
- simultaneity between human capital and labour force participation (point 2); or
- rationalising behaviour (rationalisation endogeneity) on the part of the people surveyed (point 3).

[3] Cai and Kalb's model supplemented that indicator with indicators of activities affecting health, such as drinking and smoking.

The choice of these three particular models is motivated by both pragmatism and a desire to build on state-of-the-art research. The standard multinomial logit model is a common, but somewhat unsophisticated approach to the modelling of labour force participation. The panel multinomial logit represents a recent advance on the standard multinomial logit. The increasing availability of HILDA panel data makes it a natural progression from the standard version of the model. Moreover, the standard and panel multinomial logit models are nested, which facilitates comparison. The SE model is not nested in the other models, which is a slight drawback for benchmarking purposes. However, this model is at the frontier of current research on the effects of health on labour force participation (Cai and Kalb 2006; Cai 2007), which warrants its inclusion in this study.

The research objective is, by comparing and benchmarking these models, to detect the existence and measure the effects of endogeneity in models of labour force participation. In the process, robust estimates of the marginal effects of health and education on participation are generated. As mentioned, accurate marginal effects are often a crucial input into the design of human capital policies, especially when an attempt is made to compare the benefits of these policies with their costs.

1.3 Results and implications for the projected effects of the National Reform Agenda

Results show that the traditionally assumed positive relationship between health and education, on the one hand, and labour force participation, on the other, is robust to the choice of models. Thus, even unsophisticated models of labour force participation will generally conclude correctly that raising overall health or education levels results in a higher percentage of the population in work. However, this paper's results also suggest that simple models tend to produce biased numerical estimates of the relevant effects, because of the existence of unobserved heterogeneity and other sources of endogeneity. If accurate estimates are required, then these sources of bias need to be accounted for in the modelling framework.

The existence of endogeneity bias has implications for the type of projection undertaken by the Productivity Commission (2006) in its analysis of the human capital stream of NRA. As mentioned, parameter estimates used in projections of labour force participation for that study were based on a range of published sources, none of which explicitly controlled for possible endogeneity bias. Notwithstanding some broad similarities, estimates used in Productivity Commission (2006) differ from the preferred estimates presented in this paper. For example, while the health conditions and education levels with the largest impact on participation are the same in both cases, (mental/nervous condition and degree or higher, respectively), this paper's preferred estimates of these effects are lower than those used in the Commission's NRA report (not shown).

Such differences are common in applied economic analysis, and were foreshadowed in the NRA report (Productivity Commission 2006, p. 339). The differences mean that a detailed cost–benefit analysis of changes to the prevalence of a single health condition, or educational level, would reach (potentially very) different conclusions. However, as a whole, the revised estimates presented in this paper do not affect the thrust of the Commission's NRA human capital projections. Applying the new results yields labour force participation projections that are slightly lower than those reported in Productivity Commission (2006), and overall labour productivity projections that are slightly higher.

This muted effect is explained by the fact that, although some estimates presented in this paper are lower than the corresponding estimates used in Productivity Commission (2006), others are higher. Moreover, the revised estimates presented here do not affect the bulk of the Commission's estimated labour force participation and labour productivity effects flowing from NRA. The majority of these effects were projected to arise due to work incentive measures and the effects of health and education on people *already* in the labour force (Productivity Commission 2006). These changes are not affected by the new results presented here.

The paper is structured as follows. In chapter 2, a brief literature review of the link between labour force participation and health and education is presented. Following this, a more formal statement of the endogeneity issue is provided in chapter 3 and modelling responses are discussed. The dataset used in the analysis is then considered in chapter 4. Estimation results are reported and analysed in chapter 5. Chapter 6 concludes the paper.

2 Literature review

This chapter reviews existing research about the relationship between labour force participation and health and education. The focus is on overall labour force participation; however, age and gender differences are noted where relevant.

2.1 Health and participation

Table 2.1 presents labour force participation rates,[4] averaged over the period 2001 to 2004, for people with or without the following health conditions: cancer; cardiovascular disease; mental/nervous condition; major injury; diabetes; and arthritis.

Table 2.1 **Labour force participation rates by health condition,[a] 2001–04 average**

Condition[b]	*Cancer*	*Cardio-vascular*	*Mental/ nervous*	*Major injury*	*Diabetes*	*Arthritis*
Total population	%	%	%	%	%	%
Does not have condition	80.3	82.0	80.7	80.2	80.7	82.6
Has condition	68.6	64.0	39.3	60.1	56.6	63.1
Males						
Does not have condition	89.0	90.8	89.0	88.6	89.1	91.2
Has condition	67.8	70.6	37.5	67.1	64.6	68.0
Females						
Does not have condition	72.3	74.1	73.0	72.5	72.8	74.5
Has condition	69.4	56.7	40.8	52.1	46.0	59.3

a See appendix A for a definition of the conditions. **b** For each column, people with that condition may also have one or more of the other conditions listed. Similarly, 'does not have condition' does not exclude someone from having one of the other conditions.

Source: Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

Participation rates are consistently and considerably lower for people with a health condition. Of those listed, a mental health or nervous condition is associated with the lowest likelihood of being in the labour force, especially for males. The

[4] The labour force participation rate is the sum of those employed and unemployed, divided by the total relevant population, expressed as a percentage.

participation rate for males with a mental health condition is less than half that of males without that condition.

Having one health condition does not exclude the possibility of having another. Indeed, some conditions are associated with a higher probability of experiencing another condition. The labour force participation rate for people with two or more health conditions (52.5 per cent) is lower than that for people with one (75.1 per cent). In contrast, people without any of the health issues listed in table 2.1 have a participation rate of 84.7 per cent (not shown in table 2.1).

Links between health and participation

According to human capital theory, health and labour force participation are positively related. That theory predicts that improvements in health lead to greater labour force participation. People with poor health tend to be less productive, because poor health adversely affects their work performance. Compared with this group, healthy workers can expect higher returns from work and, as a result, have a greater incentive to be in the labour force. Poor health may also lead to people spending more time out of the labour force, because the time needed to care for one's health increases as that health deteriorates (Cai and Kalb 2006).

The causality between health and participation is not necessarily one-way. There will be a feedback effect from labour force participation to health if working affects a person's health. Furthermore, participation could have either a positive or negative effect on health. For example, working might increase a person's general activity level, thus improving physical health. Conversely, the nature of one's work may lead to a deterioration in health, either because of the effects of working long hours or, at the opposite extreme, because too few hours of work may be associated with job insecurity (Dockery 2006; Adam and Flatau 2005).

The link between mental health and labour force participation is of special interest, because poor mental health is associated with a much lower probability of labour force participation than are physical illnesses or major injury (table 2.1).

Links between mental health and labour force participation

The causality between mental health and labour force participation can run both ways. First, poor mental health may lead to a reduced likelihood of labour force participation, for several reasons.

Depression can cause absenteeism and impair motivation and performance at work (Waghorn and Lloyd 2005). Prolonged absenteeism might eventually lead to complete withdrawal from the labour market. People with depression might also face limited employment opportunities if an episode of impaired motivation is interpreted by employers as reflecting a low overall motivation level (Waghorn and Lloyd 2005), or if employers ascribe low motivation to everyone who suffers from depression (statistical discrimination). People with anxiety disorders also face employment restrictions. Using 1998 Australian data, Waghorn and Chant (2005) find that the most commonly cited employment restrictions for people with anxiety disorders are, in order of importance: restrictions on the type of job performed; the need for a support person; difficulty in changing jobs; and a limitation on the number of hours worked.

Labour force participation can, in turn, *influence* a person's mental health, that is, working may have a positive or negative impact on mental health.

To explain the former, Waghorn and Lloyd (2005) cite studies showing that positive and meaningful employment experiences may lead to: improved self-concept; higher ratings of subjective wellbeing; improved self-esteem; and increased personal empowerment. Work may also provide insight into the mental health of those with less severe impairment, enabling them to improve their mental health.

On the other hand, Waghorn and Lloyd cite evidence from Lysaker et al. (1995) showing that employment can have negative consequences for some people, especially those with a pre-existing mental health condition.[5]

Work might also be stressful, and therefore lead to lower mental health, for people who initially have no mental health condition. A number of work stress theories describe how work can cause a deterioration in a person's mental health. According to Dollard and Winefield (2002), the most empirically supported of these theories is that 'work stress and its attendant mental health issues are firmly grounded in the way jobs are constructed, constituted and managed' (p. 9). People with jobs that have high demands and are low in control (for example, assemblers, cooks and waiters) experience the highest levels of stress. On the other hand, people in positions with greater autonomy (for example, managers) do not experience as much stress (even though these jobs may still have high levels of demands). Strain associated with a lack of control over decision making can cause anxiety, depression, or psychosomatic complaints (Adam and Flatau 2005), as well as job dissatisfaction, burnout or lower vitality (Dollard and Winefield 2002).

[5] Although the reason for this could not be established, it is suggested that severe cognitive impairments may interfere with the ability of some people to appreciate the purpose of a work activity, thereby making work unduly stressful (Waghorn and Lloyd 2005).

Mental health problems might also arise from not having enough work, or becoming unemployed. Adverse health consequences are more likely to arise, the more satisfied people were in the job they lost (Dockery 2006). Perceived employment stability may also influence mental health. Using data from HILDA, Adam and Flatau (2005) find that job uncertainty leads to lower mental health.

There are indications that the health–participation link may vary across different groups. Kennedy (2003a) analyses the links between mental health and labour force status for immigrants to Australia. He finds, for immigrants, that causality runs from unemployment to mental problems. A longer time spent in unemployment may also increase the severity of mental health problems. Dockery (2006) uses HILDA longitudinal data to test this hypothesis. He finds that, over the relatively short 2001–04 period, becoming or remaining unemployed does not lead to lower mental health. Dockery suggests this result might be due to the small sample size of transitions to and from unemployment, because larger movements into and out of the labour force *are* associated with large changes in mental health: exiting the labour force is associated with a deterioration in mental health, and entering into employment from outside the labour force is associated with improved mental health.

Modelling the effects of health on labour force participation

The review above shows that the theoretical relationship between health and labour force participation is complex. These difficulties have resulted in many different econometric models being used to capture the effects of health on labour force participation (see Cai and Kalb 2006 for a review).

It is usually assumed that health is a determinant of labour supply. Thus, health is often included in single-equation models of labour force participation. However, because causality can run both ways, health is endogenous to labour supply and a simultaneous equations model should be used to account for potential simultaneity bias (see chapter 3 and appendix B). Cai and Kalb (2006) allow for this and find that endogeneity does exist because participation affects health. In their results, the effect of participation on health can be positive or negative, depending on age and gender. This is consistent with the existing literature, which shows that the effect of labour force participation on health is, a priori, ambiguous.

Another issue to arise when modelling the effects of health on participation is the choice of health measure. Cai and Kalb (2006) use self-assessed health status, rather than a more objective measure, which may lead to measurement errors, such as 'rationalisation endogeneity' if people misreport their true health (box 2.1).

Box 2.1 **Subjective or objective health measures?**

The effect of health on labour force participation can be estimated using either subjective or objective health measures. Objective measures include being diagnosed with, or having symptoms of, specific physical or mental health conditions. Subjective measures are derived from individuals' responses to survey questions. For example, the HILDA survey asks the question 'In general would you say your health is: excellent; very good; good; fair; or poor?'

There is much debate regarding the merits of subjective health measures in estimating the effects of health on participation (Cai and Kalb 2005; 2006). One concern when modelling the effect of health on participation is that self-assessed health may be used as a rationalisation for labour force status. 'For example, those not in the labour force may report poor health to justify their non-participation or the receipt of disability-related benefits' (Cai and Kalb 2005, p. 11). Consequently, when self-assessed health is used to explain labour force participation, the health variable may become endogenous. This is known as 'rationalisation endogeneity'.

In a review of previous studies, Cai and Kalb (2005) find only mixed evidence of rationalisation behaviour. They also remark that using self-assessed measures of health is not likely to be problematic, because these measures are highly correlated with medically determined health status. This correlation is illustrated in the table below, showing that those who do not have a health condition tend to report higher levels of overall health, compared to people with one or more conditions.

Self-assessed health status, by health condition, 2003[a]

Health condition	*Self-assessed health rating*						
	Poor (1)	*Fair (2)*	*Good (3)*	*Very good (4)*	*Excellent (5)*	*Total*	*Average rating*
	%	%	%	%	%	%	
Cancer	7.6	26.1	35.2	26.1	4.9	100.0	2.95
Cardiovascular	9.1	25.5	41.4	20.9	3.2	100.0	2.84
Mental/nervous	20.8	42.3	27.0	7.5	2.3	100.0	2.28
Major injury	6.3	23.2	37.0	25.6	7.9	100.0	2.62
Diabetes	10.8	39.7	35.4	11.8	2.4	100.0	2.55
Arthritis	9.5	28.0	38.0	21.4	3.2	100.0	2.81
2 or more conds	15.8	38.0	32.7	11.4	2.1	100.0	2.46
No condition	0.6	6.5	32.0	44.8	16.1	100.0	3.69

a However, major injury data is taken from the 2004 survey because it is more accurately measured in that year (see appendix A).

Source: Productivity Commission estimates based on the HILDA Survey, 2003 and 2004, release 4.1.

If rationalisation endogeneity is present, then the impact of health on participation may be overstated. Unlike the endogeneity bias arising when there is feedback between participation and health (which can occur regardless of the health measure used), rationalisation endogeneity bias cannot be corrected.

In addition to simultaneity bias and rationalisation endogeneity, unobserved heterogeneity may also create estimation problems (see chapter 3 and appendix B). Chronic health conditions ‘are likely to be the results of lifestyle behaviour and unobservable individual heterogeneity that also determine the result of labour market outcomes’ (Zhang et al. 2006, p. 3). Zhang et al. (2006) use data from the Australian National Health Surveys to examine the effects of objective health measures on labour force participation, in the presence of unobserved heterogeneity.

2.2 Education and participation

The Productivity Commission (2005, p. 347) concluded that education is positively related to labour force participation and that, in 2001, ‘the age-corrected average labour participation rate of an Australian male (female) with a degree or higher was 14.2 (21.0) percentage points higher than for a person who had 10 or less years of schooling’. A positive relationship between labour market participation and education is a longstanding finding. For the period 1982 to 2000, Kennedy and Hedley (2003) show that the labour market participation of those with post-school qualifications was, on average, consistently around 15 percentage points higher than for those with no post-school qualifications. The relationship is especially strong for females (Chiswick and Miller 1994; Kenyon and Wooden 1996). A positive relationship between education and labour force participation is found for both genders in other OECD countries (IES 2001).

Research by the ABS (2006) suggests that participation is strongly related to the presence of job relevant qualifications obtained through education, as well as to work experience. For those unemployed, not in the labour force or wanting more hours of work, the ABS found that the main self-reported difficulty in obtaining work is a lack of training, qualifications or experience. Of the 107 000 people nominating those three reasons, 60 per cent had no post-school qualifications. However, 43 per cent of those 107 000 people were aged 18 to 24 and, therefore, may not have begun, or completed, job-relevant qualifications at the time of the survey.

To illustrate further the link between education and labour force participation, participation rates by gender and level of educational attainment are presented in table 2.2. Three effects are discernable from that table. Labour force participation varies:

- within age groups, by level of education;

- across age groups; and
- by gender.

Table 2.2 **Labour force participation rate by gender, age group and highest level of educational attainment, 2004**

Age group	*15–24*	*25–34*	*35–44*	*45–54*	*55–64*	*15–64*
	%	%	%	%	%	%
Males						
Degree or higher	82.5	95.6	97.6	90.2	77.5	91.2
Certificate or diploma	89.0	95.0	92.5	90.6	58.7	86.6
Year 12	88.7	91.7	87.5	87.5	60.1	85.9
Year 11 or lower	72.5	91.7	88.1	77.1	55.0	75.6
Total	79.7	93.9	91.8	86.6	60.6	83.8
Females						
Degree or higher	88.5	85.9	84.0	87.1	64.7	83.7
Certificate or diploma	85.6	73.0	74.0	79.6	48.0	73.2
Year 12	80.0	73.2	67.1	73.9	36.1	71.4
Year 11 or lower	64.1	53.8	60.8	67.2	33.7	56.0
Total	74.0	72.2	70.8	74.7	40.6	67.9

Source: Productivity Commission estimates based on the HILDA survey, 2004, release 4.1.

Within each age group, labour market participation usually increases as the level of education rises. Averaged over all age groups, males (females) with a degree or higher are 16 (28) percentage points more likely to be in the labour force than those with a Year 11 or lower level of education.

Across age groups, participation rates fall as both genders reach minimum superannuation age and then pension age. Compared with those aged 45 to 54, the decline in participation of those aged 55 to 64 is greatest for males with a certificate or diploma (32 percentage points). Making the same comparison for females, the greatest decline is for those with Year 12 education (38 percentage points). The decline in the participation of those aged 55–64, compared with those aged 45–54, is least for males with a degree or higher, at 13 percentage points.

The participation rate of females is affected by factors including child rearing. This results in a ‘U’ shaped age/participation profile between the ages of 15 and 54. The ‘U’ shape is substantially less pronounced for females with higher levels of education, such as those who have degree or higher qualifications, compared with those with Year 11 or lower education.

During the prime working age years of 25 to 54, the difference in participation between males and females is greatest when females are most likely to be caring for young children. The difference in participation between genders is also greater for those with fewer years of education. For example, females aged 25 to 34, with Year 11 or lower education, are 38 percentage points less likely to participate than similarly aged males. For similarly aged females with degree or higher qualifications, the difference with their male counterparts is only 9.7 percentage points. The gender participation rate difference for people with the same education level is least for those aged 45–54 with a degree or higher (3 percentage points).

Theoretical issues

Both labour supply and demand factors are important in shaping the relationship between education and participation. The quantity of labour supplied by individuals tends to increase with education because '[h]igher educational attainment is associated with better wages, more enjoyable jobs and with tasks that involve a lower risk of acquiring a disability' (Productivity Commission 2005, p. 347). This is notwithstanding the fact that, as wages rise, some people may opt for more leisure, rather than more income. On the demand side, employers offer higher wages to more highly educated employees because their productivity is usually higher than that of workers with lower education. Economic processes that increase the productivity gap between the two groups of workers, such as some forms of technical change, serve to accentuate the labour force participation effects of education (De Laine et al. 2000; Laplagne et al. 2001).

The observed relationship between education and participation is underpinned by complex mechanisms, and subject to some important caveats, summarised below (for a comprehensive literature review, see Lattimore 2007).

Human capital resides in the stock of physical and intellectual skills a person possesses. Educational attainment is traditionally regarded as a proxy for cognitive skills (literacy, numeracy) and interactive skills (communication, socialisation), but it is not a perfect proxy. Yet, skills are at least as important as formal qualifications for labour market success. Lee and Miller (2000) find that having excellent literacy and numeracy skills has a greater impact on labour force participation than does the attainment of tertiary qualifications *per se*. Chiswick et al. (2003) estimate that around half of the effect of education on labour force participation is due to the increase in literacy and numeracy skills associated with education. Card and Krueger (1996) find that the estimated payoff of an additional year of education increases with school quality.[6]

[6] Card and Krueger (1996) measure school quality in several dimensions — expenditures per pupil; pupil-teacher ratio; and teacher pay — which are likely to be directly related to skills acquisition.

These findings indicate that raising educational attainment may result in only a muted participation response, if literacy and numeracy skills do not also increase. This is related to the argument that early school leavers may have characteristics that predispose them to failure both at school and in the labour market (Lattimore 2007). Providing that group with more education, even if it results in higher formal qualifications, may not equip its members with the numeracy and literacy skills necessary for labour market success. In this context, projecting gains in participation from increasing educational attainment is problematic, unless the individual (and, often, unobserved) characteristics of non-completers and completers can be controlled for in the analysis.

The positive response of labour market outcomes to increased education may also become diluted by the effects of 'screening', that is, employers using educational attainment to *rank* potential employees, when they have imperfect information about candidates' productivity. Candidates with the greatest educational qualifications are matched to jobs with the highest productivity/wage, because high qualifications are regarded by employers as a signal that a potential employee has the greatest innate ability for this type of job. In this scenario, an across-the-board increase in the educational attainment of the population would not necessarily raise individual job prospects or incentives to participate, because employers' hiring decisions are based on candidates' relative, not absolute, qualifications. For this reason, the effects of greater educational attainment on labour force participation are partly a reflection of the relative supply of different qualifications at a point in time, and not only the absolute levels of qualifications. Should the balance between demand and supply of skills change over time, so will the effects of education on participation.

A final caveat is that, rather than participation *per se*, the ultimate objective of education-based human capital policies is to harness the productive capacity of those not currently contributing to the nation's output. In this respect, it may be more cost effective and expeditious for such policies to concentrate, initially, on helping the unemployed to find jobs. Discouraged job seekers and unemployed persons not available to start work in the survey reference week (that is, those 'marginally attached' to the labour force) are another pool of potential labour that might be accessed via appropriate policies. However, as people's degree of attachment to the labour force diminishes, the effectiveness of measures to encourage them into work may also diminish.

Education and the participation of younger and older workers

Much of the research into the relationship between education and labour force participation focuses on the circumstances of two groups. First, the difficulties that some young people with relatively low educational qualifications experience in entering and remaining in the workforce (table 2.2); and, second, the trend over recent decades for males with lower levels of education to retire early. These trends are important from a policy standpoint, because they limit individual lifetime earnings and they detract from Australia's potential output.

The participation of the young

As young people who have finished studying usually want to work, the young unemployed, rather than students not in the labour force, have been the focus of research. The Longitudinal Surveys of Australian Youth have been used extensively to study the linkages between education and skills, and the employment of younger workers. That body of research confirms the importance of literacy and numeracy skills, and the relationship of those skills with employment outcomes.

Lamb (1997) finds that high literacy and numeracy skills are related to better labour market outcomes at age 19. McMillan and Marks (2003) find that low literacy and numeracy skills in Year 9 are the most important predictor of post-school unemployment. Lamb and McKenzie (2001) find that those with low literacy and numeracy skills had unemployment rates around 10 percentage points greater than high achievers. Marks (2006) investigates the transition to full-time employment of young people who did not go to university. He finds that people's labour market experience immediately after leaving school, that is, whether they obtained full-time employment or remained unemployed, was a good predictor of their subsequent labour market experiences. Hillman (2005) confirms that young people without Year 12 education, who are in the lowest quarter of school achievers, are more likely to experience multiple periods out of the labour force and not in full-time education.

The participation of older Australians

In regard to males aged 55 to 64 with no post-school qualifications, Kennedy and Hedley (2003, p. 1) judge that the decline in participation since the 1970s has been 'dramatic'. While the average participation rate for males in that age group was around 90 per cent in the 1970s, it was only 60 per cent in 2004 (Productivity Commission 2005). A similar decline has not been a feature of the US economy (McEwen et al. 2005), suggesting that the fall in participation by mature age males with low skills relates to factors specific to Australia.

Karmel and Wood (2004) argue that the relationship between education and labour force participation is positive for older workers, especially women. They also find that qualifications gained later in life have as strong an influence on participation as qualifications earned earlier in life. Austen and Birch (2005), in a literature review, conclude that the participation rates of older women relate positively to the wage rate on offer. Since skilled occupations typically attract higher wages, the underlying relationship is with a woman's expected productivity, which is a function of her level of education and other forms of human capital.

Gruen and Garbutt (2003) explore the possibility that Australia's labour force participation rate will increase over coming decades to 80 per cent of the level currently attained by comparable OECD countries. They argue that the major factors contributing to such an increase could include: recent rises in education levels flowing through to workers aged 45–65 over time; government policy changes; and changes in community attitudes to the employment of older workers. Reaching that participation rate objective would not only counteract the decline in labour market participation due to population ageing, but increase output by 9 per cent more than projected in the Australian Government Treasury's (2002) intergenerational report. Gruen and Garbutt argue that one third of that increment in output would occur as a consequence of a 10 percentage point increase in the participation rate of older-aged males, most of whom, unlike females, work full time.

Links between education and health

In this paper, the effects of health and education on labour force participation are mostly analysed separately, notwithstanding empirical evidence indicating that education seems to be positively related to health (Arendt 2005; Goesling 2005).

Econometric research by Cutler and Lleras-Muney (2006) indicates that four years of additional education significantly lowers: the five-year mortality rate; heart disease; diabetes; fair or poor self-assessed health; and working days lost due to sickness. These effects are generally large. Four more years of education are estimated to lower the risk of diabetes by 1.3 percentage points, from a mean of 7 per cent points.

Numerous explanations of how education may positively affect health have been proposed. The more important ones are briefly set out below.

Those with greater education may be less likely to engage in behaviour with adverse health consequences, and more likely to engage in behaviour with positive health consequences. For example, Cutler and Lleras-Muney (2006) estimate that those with four more years of education than average are about half as likely to smoke as the average person.

Such differences in behaviour may occur as education ‘helps people choose healthier life-styles by improving their understanding of the relationships between health behaviour and health outcomes’ (Kenkel 1991, p. 288). Kenkel tests whether greater health-specific knowledge improves the choice of health-related inputs, such as the consumption of cigarettes, alcohol and exercise. Further, he tests whether improved health-specific knowledge derives from schooling (education) or operates separately from it. He finds that, after controlling for the level of health knowledge, most of schooling’s effect on health behaviour remains. Thus, schooling and health-specific knowledge have a separate influence on health behaviour.

Other researchers argue that, in any case, the healthy behaviour hypothesis explains only a minor part of the effect of education on health (Cutler and Lleras-Muney 2006; Marmot 1994). Several reasons are advanced to explain the remainder of the effect. First, some researchers have suggested that improved reading, writing and cognitive skills, including the ability to accept and interpret the results of health-related scientific research, are an important health-improving outcome of education.

Second, people may differ in unobservable ways, such as in their rates of time preference or their levels of ability. ‘Individuals who invest in education have low rates of time preference (a low discount rate) and individuals with a low rate of time preference will also invest more in health’ (Kennedy 2003b, p. 2).

Other hypotheses are that the health returns to education may derive from:

- the increased financial returns of greater education facilitating greater access to, and willingness to use, health services;
- the improved working environment, higher status and lower stress associated with the jobs undertaken by the more highly educated; and
- further education leading to the development of social skills and networks that reduce social isolation and its accompanying mental health problems.

The overall health returns of education appear to be significant. Cutler and Lleras-Muney (2006) estimate that the health returns of education increase the total returns to education by between 15 and 55 per cent, depending on the discount rate used.

Causation between education and health may also operate in the opposite direction. A health problem may limit a person’s ability to acquire education, leading to adverse labour market outcomes:

> The onset of mental illness can truncate primary, secondary or tertiary educational attainment and vocational training, and disrupt normal career development. For psychotic disorders, this may occur because the typical onset age is from 10–30 years …Through disrupting education, mental illness can indirectly cause long-term unemployment and limit career prospects. (Waghorn and Lloyd 2005, p. 10).

To summarise, although there is much evidence that health and education are positively related, the precise mechanisms linking the two variables are complex. Nonetheless, if education improves health, then it would also increase labour force participation indirectly, through health outcomes. This type of effect can only be accounted for in simultaneous equations models (Cai 2007; Cai and Kalb 2006; Zhang et al. 2006). These models generally show positive indirect effects of education on participation. A similar model is developed and estimated in coming chapters.

3 Endogeneity between human capital and participation

This chapter provides a more formal discussion of the endogeneity issues that were described in preceding chapters.

Assume the following model of labour force participation:

$$l = \alpha + \gamma'\mathbf{Ed} + \lambda'\mathbf{H} + \beta'\mathbf{x} + \varepsilon \qquad (1)$$

where l = a latent variable measuring the propensity to participate in the labour force. In reality, only the binary states of l (0, 1) are observed.

α = a constant

Ed = a vector of education indicators

H = a vector of health indicators

x = a vector of explanatory variables, such as demographic characteristics

ε = a normally distributed error term with zero mean

Using a standard binomial probit or logit model to estimate the coefficients of equation (1) implicitly assumes that the right-hand-side variables are *exogenous* to the participation decision, that is, their values are not affected by labour force participation. In reality, some of these variables may be *endogenous*, with values determined within the model. In other words, their values cannot be regarded as being independent of the value taken by l.

Endogeneity of some explanatory variables in a model can arise for several reasons:

1. Simultaneity: for example, when **H** influences l and, in turn, l influences **H**.
2. Unobserved individual heterogeneity: for example, when l and **H** are both influenced by a person's unobserved characteristics (that is, those characteristics not appearing in **x**).

3. Systematic bias in the reporting of self-assessed health status or specific health conditions, perhaps due to rationalisation endogeneity.[7]

In all these cases, failure to take account of the endogeneity of an explanatory variable will result in biased and inconsistent estimates of that variable's relationship with l (see appendix B). Solutions exist, but only to correct for simultaneity bias and unobserved heterogeneity bias (reasons 1 and 2 above). When subjective health measures are used, bias due to rationalisation endogeneity (reason 3) may occur, with no avenue for correction. However, its direction can be predicted, and its magnitude may be inferred from the estimated parameters (see section B.3).

As discussed in the previous chapter, the relationship between health and labour force participation is viewed by many researchers as one of simultaneity or joint determination. Reasons underlying this claim include the possible health effects of work in general, and some jobs in particular, and the effect of health on work incentives.

If simultaneity is present, using a single equation produces biased estimates of the relationship of interest. One solution to this problem, adopted by both Cai and Kalb (2006) and Cai (2007), and used in this paper, is to include an explanation of how l influences $\mathbf{H}$ (or one of its elements) in the model. That is, a second equation is added to the model, in which $\mathbf{H}$ is the dependent variable, and l an independent variable. The model now becomes:

$$l = \alpha + \gamma'\mathbf{Ed} + \lambda'\mathbf{H} + \beta'\mathbf{x} + \varepsilon_l \qquad (2)$$

$$\mathbf{H} = \theta l + \eta'\mathbf{y} + \varepsilon_H \qquad (3)$$

where $\mathbf{y}$ = a vector of explanatory variables, such as demographic and social characteristics (including education indicators), which may, in part, overlap with the $\mathbf{x}$ vector

If the system of equations above is an appropriate representation of the health–labour force participation link, then this will be reflected in a significant parameter estimate of θ, and in the correlation of the ε_l and ε_H error terms.

The error terms will also be correlated if the health–participation relationship is affected by unobserved heterogeneity (Cai 2007; Zhang et al. 2006). Zhang et al.

7 Rationalisation behaviour is a form of measurement error. In general, the direction of the bias caused by measurement error in explanatory variables cannot be predicted. However, with rationalisation endogeneity, the effects of measurement error on the estimated coefficients can be known (see appendix B).

(2006) posit the existence of unobserved characteristics that simultaneously influence labour force participation and the value of objective health measures (that is, diagnosed health conditions). They suggest that such characteristics may be related to 'genetics and lifestyle factors' (p. 28).

In this paper, equations (2) and (3) are estimated using the full information maximum likelihood (FIML) method. A two-stage estimation could be used instead, but it would not allow the equations to be solved simultaneously or the correlation coefficient between the error terms to be estimated. As Cai and Kalb (2006) show, the correlation coefficient between the error terms is required to determine whether or not the simultaneous system of equations, (2) and (3) above, is an appropriate specification. Chapter 5 will more formally develop the test for simultaneity.

Unobserved individual heterogeneity has also been identified by some authors as a possible source of endogeneity bias in the relationship between educational attainment and labour market outcomes such as wages (Klein and Vella 2006; Gangji et al. 2005), employment and participation (Gray and Hunter 2002). According to this literature, unobserved individual characteristics can influence both the highest level of educational attainment reached and the decision to engage in paid work.

If heterogeneity underlies the observed data, then the effect of unobserved characteristics on the probability of labour force participation will be captured by the error term of equation (1), ε. That term will, therefore, be a composite of individual-specific effects (time invariant) and a random error. It can be shown that this composite error is correlated with some of the explanatory variables in the model (see appendix B). This estimation issue, a form of omitted variable bias (see appendix B), is sometimes called 'selection on unobservables or omitted variables' (van Ours and Williams 2006).

In the presence of unobserved heterogeneity, equation (1) can be efficiently estimated using longitudinal (panel) data.[8] Fitting the model with panel data is equivalent to estimating the following equation:

$$l_{it} = \alpha + \gamma'\mathbf{Ed}_{it} + \lambda'\mathbf{H}_{it} + \beta'\mathbf{x}_{it} + a_i + u_{it} \qquad (4)$$

where a_i = an individual, time-invariant unobserved effect for person i

u_{it} = a normally distributed random error term for person i at time t, with mean zero

[8] Another modelling solution in the presence of unobserved heterogeneity is that adopted by Zhang et al. (2006). They estimate a system of four equations (a labour force participation equation and three health condition equations) in which all error terms are correlated.

Depending on the assumptions made about a_i, equation (4) may be estimated using a fixed effects or a random effects panel data model. The former assumes that a is fixed for each individual, and is correlated with some of the explanatory variables. It also assumes that α is zero. The random effects model assumes that a is a random term with a normal distribution, and is uncorrelated with any of the explanatory variables.

A random effects model is preferred in situations where some or all of the observed explanatory variables of interest are time-invariant. Over the four successive HILDA surveys used in this study, this is true of both health and education for the majority of people in the sample. For most persons, health indicators tend not to change over four years. Regarding education, the highest level of educational attainment reported at the time of each yearly survey changes little, if at all.

The modelling of binary (0, 1) participation outcomes using panel data and assuming random effects is relatively common in the labour economics literature. Typically, it relies on the estimation of panel probit or panel logit models. In this paper, a more general version of the random effects binary logit model is used, called a 'random parameters logit' model, which is capable of modelling multiple categorical outcomes using panel data and assuming random effects (Greene 2002, 2003; Train 2003). This model, the panel data equivalent of a multinomial logit model, belongs to a family of models known as Generalised Linear Mixed Models (GLMM). The probability values it estimates may be expressed as:

$$P(\text{choice } j|i,t) = \frac{\exp(\alpha_{j,i} + \beta_i^{'}\mathbf{x}_{itj} + \gamma_{j,i}^{'}\mathbf{z}_{it})}{\sum_{j=1}^{J(i,t)} \exp(\alpha_{j,i} + \beta_i^{'}\mathbf{x}_{itj} + \gamma_{j,i}^{'}\mathbf{z}_{it})} \tag{5}$$

where P(choice j | i, t) = probability of individual i choosing outcome j at time t

$\alpha_{j,i}$ = individual and outcome specific random constant term[9]

$\mathbf{x}_{itj}$ = individual, outcome and time specific vector of characteristics

$\mathbf{z}_{it}$ = individual and time specific vector of characteristics

$J(i,t)$ = total number of alternatives in i's choice set at time t

The random parameters model offers many modelling advantages over the standard multinomial logit model:

- It can be fitted using panel data and can, therefore, control for unobserved heterogeneity.

[9] Within a random parameters logit model, it is possible to assume that *any* of the explanatory variables, not just the constant, follows a random determination process for each individual (Greene 2002). However, in order to replicate the standard random effects model for panel data, only the constant should be allowed to be random.

- It allows explanatory variables to be outcome-independent (for example, age and location) or outcome-dependent (for example, the notional amount of government benefits a person would receive, conditional on the labour market status of that person).
- It allows estimated coefficients to vary across individuals, as outcomes from random draws. This means that the slope coefficient of a particular explanatory variable is not restricted to being identical across observations.
- It does not require the 'independence of irrelevant alternatives' (IIA) assumption to hold. That is, it is not necessary to make the strong assumption that the odds of choosing one labour market state over the base outcome (for example, full-time employment over not in the labour force) are unaffected by the existence of other states.

In an analysis of female employment in HILDA, Haynes et al. (2005) set out to benchmark standard multinomial logit models using pooled data against random effects multinomial logits using panel data. They find that random effects multinomial logit models, although computationally intensive, produce significant evidence of unobserved heterogeneity. Moreover, their results show that the IIA assumption is unlikely to hold, suggesting that a standard multinomial logit model is not appropriate for modelling participation and employment.

4 Data source

A single dataset is used to estimate the three models set out in chapter 3, namely the HILDA survey. For a meaningful comparison of the performance of alternative models, it is important that they are fitted with the same data. It is also desirable that they comprise, as far as possible, the same dependent and independent variables. This is the case here, with a few exceptions noted below and in appendix A.

All three models are estimated using unweighted data from the four waves of the HILDA survey available at the end of 2006 (covering the period 2001–04). For the standard multinomial logit model and simultaneous equations (SE) model, the data from all four years are pooled to maximise the degrees of freedom available for the estimation. Given its longitudinal nature, the HILDA survey contains, in the main, repeated annual observations on the same individuals. This means that the error terms relating to the same person cannot be assumed to be independent over time. Put differently, unobserved characteristics of individuals are likely to influence their labour supply behaviour in the same way, year after year. To correct standard errors for this characteristic of the data, a clustering technique is used.

The panel multinomial logit uses the same data as the other two models but, instead of treating successive observations on the same person as notionally distinct, their relationship across time is exploited in a panel data framework. This means that the estimation specifically accounts for possible unobserved individual heterogeneity.

The dependent variable differs slightly across models. In the two multinomial logits, it consists of four possible labour market states: full-time employment; part-time employment; unemployment; and not in the labour force. In the SE model, there are only two states: in the labour force; and not in the labour force. In all models, the probability of interest is that of being in the labour force. The detailed labour market states of people who are in the labour force are of secondary interest in this paper.[10]

Explanatory variables entering the three models are those commonly found in the labour supply literature (see Austen and Birch (2005) for a review). They belong to

10 However, Wald tests suggest efficiency gains, for the multinomial logit models, from keeping the four outcomes separate instead of combining them into three or two. Equivalent tests could not be performed on the SE model, so that the merits of introducing more than two possible labour market outcomes into that model could not be assessed.

several categories of determinants of labour force participation: demographic characteristics; location; ethnicity and language; and human capital (education; health; and work experience).

The focus of this paper is on the explanatory power of two broad human capital variables: health and education. The detailed education variables used in estimation are those frequently found in the literature, based on the highest level of education achieved, aggregated into four categories: degree or higher; diploma or certificate; Year 12 completion; or Year 11 completion or lower (see appendix A).

This paper uses an innovative approach to the measurement of health. Following some earlier studies (Cai and Kalb 2006; Cai 2007), a self-assessed measure of overall health is used. However, this paper differs from most other models of labour force participation in that it also uses information on five specific health conditions: cancer; cardiovascular disease; mental/nervous condition; diabetes; and arthritis. A sixth health variable, major injury, is constructed from other variables. Zhang et al. (2006) also identify specific conditions, but they number only three (diabetes; heart conditions; and mental illnesses).

In the HILDA survey, detailed information on health conditions is only available for 2003 (2004 for injury). Information on health conditions in other years was imputed. Details of the construction of these and other variables are provided in appendix A. Descriptive statistics are also available in that appendix.

The sample used in the estimation of all models comprises all persons over 15 years of age who responded to the HILDA survey between 2001 and 2004, but excludes:

- men aged 65 or older, and women who have reached pensionable age;[11] and
- all persons in full-time study or still at school.[12]

Due to these exclusions, and because of natural panel attrition, the dataset used in the estimation of the panel multinomial logit is an unbalanced panel.

All three models are estimated separately for women and men. In addition, the SE model is estimated separately for two broad age groups: 15–49; and 50–64 (62 for women). This approach is not replicated in the estimation of the multinomial logit models; given the greater number of possible labour market outcomes in these models, estimating specific models for different age groups reduces the sample size. This, in turn, increases the risk of some explanatory variables being perfect

[11] Females were progressively dropped from the sample if they were aged 61 or over in 2000, 62 or over in 2001 and 2002, and 63 or over in 2004.

[12] The labour supply behaviour of that group is likely to differ markedly from that of people whose main occupation is not some form of study.

predictors of one or more labour market states. Multinomial logit models are therefore estimated on the basis of all ages combined, with binary variables identifying the following age groups: 15–24; 25–49; and 50–64 (62 for women). In those models, potential differences in the effects of education, by age group, are captured via interaction variables (see appendices A and C).

5 Results and discussion

In the first two sections of this chapter, econometric results relating mainly to the effects of selected education variables and health conditions on labour force participation are presented for the three models. Because the focus is on the marginal effects of these variables, coefficient estimates from the models are not discussed (they are provided for reference in appendix C). These estimates are, in the main, of the expected sign. The marginal effects from the three models are initially compared without prejudging the possible impact that endogeneity bias might have on them. Following that discussion, in the third section, the three models are compared in terms of their goodness of fit. In the final two sections, evidence regarding the existence of simultaneity, rationalisation endogeneity and unobserved heterogeneity is assessed.

To foreshadow the results detailed below, the conventional positive association linking health and education to labour force participation is found to be robust to the choice of model. However, measurement of that link is sensitive to controlling for possible sources of endogeneity. In particular, results suggest that unobserved heterogeneity is a significant influence on the labour supply decision of women. Another conclusion is that simultaneity between health and labour force participation is likely to cause bias in single-equation models. These conclusions are supported by the various statistical tests applied to the models.

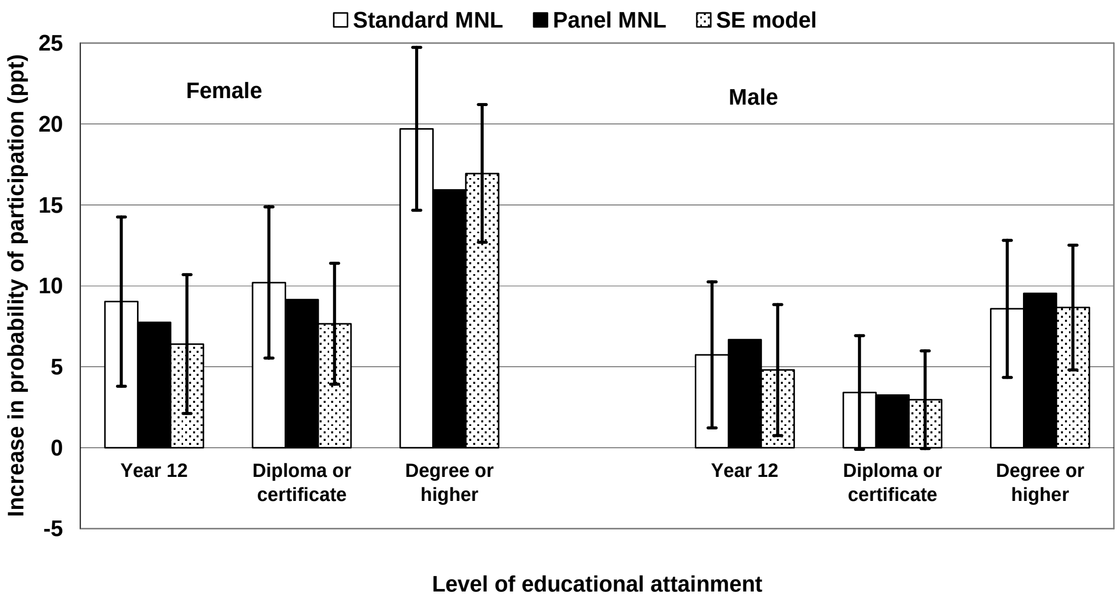
5.1 Impact of greater educational attainment on labour force participation

The estimated increase in the probability of labour force participation, if people with Year 11 or lower education were to increase their education above that level, is reported for the three models in figure 5.1.[13] An increase in educational attainment from Year 11 or lower increases the probability of participation significantly, except for the estimates for males who gain a diploma or a certificate. All marginal effects of education are of the expected sign.

[13] The probability of labour market participation ranges from 0, for an individual definitely not in the labour force, to 100 percentage points, for an individual definitely part of it. The participation increases in figure 5.1 only relate to the base level, Year 11 or lower.

Figure 5.1 **Marginal effects of greater educational attainment on labour force participation,[a,b] 2001–04**

Educational attainment relative to Year 11 or lower



a The bars show the 95 per cent confidence interval for the estimates for the standard multinomial logit model and the SE model (bootstrapped standard errors were used for the latter). If, for a given variable and gender, the bars of two marginal effects overlap, then those estimates are not statistically different at the 5 per cent level of confidence. If a confidence interval bar reaches the horizontal axis, that marginal effect is not significantly different from zero, at the 5 per cent level of confidence. Confidence interval bars are not provided for the panel multinomial logit model, as they cannot be estimated. **b** The marginal effects presented here are mean marginal effects, rather than marginal effects evaluated at the means.

Data source: Table C.5.

For both males and females, the largest effect is that associated with a degree or higher qualification. However, relative to Year 11 or lower (the comparator category), even completion of Year 12 results in a significant increase in the probability of participation. For example, in the SE model, females with Year 12 increase their estimated probability of labour force participation by around 6 percentage points (figure 5.1). To illustrate, for a female initially as likely to be in the labour force as not in it, an increase of 6 percentage points would add 12 per cent to her probability of participation ([50 + 6]/50).[14]

For a given educational level, the estimated increase in female participation is consistently higher than that of males, regardless of the model used. An example can put this gender differential into perspective. The average increase in

[14] In reality, the result may not be exactly 12 per cent, as the reported marginal effect (6 percentage points) represents the mean marginal effect for all persons in the sample.

participation for a female with a diploma or a certificate (9 percentage points) is the same as for a male with a degree or higher.

The amount by which the expected increase in female participation exceeds that of males can vary substantially, depending on the model used. For example, while males with a degree or higher are predicted to increase their probability of participation by 9 percentage points, females with a degree or higher increase their probability by over twice that amount (20 percentage points), according to the standard multinomial logit model estimate. The gender gap for degree or higher is also large according to the estimates from the SE model (9 percentage points for males, compared with 17 percentage points for females) and the panel multinomial logit model (10 percentage points for males, compared with 16 percentage points for females).

The estimates from the different models of the increase in the probability of participation within an education category vary more for females than males (figure 5.1). This is caused by the amount of inter-model variation for both females who gain a diploma or a certificate, and for those who gain a degree or higher.[15] For example, for females with a degree or higher, the standard multinomial logit model estimates the increase in the probability of participation at 20 percentage points. By contrast, the panel multinomial logit model estimates the increase at about three-quarters of that amount (16 percentage points). For males with a degree or higher, there is little variation between the three models. The overlap between the confidence interval estimates for the standard multinomial logit model and the SE model indicates that the differences in the education-effect estimates (by gender) of these two models are not statistically significant.[16]

By and large, results regarding the effects of education on labour force participation are consistent with those obtained by other researchers. Recent Australian studies have highlighted the large and significant impact of having degree or higher qualifications on participation (for example: Wilkins 2004; Dawkins et al. 2004; Zhang et al. 2006; Cai 2007). As in this study, authors who have looked at the impact of education by gender have found that it is larger for women than for men.

[15] The standard deviation of the three female ‘degree or higher’ estimates (2.0) and the three female ‘diploma or certificate’ estimates (1.3) are substantially higher than the equivalent male estimates (of 0.5 and 0.2).

[16] Standard errors and confidence intervals could not be calculated for the marginal effects produced by the panel multinomial logit. However, graphically, for each gender, the marginal effect estimates from that model could not be statistically different from those of the other models (figure 5.1).

One area of difference with some papers is in relation to the impact of diploma and certificate qualifications, relative to Year 12 completion. Both Wilkins (2004) and Zhang et al. (2006) find that having a vocational diploma or certificate has a larger impact on the participation of both men and women than having completed Year 12. Conversely, Cai (2007) finds the reverse to be true for both genders. Breusch and Gray (2004), finally, present results that accord with those of Cai for men, and with the other two studies for women. Results in this paper are similar to Breusch and Gray's, with diploma and certificate having a larger effect than Year 12 for women, and a lower one for men (figure 5.1).

The lower participation rate effect for men who improve their education from Year 11 or lower to a diploma or certificate, compared with those who improve it to Year 12, could arise from several sources. The discrepancy could arise from Year 12-equivalent qualifications, achieved as a part of a diploma or certificate, not being equivalent to Year 12 qualifications obtained from completing secondary schooling. The difference could also relate to a selection effect between those with Year 12-only qualifications and those with a diploma or certificate. That is, the two groups may have had different employment-related characteristics before the qualification was completed. The participation rate difference could also arise because people with TAFE qualifications are more specialised than Year 12 completers, and may receive fewer job offers. Finally, the discrepancy could arise as a result of differences in the classification of vocational diplomas and certificates between the studies.[17]

Finally, it is worth noting results pertaining to the interaction between education and health. If, as discussed in chapter 3, a higher level of educational attainment results in greater health awareness and better lifestyle, then education will have a positive effect on labour force participation via health. Through its simultaneous equations structure, the SE model is the only one of the three models that can distinguish such indirect effects of education.

In the self-assessed health equation of the SE model, almost all of the education coefficients are positive for each age and gender group estimated (table C.4). Thus, education generally has a positive effect on health. Importantly, the coefficients for degree or higher, and Year 12, are positive and significant at the 5 per cent level for all demographic groups, except older women. The education coefficients in the health equation are larger for males than females. However, education was shown

[17] In contrast to the other papers mentioned, the classification adopted by the International Standard Classification of Education is implemented in this paper. Under that classification, Certificate I and II qualifications are considered to be equivalent to Year 11 or lower education. Certificates III and IV are equated with above Year 12 education in the international nomenclature, and are therefore classified accordingly here, as 'diploma or certificate'.

above (figure 5.1) to have a larger impact on female than on male participation. Taken together, these results suggest that it is the direct effect of education on participation, not the indirect effect via health, that explains the larger increase in participation from increased education for females, compared with males.

5.2 Impact of improved health on labour force participation

The estimated marginal effects on the probability of labour force participation of the six health conditions identified in this study are reported in figure 5.2. These marginal effects are presented as positive values, to facilitate comparison with the education effects. Thus, the health effects may be thought of as ‘prevention’ effects, due to changes in behaviour or living conditions that prevent individuals from acquiring a health condition (Marmot 1994). Alternatively, they are also akin to health ‘treatment’ effects, as measures aimed at early detection and treatment, and improved methods of treatment, can also reduce the incidence of conditions (Productivity Commission 2006).[18] The health conditions modelled are: cancer; cardiovascular disease; mental or nervous condition; major injury; diabetes; and arthritis. For all three models, the prevention effects are of the expected sign. With a few exceptions, they are also significant (however, significance could not be calculated for the prevention effects of the panel multinomial logit).

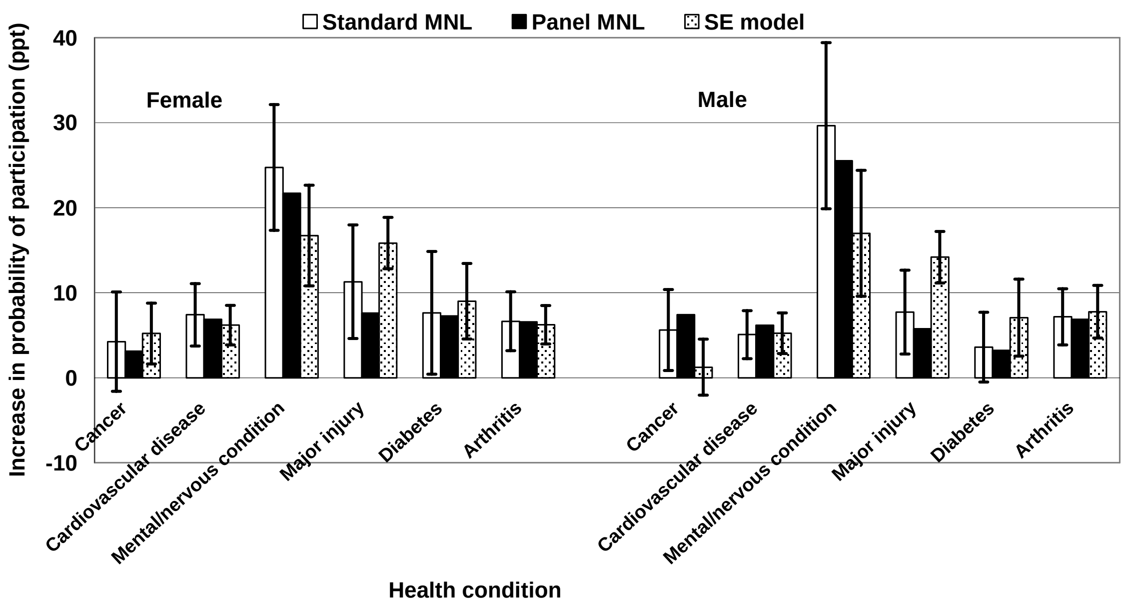
The marginal effects are largest for either males or females for whom a mental health or nervous condition is averted or successfully treated. The increase in the probability of participation for a male (female) is 26 (22) percentage points for the panel multinomial logit model, and 30 (25) percentage points for the standard multinomial logit model. For the SE model, the increases are somewhat smaller, at 17 percentage points for males and females.

The second largest marginal effects relate to the successful prevention of a major injury, except for the panel multinomial logit model for males. For the SE model, the estimated increase in the probability of participation following the successful prevention of a major injury is 14 percentage points for males and 16 percentage points for females.

18 Marginal effects are here referred to as prevention effects, rather than treatment effects, as many of the NRA suggested improvements in health (and education) relate to changes in behaviour, not to improvements in medical treatment. This analysis is not unusual. Marmot (1994), for example, attributes improvements in overall community health overwhelmingly to health-improving changes in societal behaviour and conditions, not to advances in medical treatment. The term ‘prevention effect’ here should therefore be read as including ‘detection effects’ and ‘treatment effects’.

The prevention effects of the remaining health conditions — cancer, cardiovascular disease, diabetes and arthritis — cannot easily be ranked as the gender-specific estimates for a condition can vary widely between the three models. For example, although cancer has the smallest marginal effect (1.2 percentage points) of all of the estimates for males, according to the SE model, the panel multinomial logit estimate of that effect is far higher (7.4 percentage points).

Figure 5.2 **Marginal effects of preventing selected health conditions on labour force participation,[a,b] 2001–04**



a The bars show the 95 per cent confidence interval for the estimates for the standard multinomial logit model and the SE model (bootstrapped standard errors were used for the latter). If, for a given variable and gender, the bars of two marginal effects overlap, then those estimates are not statistically different at the 5 per cent level of confidence. If a confidence interval bar reaches the horizontal axis, that marginal effect is not significantly different from zero, at the 5 per cent level of confidence. Confidence interval bars are not provided for the panel multinomial logit model, as they cannot be estimated. **b** The marginal effects presented here are mean marginal effects, rather than marginal effects evaluated at the means.

Data source: Table C.5.

Notwithstanding these differences in size, estimates from the standard multinomial model and the SE model cannot be distinguished statistically, for a given health variable and gender. As previously mentioned, confidence intervals from the panel multinomial logit could not be calculated. However, based on graphical analysis of the size of that model's marginal effects, it is clear that, with the possible exceptions of major injury (males and females) and cancer (males) in the SE model, they are not statistically different from those of the other models.

Whereas, for education, the average estimated increase in the probability of participation from further education is around twice as large for females, compared with males, there is little or no difference in participation between genders in terms of the successful prevention of a health condition. The average estimated male–female differential across models and conditions is less than 1 percentage point.

A limitation of the models is that the mortality rates associated with some health conditions have not been accounted for. For example, cancer, cardiovascular disease and major injury are associated with significant mortality rates (Productivity Commission 2006). The models in this paper are likely, therefore, to underestimate the marginal effect of successfully preventing those conditions, because they do not take any accompanying mortality reduction into account.

How do the health results compare with similar models?

As Zhang et al. (2006) have recently estimated the effect of health on labour force participation, the prevention effects presented above may be compared to theirs. Because these authors estimate the effects separately for younger and older males and females, the natural comparator in this paper is the SE model (table 5.1).

Table 5.1 **Comparison of health marginal effects with those of Zhang et al. (2006)[a,b]**

Gender	*Male*				*Female*			
Age group	18–49	15–49	50–65	50–64	18–49	15–49	50–65	50–62[c]
Author	Zhang	SE model	Zhang	SE model	Zhang	SE model	Zhang	SE model
Mental health	19.1	12.6	36.2	28.0	12.3	16.0	22.2	19.1
Diabetes	6.9	5.9	18.2	10.0	12.1	9.4	17.2	7.6
Heart disease	4.3	3.9	14.5	8.7	4.7	5.8	13.3	7.5

a Zhang et al.'s results are based on data from the 2001 and the 2004–05 Australian National Health Surveys. SE model results are based on the HILDA survey, 2001–04, release 4.1. **b** All SE model prevention effects are significant at the 95 per cent level of confidence. Zhang et al. do not report the level of significance level of their estimated prevention effects. **c** For women, the SE model dataset was limited to women aged 15 to 60 in 2001, increased to those aged 61 for 2002 and 2003, and to 62 for 2004.

Source: Zhang et al. (2006) and Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

Consistent with the contents of figure 5.2, Zhang et al.'s (2006) research indicates that the successful prevention of mental illness has the largest impact on labour force participation of the conditions modelled.[19] In order of decreasing prevention

[19] This review of Zhang et al.'s paper is based on a version of their paper presented at the Australian Health Economists Society Conference, held in September 2006. The authors have indicated that an updated version of their paper, which adds an 'all other chronic conditions' variable and equation, is being drafted.

effect, they find mental illness, diabetes and heart disease to have the largest effects.[20]

In the SE and the multinomial logit models, major injury is the health condition with the second largest prevention effect (figure 5.2). Zhang et al. do not model major injury, but the results in this paper suggest that, had it been included in their research, it may have displaced diabetes as the condition with the second largest prevention effect.

Overall, Zhang et al. find the health effects to be substantially larger for the older age groups than for the younger age groups, and largest for older males (table 5.1). This is paralleled in the SE model, except for the impact of diabetes on older women, which is lower than for younger women. That said, the prevention effects are generally smaller in the SE model than in Zhang et al.'s model, except for heart disease and mental health for younger females. The largest differences between the two sets of estimates occur for older females with diabetes, and for older males with either diabetes or a mental health condition.

In part, the differences in marginal effects between the two studies may relate to the use of different datasets, and to the imputation of the health variables in the present study. As a robustness check of the imputed health data used in this paper, the marginal effects from preventing health conditions in the SE model were re-estimated using unimputed, cross-sectional data.[21] This re-estimation of the marginal effects does not change the qualitative results. The ranking of conditions remains unchanged and the size of the marginal effects is very similar, except for major injury which is consistently larger in 2004 (in absolute terms) across all age and gender groups (results not shown).

5.3 Goodness of fit of the models

How well the estimated models 'fit' the same dataset is now investigated. Goodness of fit is a notoriously difficult concept to measure and caution needs to be exercised. Many different scalar measures of the overall fit of a model have been developed, to allow objective comparisons across models. Some of these indicators are presented in table 5.2. These measures complement, but do not replace, other forms of model

[20] Zhang et al. (2006) pool data from the 2001 and the 2004-05 Australian National Health Surveys to examine possible endogeneity between health and labour force participation.

[21] Cross-sectional marginal effects were calculated for 2003, and then for 2004, as the health variables were not imputed in 2003, except for major injury which was not imputed in 2004. See appendix A for details.

assessment, based on theory, and the sign and the magnitude of the estimated coefficients, and previous research in the area.

Table 5.2 **Goodness of fit indicators**[a]

	Standard MNL	*Panel MNL*	*SE model*
Females			
Count R-square	0.781	0.792	0.791
McFadden's R-square	0.184	0.282	na
AIC	29 808	26 290	51 270
BIC	30 449	27 023	51 583
LR test (ranking)	2	1	3
Log-likelihood	-14 820	-13 049	-25 594
n	15 232	15 232	15 232
Males			
Count R-square	0.895	0.896	0.902
McFadden's R-square	0.183	0.270	na
AIC	18 354	16 429	42 203
BIC	18 897	17 154	42 512
LR test (ranking)	2	1	3
Log-likelihood	-9 093	-8 119	-21 061
n	13 955	13 955	13 955

a *Count R-square* = proportion of all observations correctly predicted by the model to be 'in the labour force' or 'not in the labour force'. A higher value indicates a better fit. *McFadden's R-square* = 1 – (log-likelihood of full model/log-likelihood of constants only model). A higher value indicates a better fit. *AIC* = Akaike's Information Criterion (see Greene 2003). A lower value indicates a better fit. *BIC* = Bayesian Information Criterion (see Greene 2003). A lower value indicates a better fit. *LR test* = likelihood ratio test (see Greene 2003). Numbers in this row indicate the preference ranking of the models, as indicated by a series of LR tests (tests significant at the 1 per cent level). *Log-likelihood* = maximum value of the log-likelihood function resulting from estimation. *n* = number of observations used to estimate the model. **na** Not applicable.

Source: Productivity Commission estimates.

In table 5.2, measures of goodness of fit are compared across the three models, and for each gender. The first indicator — the count R-square — is included for completeness only. It is strongly influenced by the preponderance of one labour market state in the data ('in the labour force' in this case). In any event, the values by gender taken by this indicator are virtually indistinguishable between the three models.

The McFadden's R-square indicator measures, for each model viewed in isolation, the increase in the likelihood function over a model containing constants only. While this type of pseudo R-square value cannot strictly be interpreted as measuring goodness of fit, a higher value is considered preferable to a lower one (Greene

2003). As shown in table 5.2, the value of the McFadden's R-square is consistently higher for the panel multinomial logit than for the standard multinomial logit.[22]

The next two indicators — AIC and BIC — are information measures specifically designed to allow comparisons of nested and non-nested models.[23] They are calculated in such a way that a lower value indicates a better model fit. As table 5.2 illustrates, both the AIC and BIC measures point to the panel multinomial logit being preferred to the standard multinomial logit and to the SE model, in that order.

The LR test is a test of the significance of the difference in log-likelihood between any two models. Strictly, one of these models must be nested in the other, although some authors have suggested that the test can validly be used to compare non-nested models also (Harris and Zhao 2007). On the basis of repeated pairwise LR tests of the models, it is possible to conclude, at the 1 per cent level of significance, that the panel multinomial logit is superior to the standard multinomial logit, which is, in turn, superior to the SE model.

On the basis of the indicators in table 5.2, the panel multinomial logit appears to be the model with the best fit overall. However, some uncertainty remains given that one of the models is non-nested, and because the models differ in some respects. Moreover, goodness of fit is not, in itself, sufficient to establish the existence of endogeneity biases due to simultaneity or unobserved heterogeneity. Since taking into account these biases, when estimating marginal effects, is the central objective of this paper, the relevant evidence in support of endogeneity is now assessed.

5.4 Evidence of endogeneity due to simultaneity and rationalisation

The SE model allows for a feedback effect from labour force participation to self-assessed health. This is modelled using two (simultaneous) equations.[24] In the first equation, labour force participation is the dependent variable and self-assessed health is one of the explanatory variables (as is education). In the second equation, self-assessed health is the dependent variable and labour force participation is an explanatory variable (as are education and health conditions). The error terms in both equations are assumed to be correlated. This approach is more complex than a

[22] This indicator cannot be computed for the SE model.

[23] The two multinomial logit models are nested, which means that they are variants of the same general model. However, the SE model and the multinomial logit models are non-nested.

[24] For a more detailed explanation of the simultaneous equations model structure, see appendix B and Cai and Kalb (2006).

single equation model, which could be used if participation were not thought to affect self-assessed health. Therefore, testing whether or not there is endogeneity in the model will determine if the simultaneous equations specification is warranted.

Cai and Kalb (2006) apply a test of endogeneity to their model, which can be used in the SE model also. If self-assessed health is exogenous to labour force participation, both the coefficient on labour force participation in the health equation and the correlation coefficient between the error terms in each equation should be zero. Thus, a null hypothesis of exogeneity can be tested, by performing a Wald test on the joint significance of the labour force participation coefficient (in the self-assessed health equation) and the correlation coefficient between the error terms. These results are presented for the four different age and gender groups in table 5.3. All of the test statistics are significant at the 1 per cent level, meaning that the null hypothesis of exogeneity is rejected, and self-assessed health should be treated as an endogenous variable.

Table 5.3 **Wald-test results for exogeneity in the simultaneous equations model**

	Males 15–49	*Females 15–49*	*Males 50–64*	*Females 50–62*[a]
$\chi^2(2)$ value	74.09***	70.42***	77.06***	247.76***

a The female upper age limit ranges from 60 to 62, in accordance with changes in the female pension age between 2001 and 2004. ******* Significant at the 1 per cent level of confidence.

Source: Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

The Wald-test results provide evidence that endogeneity is present, but do not shed light on whether or not it is rationalisation endogeneity. For insight into this, it is necessary to look at individual coefficients, as 'rationalisation endogeneity of self-assessed health to labour force participation implies that in the health equation the coefficient on labour force participation would be positive' (Cai and Kalb 2004, p. 21).[25]

For younger males, the participation coefficient is negative and significant. This is consistent with results for younger men in Cai and Kalb (2006) and for all males in Cai (2007). From chapter 3 (and appendix B), the direction of the impact of 'true' endogeneity (due to simultaneity) is, a priori, ambiguous. That is, health can have a positive, negative or non-existent effect on health. In contrast, rationalisation

25 Rationalisation endogeneity is not the only possible explanation for a positive coefficient. Another explanation could be that labour force participation gives people the financial resources they need to achieve good health. In the estimation of the SE model, this possible effect is controlled for by including household income as a regressor of self-assessed health. Coefficient estimates for the income variable are positive and significant for each age and gender group (table C.4).

endogeneity always implies that labour force participation has a positive effect on health. Therefore, the negative estimate for younger males suggests that, if rationalisation does exist, it ‘must be small and outweighed by the negative effects resulting from the true endogeneity’ (Cai 2007, p. 23). From the literature review in chapter 2, factors consistent with a negative coefficient on participation in the health equation include work stress and burnout.

For older females, the coefficient on labour force participation is positive and significant, which suggests rationalisation endogeneity might be present. This result is consistent with Cai and Kalb (2006). Although rationalisation might be a cause of the positive coefficient for older females, it could also reflect positive ‘true’ endogeneity (due to simultaneity).

Finally, the labour force participation coefficients in the health equation for younger females and older males are positive, but not statistically significant. This could imply that, for these groups, there is no rationalisation endogeneity or, if there is, that it is offset by other factors.

That rationalisation endogeneity may affect some groups, and not others, may explain why the marginal effects obtained for the SE model are sometimes greater, and sometimes smaller, than those of the standard multinomial logit (figures 5.1 and 5.2). As explained in appendix B, rationalisation endogeneity is expected to bias the coefficients of the health conditions and education downward. This appears to be the case with education in the SE model, compared with the standard multinomial logit model, especially for women. Regarding health conditions, it is not possible to generalise.

5.5 Evidence of endogeneity due to unobserved heterogeneity

Econometric results are now analysed for any evidence of unobserved individual heterogeneity. First, a comparison of marginal effects from the two multinomial logit models shows that, for females, effects from the panel multinomial logit are always smaller than those from the standard multinomial logit (figures 5.1 and 5.2). As discussed in appendix B, this difference is consistent with the existence of unobserved heterogeneity.[26]

For males, the gap between the two multinomial logits is not uniform, ranging from positive to negative. However, it may be argued that unobserved heterogeneity is

[26] In situations where the unobserved variable (for example, motivation) is positively related to both the dependent and independent variables, which is likely to be true here.

more likely to affect the labour force participation decision of females, since most males are in the labour force to begin with.

A second test of unobserved heterogeneity is whether the hypothesis of random constant terms in the panel multinomial logit is supported. This is assessed by inspection of the level of significance of the standard deviations of the intercepts in the panel multinomial logit. These deviations are estimated jointly with all other coefficients of the model, and will be significant if the model's individual-specific intercepts are consistent with a random draw from a normal distribution (that is, random effects). Results from the panel multinomial logit show the estimated standard deviations of the random constant terms to be highly significant, for both men and women (see appendix table C.2). Therefore, the results are consistent with the hypothesis of unobserved heterogeneity.

Finally, it is desirable to gauge whether estimating a standard multinomial logit would violate the IIA assumption. This assumption holds if the constant terms in the equations of the multinomial logit model are uncorrelated. Results for the panel multinomial logit indicate that these terms are highly correlated for males (see table C.3). This suggests that the standard multinomial logit model is inappropriate for the male sample.[27]

On balance, the results above support the hypothesis of unobserved heterogeneity in the data, especially for females. This is consistent with Cai's (2007) results. Unobserved heterogeneity means that the coefficients from the standard multinomial logit model are likely to be biased upward (see appendix B). Therefore, a panel data model will outperform a cross-sectional model in the estimation of the probability of choosing between the various labour market states modelled here.

However, it is not possible to conclude that, among panel data models, random effects are the best option for taking account of individual heterogeneity. The underlying assumption that individual effects are uncorrelated with any of the model's explanatory variables is difficult to accept intuitively when modelling labour force participation. It would be desirable to test whether fixed effects offer a more efficient panel data alternative for modelling participation. Unfortunately, a model capable of fitting a panel multinomial logit with fixed effects is not yet available.

27 Interestingly, the Small and Hsiao test for IIA in the standard multinomial logit model rejects the independence assumption for both males and females, in terms of full-time and part-time employment. That is, the odds of either gender choosing full-time employment over staying out of the labour force (the base category) are affected by the inclusion of part-time employment as a possible outcome. That this should be the case for males is unexpected.

6 Conclusion

This paper has examined the impact of endogeneity bias on the relationship between labour force participation and selected human capital variables. This research question stems from the growing interest of economic policy makers and researchers in the potential for better health and education to meet some of the economic challenges created by population ageing. Policy makers reason that, by preventing the occurrence of health conditions, and by promoting better education and training, greater incentives to work may be created, thus alleviating the predicted decline in labour force participation due to the ageing of the population.

As mentioned in chapter 1, this is the rationale that underlies part of the human capital stream of COAG's National Reform Agenda (NRA). In its assessment of the economic and fiscal impacts of that stream, the Productivity Commission (2006) found it useful to supplement published estimates of the effects of health and education on labour force participation with its own quantitative analysis. This paper forms one output from this ongoing research, and seeks to inform and strengthen the policy evaluation process.

6.1 Impact of endogeneity

In recent times, several researchers have investigated the effects of one or more forms of endogeneity on aspects of the human capital–labour market outcomes link in Australia (Cai 2007; Cai and Kalb 2006; Zhang et al. 2006; Klein and Vella 2006). This paper adds to this growing body of research in several ways. By benchmarking alternative models of labour force participation, by using up-to-date data, and by exploiting longitudinal data, it is able to identify the existence of endogeneity bias, control for it, and, hence, provide improved estimates of the relationships of interest. In the process, some technical innovations are introduced that may appeal to other researchers in the field, such as the construction of detailed health condition variables for each wave of the HILDA survey.

From the analyses presented in preceding chapters, a number of observations are possible. First, the modelling results in this paper confirm that human capital embodied in health and education has the potential to lift the rate of labour force participation, by a substantial amount in some cases. The magnitude of the predicted effects varies according to the human capital variable considered, the model used and the demographic group targeted. In the health area, the modelling corroborates the results of other studies, by showing that the largest impact is obtained following the successful prevention of a mental health or nervous condition. Such intervention is predicted to raise the probability of labour force participation, of both men and women who would have experienced that condition, by between 17 and 26 percentage points in the two preferred models (figure 5.2).

With respect to education, a bachelor’s degree or higher is the level of educational attainment which, relative to completion of Year 11 or lower, results in the greatest boost to the probability of participation (figure 5.1). However, the effect on female participation (of around 17 percentage points in the preferred models) is consistently larger than for males (around 9 percentage points).

Overall, the importance of good mental health and a university education for labour force participation, detected here, is consistent with the results obtained by other researchers.

A second conclusion from the research presented in this paper is that it is essential to control for unobserved heterogeneity when modelling the relationship between human capital and labour force participation. That is, it is important to allow for the existence of unobserved characteristics that simultaneously influence education or health status, on the one hand, and labour force status, on the other. This appears to be especially true for women. Compared with men, the propensity of women to participate is lower and more variable. Therefore, it is likely that, other factors being equal, women with certain traits (for example, innate ability or motivation) are primarily drawn into the labour force because of the wage premium these traits command. Conversely, women whose (unobserved) preferences lie toward unpaid work tend to participate less frequently than their observed characteristics would suggest.

Failure to account for heterogeneity in the data will result in the overestimation of the importance of measurable human capital attributes for labour force participation. By implication, it may also result in overly optimistic predictions of the scope for human capital policies to alleviate the participation effects of population ageing.

A third conclusion reached in this paper is that the relationship between health and labour force participation is one of joint determination. That is, a person’s overall health status both influences, and is influenced by, labour force participation. Many possible reasons for this exist, which do not rely on health status being invoked ex-post to ‘justify’ a non-participation decision. Ignoring simultaneity and treating all health variables as exogenous will result in biased estimates of the effects of health on participation. Unfortunately, it is not possible to predict the direction of that bias with any certainty, so that earlier published estimates cannot be adjusted accordingly (for example, by treating them as upper or lower bound estimates).

Finally, the paper provides evidence of some rationalisation endogeneity occurring when subjective health measures are used. This form of endogeneity arises when self-assessed health status is used to ‘justify’ a prior labour force participation decision. Results presented here accord with those of Cai and Kalb (2006) in suggesting that such behaviour is not likely to significantly bias the analysis of the health–participation relationship, except perhaps in the case of older women.[28] While rationalisation endogeneity cannot conclusively be ruled out for the other age and gender groups, any influence it may have on them appears to be offset by other factors. Nonetheless, the possibility of rationalisation endogeneity bias should be borne in mind by researchers using subjective health measures, as its effects cannot be corrected.

6.2 Policy implications

To have the desired impact on labour force participation, health and education policies aimed at raising human capital should be based on accurate projections of their likely effects. Not accounting for the existence of endogeneity bias in the measurement of these effects may result in erroneous estimates of the relationships of interest being selected. This, in turn, may lead to sub-optimal policies being adopted.

Conceivably, policy makers may guard against selecting the wrong marginal effects with which to assess the labour force participation effects of proposed measures. To that end, a number of strategies are possible; they include:

- Erring on the side of caution by consistently selecting the *lowest* published marginal effect associated with each variable of interest. This conservative strategy would ensure that a comparison of policy benefits and costs provides a lower bound estimate of expected net benefits.
- Undertaking sensitivity testing, using the marginal effect estimates available from various sources. If sufficiently broad, this approach may be able to provide policy makers with a sufficient degree of confidence in the range of effects that may be expected from a particular policy variable.
- Conducting a systematic analysis of previously published research about a marginal effect of interest. Techniques such as meta-regression analysis provide

[28] Cai (2007), who does not distinguish between different age groups, finds that rationalisation endogeneity may be present for women, but not for men.

a formal means of abstracting from inevitable differences in methodology, dataset, regressors, etc., to obtain the 'true' value of the relevant marginal effect.

However, all of these potential strategies for dealing with the multiplicity of published estimates involve a risk of adopting an erroneous estimate as the 'best bet'. Moreover, it may be argued that such simplifying approaches cannot replace a thorough understanding of the technical and theoretical reasons for preferring one estimate to another.[29]

Implications for the projected effects of the National Reform Agenda

As an illustration of the dilemma facing policy makers, it is instructive to examine what the implications for the effects of NRA, as assessed by the Productivity Commission (2006), are of the results from the two preferred models presented in this paper. Because these results were only finalised after publication of the Commission's *Potential Benefits of the National Reform Agenda* report (2006), the marginal effects estimates underlying that report differ somewhat from those presented in chapter 5. This means, in turn, that some labour market projections contained in the NRA report differ from those that would apply if this paper's preferred models were used instead (table 6.1).

Table 6.1 **Comparison of labour market projections in NRA and in this paper**

Deviations from base 2030 values

	Units	*NRA*	*SE Model*	*Panel MNL*
Labour force participation	ppt	4.9	4.6	4.6
Unemployment rate	ppt	-0.6	-0.6	-0.6
Average hours worked	hours	-0.7	-0.7	-0.7
Labour productivity – Additional participants[a]	%	-0.6	-0.5	-0.5
Labour productivity – Overall	%	1.3	1.4	1.4
Effective labour supply	%	8.0	7.6	7.6

[a] 'Additional participants' refers to the people who (re)join the labour force as a result of NRA policies.

Source: Productivity Commission (2006) and Productivity Commission estimates.

A key result from comparing the Commission's NRA projections with those implied in this paper occurs in the area of labour force participation: the projected increase in participation implied in this paper is 0.3 percentage points lower than that assumed in the NRA report (4.6 instead of 4.9, that is 6.1 per cent lower). This discrepancy is muted because, although some marginal effects estimates presented

[29] Even when, as happens in this paper, the competing estimates are indistinguishable statistically.

in this paper are lower than the corresponding estimates used in the NRA report, others are higher (not shown).

The impact on overall labour force participation generated by the two preferred models is identical. However, this result is due to inter-model differences in individual effects cancelling each other out, not to the individual effects of each model being equivalent.

A smaller increase in participation than projected in the NRA report has flow-on repercussions on some other components of effective labour supply, such as overall labour productivity, which is higher than calculated in the NRA report.[30]

Lower overall participation than assumed in the NRA report, and higher overall labour productivity, partly offset each other, so that the overall effect of the new estimates on the projected increase in the effective supply of labour is small (5 per cent lower than that projected in the NRA report). This result suggests that the broad conclusions reached in the Commission's NRA report regarding macroeconomic aggregates would be unlikely to change significantly, were this paper's estimates substituted for those used in the report.

Nonetheless, it may be preferable for future cost–benefit analyses to use this paper's estimates of the effects of health and education. This would be especially warranted if such analyses focussed on, say, policies to reduce the prevalence of a single health condition. Although substituting this paper's estimates for those used in the NRA report makes little or no difference to broad labour market and (most likely) macroeconomic aggregates, the same cannot be said about detailed analyses. For specific conditions, such as cardiovascular disease, this paper's estimates differ measurably from those used in the NRA report. Such differences are capable of significantly altering the outcome of an analysis of the net benefits of reducing the prevalence of a specific disease.

That said, future cost–benefit analyses should also recognise that the estimates contained in this paper pertain to a particular time period. They may not apply in future when, for example, the institutional framework and the population structure may be different from what they are today. In that event, the methodological approach would remain valid, but numbers would inevitably change.

30 People (re)joining the labour force ('additional participants') are assumed to have lower labour productivity levels than people already in the labour force ('baseline participants'). As this paper's results imply fewer additional participants than assumed in the NRA report, the projected overall labour productivity increase is greater.

Which estimate?

Problems remain, for cost–benefit analyses, when two sets of 'preferred' estimates are available, both of which are theoretically sound in the context of a particular form of endogeneity bias. This is the case in this paper, in which different models are used to control for unobserved heterogeneity and simultaneity biases. If both types of bias were known to be of the same sign, it would be possible to state unequivocally that estimates from any uncorrected model are likely to be too high or too low. One of the two preferred models may then be used confidently as a conservative estimate. Unfortunately, this is not the case here: unobserved heterogeneity bias is uniformly upward, but simultaneity bias may be upward or downward. To complicate matters further, rationalisation endogeneity may be biasing simultaneity-corrected estimates downward (see appendix B).

These complexities notwithstanding, it is possible to propose a practical decision rule for choosing estimates, based on the knowledge that:

- unobserved heterogeneity biases the standard multinomial logit model upward;
- simultaneity bias is shown to affect all estimates; and
- rationalisation endogeneity may be a significant factor for some age and gender groups.

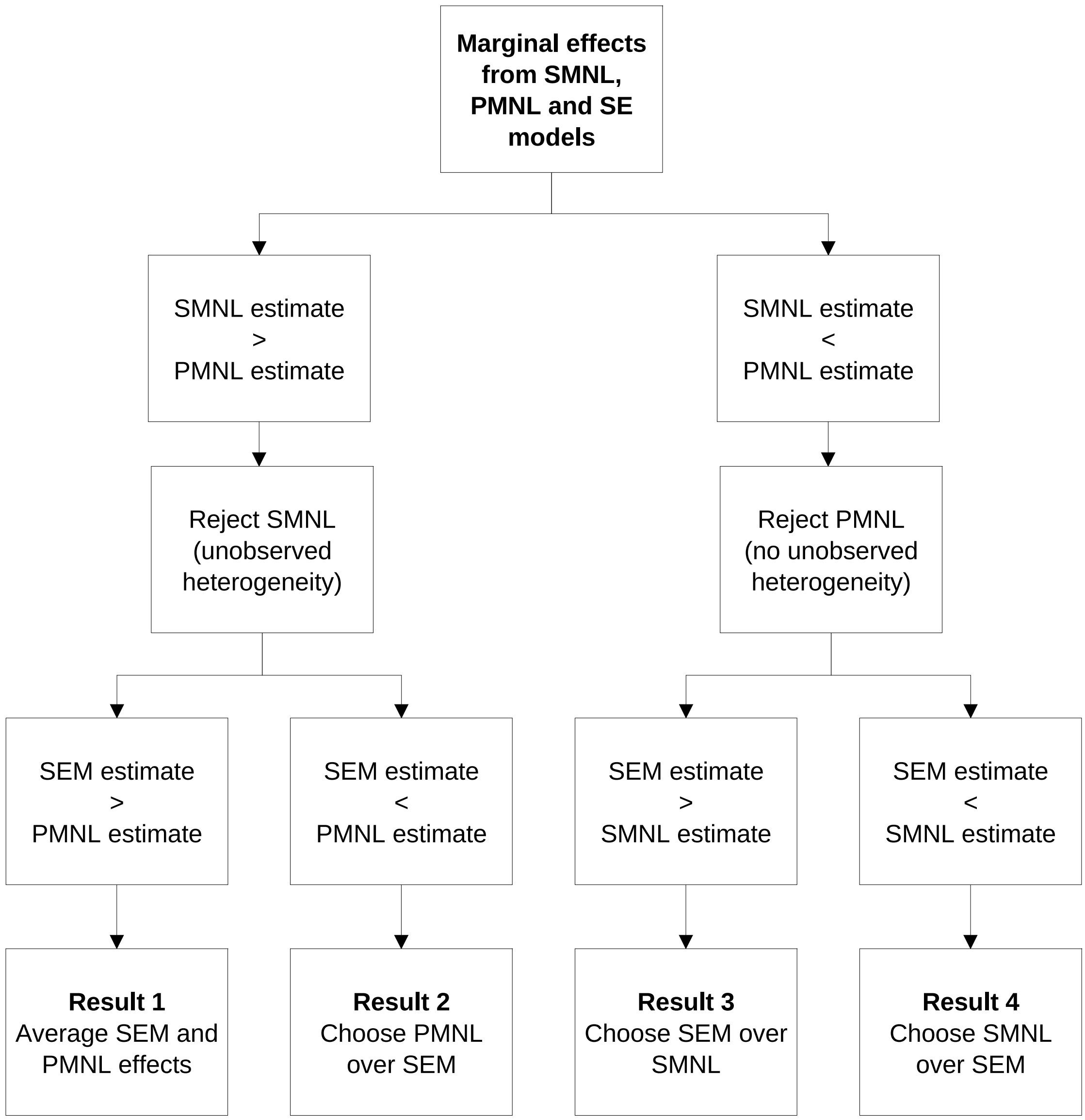
The decision rule is illustrated in figure 6.1. The operation of the rule can be summarised as follows:

- *Result 1*: if the standard MNL (SMNL) estimate is greater than the panel MNL (PMNL) estimate, unobserved heterogeneity is likely and the SMNL estimate should be rejected. If the simultaneous equations model (SEM) estimate is greater than the PMNL estimate, it is a valid estimate, even in the presence of rationalisation endogeneity (in which case the 'true' SEM estimate would be even higher). However, there is no way of choosing between the SEM and PMNL estimates, so the two should be averaged.
- *Result 2*: the SMNL estimate is again rejected because of the likelihood of unobserved heterogeneity. If the SEM estimate is smaller than the PMNL one, the PMNL estimate should be chosen as a conservative estimate, because the SEM estimate may be biased downward by rationalisation endogeneity (the 'true' SEM estimate may be higher than the PMNL estimate, so it would not make sense to average the PMNL estimate and the biased SEM estimate).
- *Result 3*: if the SMNL estimate is lower than the PMNL estimate, unobserved heterogeneity is unlikely and the PMNL estimate should be rejected. If the SEM estimate exceeds the SMNL one, then the SEM estimate should be chosen

because, even allowing for rationalisation endogeneity, it is simultaneity corrected, and hence necessarily better than the SMNL estimate.

- *Result 4*: the PMNL estimate is again rejected because of the absence of unobserved heterogeneity. If the SEM estimate is lower than the SMNL one, then the SMNL estimate should be chosen, because the SEM estimate could be biased downward by rationalisation endogeneity (thus, the true SEM estimate could lie higher than the SMNL estimate).

Figure 6.1 **Possible decision rule for selecting marginal effects**[a]



[a] **SMNL**: standard multinomial logit model. **PMNL**: panel multinomial logit model. **SEM**: simultaneous equations model.

To illustrate, the application of this decision rule would result in PMNL or SEM estimates (or an average of both) being preferred for 16 out of the 18 marginal effects estimated in this paper (table C.5). Only in two cases would an SMNL estimate be selected. That said, although the rule makes it more likely that an unbiased or, at least, a conservative estimate of a particular marginal effect is selected, it cannot guarantee that this will always be the case.

6.3 Future research directions

The research contained in this study has illustrated the difficulty in obtaining accurate measures of the impact of health and education on labour force participation. Even though simple models of these relationships are likely to conclude correctly that health and education are positively associated with labour force participation, endogeneity bias means that these models are unlikely to yield correct estimates of the relevant marginal effects. Accordingly, a methodological approach was designed that could address some possible sources of endogeneity bias in the estimation of the relationships of interest. Results support the hypothesised existence of both unobserved heterogeneity and simultaneity. The marginal effect estimates reported here may, therefore, be less open to criticism on those two grounds.

These advances notwithstanding, room remains for improvement in a number of areas. First, it would be desirable to attempt fixed effects panel data modelling of labour force participation, to allow for the possible correlation of unobserved characteristics, labour force status and human capital characteristics. As random effects assume away such correlation, they are more difficult to justify in the present context.

Second, it would be preferable not to have to impute health variables in some years of the HILDA survey. Even though robustness checks undertaken for this paper indicate that imputation is unlikely to have altered qualitative results, it nonetheless leaves room for some uncertainty.

Third, a more realistic picture could be provided of the differences in participation between persons with and without certain health conditions or educational qualifications. Two examples can illustrate this point:

- Having a particular health condition increases a person’s likelihood of also having another condition. This phenomenon is known as ‘co-morbidity’. For instance, Zhang et al. (2006) report that, compared with its prevalence in the general population, heart disease is twice as prevalent among diabetes sufferers. This implies that labour force participation by this group is likely to be even more limited than the marginal effect of diabetes alone would imply.

- People with higher qualifications tend to experience better health, compared to people with lower qualifications. Yet, the marginal effects of education presented in this paper assume all else equal, including the existence or absence of health conditions. A more telling approach might be to compare the labour supply behaviour of, say, a 'typical' degree educated woman with that of a 'typical' Year 12 educated woman, once education-related differences in health and other characteristics are taken into account.

While such detailed scenarios were outside the scope of this paper, they could readily be investigated using the models contained herein.

Finally, the addition of an education equation to the SE model might allow a better understanding of the interaction between health and education, in terms of how they both affect labour force participation and each other. Specifically, that third equation might shed light on whether health status influences educational attainment (for some or all age groups), or whether they are both determined by the same unobserved variables.

A Variable construction and descriptive statistics

The variables used in the estimation of the three models are based on the first four waves of the HILDA survey data, covering the period 2001–04. This appendix explains the construction of the health and education variables, and provides some descriptive statistics of the estimation sample.

A.1 Variable construction

Using data from waves 1 to 4 of the HILDA survey, and after dropping some observations, there are around 30 000 observations in the estimation sample. Observations dropped include people under 18 who are still at school, full-time students, people who have reached pensionable age, and incomplete responses. (For example, respondents who did not return the self-completion questionnaire or did not complete relevant questions).

Construction of health variables

Data on the incidence of specific illnesses (except major injury) are only available from wave 3 of HILDA. However, if the person was interviewed in wave 3, it is sometimes possible to infer data for that person in other waves. In wave 3 of HILDA only, there is a self-completion questionnaire containing questions about specific, diagnosed health conditions. In addition, there is another questionnaire for that year which asks whether or not a person has any long-term health condition, and in which year it first developed. In wave 4, there is a question asking if a person has a long-term health condition only. With responses to these questions from waves 3 and 4, it is possible to impute specific health conditions for persons observed in each year of HILDA. The details of how this was done are set out below.

Cardiovascular disease, diabetes, cancer and arthritis

In the self-completion questionnaire of wave 3 only, respondents are asked whether or not they have been diagnosed with cardiovascular disease, diabetes, cancer or arthritis, and in which year they were first diagnosed. To illustrate how the variables for these conditions were constructed, arthritis is used as an example. A person who responded 'yes' to having arthritis in 2003 is reported as having arthritis in that year. Then, the more general question relating to what year the person's condition first developed is used to impute a person's health status in earlier years. For example, if the person said the year he or she developed a health condition was 2003, it is assumed that the person did not have arthritis in wave 1 (2001) or wave 2 (2002). Alternatively, if the person said the year of developing a health condition was 2002, that person is flagged as not having arthritis in wave 1, but as having arthritis in waves 2 and 3.

The above example assumes the person only has one diagnosed health condition. Problems can arise for people who report more than one specific health condition in the self-completion questionnaire of wave 3. This is because the other survey question, relating to the year a person's condition first developed, does not specify what the condition is. It only asks whether any health condition is present, including, for example, arthritis, asthma or heart disease. So, for example, a person may report having arthritis and cancer in the self-completion questionnaire from wave 3. When imputing the health status of this person, he or she is assumed to have arthritis *and* cancer in 2002, if the person said the year the health condition first developed was in 2002. However, that person may have actually developed arthritis in 2003, but developed cancer in 2002. The health variables potentially affected in this way are: cardiovascular disease, diabetes, cancer and arthritis. The other two health variables are generated from different survey questions (see below). Nevertheless, from an inspection of the data for people with multiple conditions, such potential anomalies are likely to be few.

To impute specific health conditions in 2004, the question asking if a person has any long-term health condition is used. If a respondent said 'no' to having any type of long-term health condition in wave 4, then it is assumed that he or she had no specific health condition for 2004. However, if the person said 'yes' to having a long-term health condition, it is assumed that this person still had all of the specific health conditions that were reported in wave 3. Note again that errors may arise using this approach, because it assumes that a person reporting multiple health conditions in 2003, and a long-term health condition in 2004, still has the multiple conditions in 2004. Also, if a person has a long-term health condition in 2004, but reports no specific health condition in wave 3, it is impossible to determine which, if any, of those conditions used in the modelling the person might have in 2004. As such, it is assumed that the person does not have any of the specific health conditions used in the analysis.

Mental illness or nervous condition

Wave 3 of HILDA has a question asking whether or not a person has a mental illness which requires help, or a nervous (or emotional) condition requiring treatment. In the wave 3 survey, people who responded ‘yes’ to having either of these conditions also reported the year in which they first developed it. The questions were repeated in wave 4.[31] As a result, the mental/nervous condition variable can be more accurately constructed for each year than for the other health condition variables.

Major injury

In waves 2, 3 and 4, the HILDA self-completion questionnaire has a question asking if a person has sustained a serious personal injury or illness in the past 12 months. In wave 4 only, there is a question asking if a person has been a patient in hospital overnight during the past 12 months.

People who responded ‘yes’ to both the injury/illness *and* hospital stay questions in wave 4, are regarded as having a serious injury in wave 4.[32] Responses are imputed for other waves by assuming that the proportion of people going to hospital because of injuring themselves was the same as in 2004. Because data on the number of people sustaining an injury were available in waves 2 and 3, an estimate for the number of people with a major injury can be calculated. However, it is impossible to determine which of the people who had sustained an injury in the past 12 months would also be likely to have had a major injury. Therefore, each person who had an injury is given the same value, the probability of having a major injury. This

[31] The year it first developed was not asked in wave 4. However, as it was asked in wave 3, the date it was first diagnosed can be accurately inferred for people who responded to both the wave 3 and wave 4 surveys.

[32] The wording of the HILDA self-completion questionnaire question on injury/illness (B16f) means that people who answered it in the affirmative may have been reporting an injury or an illness, or both. Using this variable may, therefore, introduce bias into the measurement of the effects of injury alone. Sensitivity testing was conducted, which assumed that people who, in a given year, reported one of the five health conditions identified in the paper and answered ‘yes’ to question B16f were ill, not injured. Test results suggest that this scenario does not lead to a consistent or large bias in the marginal effects of injury computed in this paper. Unfortunately, due to data limitations, the sensitivity testing could not investigate the effects of respondents to question B16f reporting an illness other than the five identified in this paper, or reporting an illness and an injury.

probability (0.485) is the proportion of people in wave 4 who sustained an injury and also went to hospital. In contrast, for wave 4, each person either had a value of 1 for major injury or 0 otherwise. For wave 1, *every* person is assigned the same probability value (averaged across waves 2–4) of having a major injury. Note that because, in waves 1, 2 and 3, the same proportional estimate is used for many individuals, incorrect standard errors may be obtained for coefficient estimates of the major injury variable.[33]

Definition of education variables

To model the effects of education, four aggregated levels of highest educational attainment are used: degree or higher; diploma or certificate; Year 12; and Year 11 or lower. In the HILDA survey, there are 10 possible levels of highest attainment a person can report. These levels are listed in table A.1 and the corresponding education category used in the modelling is listed next to them. Note that Year 11 or lower is the benchmark from which the effects of the other three categories of highest education level are estimated and compared. As such, Year 11 or lower does not appear in the modelling results.

Table A.1 **Education variables used in the modelling**

HILDA survey response	*Aggregated education level*
Postgraduate degree (Masters or doctorate)	Degree or higher
Graduate diploma, graduate certificate	Degree or higher
Bachelor degree	Degree or higher
Advanced diploma, diploma	Diploma/Certificate
Certificate III or IV	Diploma/Certificate
Certificate I or II	Year 11 or lower
Certificate not defined	Year 11 or lower
Year 12	Year 12
Year 11 and below	Year 11 or lower
Undetermined	Observation dropped[a]

[a] Observations were also dropped if the answer was incomplete.

Source: Based on the HILDA survey, 2001–04, release 4.1.

A.2 Descriptive statistics

The mean, standard deviation and definition of all variables used in the three

[33] To check the robustness of the standard errors of this variable, the model was also estimated using 2004 data only. The standard errors were of similar magnitude when using 2004 data and 2001–04 data.

models are presented in table A.2. Most variables are binary (have the value 1 or 0), with exceptions noted in the table. There are some variables in the SE model which are not used in the multinomial logit models, and vice versa. In table A.2, the column ‘Model’ indicates which model(s) the corresponding variable is used in.

Table A.2 **Variable definition and descriptive statistics,[a] 2001–04**

Variable	*Definition*	*Model*[b]	*Mean*	*Std Dev.*
	Dependent variables			
Labour force	– 1=employed full-time, 2=employed part-time, 3=unemployed, 4=not in labour force	AB	1.90	1.19
	– 1 if in labour force, 0 if not in labour force	CD	0.79	0.41
Self-assessed health	0=poor, 1=fair, 2=good, 3=very good, 4=excellent	CD	2.46	0.96
	Independent variables[c]			
Demographic				
Age[d]	Age deviation from base age (15 or 50)	CD	16.49	9.96
Age squared[d]	Age deviation squared	CD	371.29	349.21
Age1524	1 if aged 15 to 24, 0 otherwise	AB	0.11	0.31
Age50plus	1 if aged 50 or over	AB	0.26	0.44
Married	1 if married or de facto	ABCD	0.67	0.47
Children04	Count of own resident children aged 0-4 yrs	ABC	0.22	0.54
Children514	Count of own resident children aged 5-14 yrs	ABC	0.49	0.89
Children014[e]	Count of own resident children aged 0-14 yrs	C	0.71	1.07
Children1524	Count of own resident children aged 15-24 yrs	ABC	0.25	0.60
Indigenous	1 if indigenous or Torres Strait Islander	ABCD	0.02	0.14
NESB	1 if country of birth is non-English speaking	ABC	0.12	0.33
Region	1 if does not live in major city	ABCD	0.40	0.49
Education				
Degree or higher	1 if bachelor degree or higher	ABCD	0.22	0.42
Year 12	1 if completed Year 12	ABCD	0.14	0.35
Diploma/Certificate	1 if diploma or certificate	ABCD	0.30	0.46
Health				
Cardiovascular disease	1 if heart/coronary disease; or high blood pressure/hypertension; or other circulatory condition	ABD	0.14	0.34
Diabetes	1 if diabetes	ABD	0.03	0.18
Cancer	1 if any type of cancer	ABD	0.03	0.17
Mental/nervous	1 if nervous or emotional condition requiring treatment; or mental illness requiring help	ABD	0.03	0.18
Arthritis	1 if arthritis	ABD	0.15	0.35
Major injury	1 if had injury and attended hospital	ABD	0.04	0.13
Employment history				
Experience[f]	Years in paid work (since leaving school)	ABCD	18.70	12.07

(Continued next page)

Table A.2 (continued)

Variable	*Definition*	*Model*[b]	*Mean*	*Std Dev.*
Experience squared	Experience squared	ABCD	495.15	523.89
Unemployment history[g]	Proportion of time (since leaving school) in unemployment	ACD	0.03	0.10
Household disposable income	Weekly household disposable income ($'000)	D	1.16	0.82
Interactive variables				
Degree x age1524	Interaction between Degree and age1524	AB	0.01	0.12
Diploma/Certificate x age1524	Interaction between Diploma/Certificate and age1524	AB	0.03	0.16
Year 12 x age1524	Interaction between Year 12 and age1524	AB	0.03	0.18
Degree x age50plus	Interaction between Degree and age50plus	AB	0.05	0.21
Diploma/Certificate x age50plus	Interaction between Diploma/Certificate and age50plus	AB	0.07	0.26
Year 12 x age50plus	Interaction between Year 12 and age50plus	AB	0.02	0.15
Wave identifiers				
Wave 2	1 if wave 2 observation	B	0.25	0.43
Wave 3	1 if wave 3 observation	B	0.25	0.43
Wave 4	1 if wave 4 observation	B	0.24	0.43

a Reported means and standard deviations are unweighted. **b** A: standard multinomial logit model; B: panel multinomial logit model; C: SE model (labour force equation); D: SE model (self-assessed health equation). **c** For binary or categorical independent variables (for example, NESB or education), the omitted category is not listed. The omitted categories are, in the same variable order as in the table: aged 25 to 49; non-Indigenous; born in Australia or in an English-speaking country; living in a metropolitan centre; Year 11 or lower education; does not have the health condition; surveyed in 2001 (wave 1). **d** Age and Age squared are left out of the C and D models for older men, to facilitate convergence. **e** Children014 is only used for older age groups. For these age groups, there are insufficient observations to be able to disaggregate the total number of children under 14 years into separate groups of children aged 4 and under, and children aged between 5-14. **f** In the panel multinomial logit (model B), the 'experience' variable is rescaled (divided by 100), to facilitate convergence. **g** This variable is left out of the panel multinomial logit model, to facilitate convergence.

Source: Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

B Direction of endogeneity bias

B.1 Endogeneity bias in the presence of unobserved heterogeneity

The discussion below, based on Wooldridge (2006), summarises the effects of unobserved heterogeneity on the estimated coefficient for education in a model of labour force participation. The same conclusions would be reached in relation to the coefficient for health, provided the omitted variable (in this example, motivation) was positively associated with both health and labour force participation.

Assume the following model of labour force participation:

$$l = \alpha + \gamma Ed + \lambda H + \psi M + \varepsilon \tag{B.1}$$

where l = a latent variable measuring the propensity to participate in the labour force

α = a constant

Ed = a single education variable

H = a single health variable

M = a person's level of motivation

ε = error term

If M does not influence l, so that ψ is zero, or if M is uncorrelated with Ed and H, then the omission of M from equation (B.1) does not bias the coefficients on Ed and H (γ and λ, respectively). Further, neither Ed nor H are correlated with ε, meaning that they are not affected by endogeneity.

Assume now that a person's motivation does influence both labour force participation l and educational attainment Ed. Assume also that Ed and H are uncorrelated.

If the motivation variable is omitted, the estimated equation becomes:

$$l = \tilde{\alpha} + \tilde{\gamma} Ed + \tilde{\lambda} H + v \quad \text{(B.2)}$$

where $v = \psi M + \varepsilon$

the tilde (~) sign denotes an estimator biased by the omission of M from the equation

Unlike the expected value of the estimated coefficient on education in equation (B.1), the expected value of $\tilde{\gamma}$ in equation (B.2) will be different from the true value of γ. This is due to endogeneity bias, meaning that the values of v and Ed in equation (B.2) are not independent. The difference between $E(\gamma)$ and $E(\tilde{\gamma})$ is the amount of bias, B, due to the omission of M from the estimation, and equal to:

$$B = \psi \tilde{\omega} \quad \text{(B.3)}$$

where $\tilde{\omega}$ = estimated slope coefficient of the regression of M on Ed (unknown).

B is a form of endogeneity bias known as *omitted variable bias*. If M is assumed to be an individual, time-constant variable M_i, then B is a special case of omitted variable bias, known as (unobserved) *heterogeneity bias*. In the absence of information on M, this type of bias affects the estimation of equation (B.1) using cross-sectional data or pooled data, as the standard multinomial logit model does in this paper. This bias is amenable to correction through panel data techniques, as used in the panel multinomial logit model.

The size of the bias cannot be known precisely, but its sign may be inferred from a priori knowledge of the sign of its components. In the present example, it is likely that both ψ and $\tilde{\omega}$ are positive, so that their product is positive also. This implies that the omitted variable bias due to unobserved heterogeneity will cause the coefficient of the education variable in the standard multinomial logit model to be *overestimated*, if averaged over several random samples of the population.[34] By contrast, the coefficient obtained from the panel multinomial logit model should be unbiased, as it implicitly accounts for the influence of M on l and Ed. By allowing the constant term in equation (B.1) to assume a different value for each person in the sample, panel data models are able to remove the endogeneity between explanatory variables and the error term which unobserved heterogeneity causes. The value of the constant may be assumed to be fixed and time invariant (fixed effects) or it may be assumed to be randomly drawn from a normal distribution

[34] Note that, when Ed and H are correlated, or when H and M are correlated, the likely direction of the heterogeneity bias cannot easily be predicted. For simplicity, these two correlations are typically assumed away.

(random effects). The relative merits of the two approaches are discussed in chapter 3.

B.2 Endogeneity bias in the presence of simultaneity

Note that, in this paper, as in Cai and Kalb (2006) and Cai (2007), only the possibility that labour force participation is simultaneously determined with a *summary* measure of health is considered. Unlike in Zhang et al. (2006), possible simultaneity between participation and *objective* health conditions (for example, diabetes) is not considered. Nevertheless, it is useful to discuss simultaneity involving the summary measure of health, as it has implications for the coefficient estimates pertaining to the objective measures (discussed in the next section). This discussion is based on Wooldridge (2006).

Assume that, because of simultaneity between health and labour force participation, the appropriate model consists of the following system of two equations:

$$h = \gamma_1 l + \eta' \mathbf{y} + \varepsilon_1 \quad \text{(B.4)}$$

$$l = \gamma_2 h + \beta_2' \mathbf{x} + \varepsilon_2 \quad \text{(B.5)}$$

The notation is as previously given, except for *h*, measuring 'true' health, which may or may not be equal to self-assessed health. (The case when the two differ is considered in the next section.) Note that true health, like self-assessed health, is a summary health status variable. For example, it may be ranked between 1 (poor) and 5 (excellent). It is influenced by exogenous variables in the **y** vector, some of which denote the presence or absence of diagnosed health conditions.

For simplicity of exposition, the intercept terms have been ignored in equations (B.4) and (B.5), and the education variables subsumed into the **y** and **x** vectors.

Substituting the second equation into the first gives the following reduced form equation:

$$h = \gamma_1 [\gamma_2 h + \beta_2' \mathbf{x} + \varepsilon_2] + \eta' \mathbf{y} + \varepsilon_1 \quad \text{(B.6)}$$

Collecting terms and simplifying:

$$h = \left[\frac{\gamma_1 \beta_2'}{1-\gamma_1\gamma_2}\right]' \mathbf{x} + \left[\frac{\eta'}{1-\gamma_1\gamma_2}\right]' \mathbf{y} + \frac{\gamma_1 \varepsilon_2 + \varepsilon_1}{1-\gamma_1\gamma_2} \quad \text{(B.7)}$$

Assuming that $\gamma_1\gamma_2$ is not equal to one, and that γ_1 is different from zero, *h* and ε_2 are correlated. Their covariance is given by:

$\text{cov}(h, \varepsilon_2) = \text{E}\{[h - \text{E}(h)].[\varepsilon_2 - \text{E}(\varepsilon_2)]\}$ (B.8)

Using (B.7), $h - E(h) = \dfrac{\gamma_1 \varepsilon_2 + \varepsilon_1}{1 - \gamma_1 \gamma_2}$ (B.9)

It is assumed that ε_2 has standard OLS properties (that is, $\text{E}(\varepsilon_2) = 0$), so that:

$\varepsilon_2 - \text{E}(\varepsilon_2) = \varepsilon_2$ (B.10)

Substituting (B.9) and (B.10) into (B.8):

$$\text{cov}(h, \varepsilon_2) = E\left[\varepsilon_2 . \frac{\gamma_1 \varepsilon_2 + \varepsilon_1}{1 - \gamma_1 \gamma_2}\right] \qquad \text{(B.11)}$$

Assuming that ε_1 and ε_2 are uncorrelated:

$$\text{cov}(h, \varepsilon_2) = \frac{\gamma_1}{1 - \gamma_1 \gamma_2} \cdot E\left(\varepsilon_2^2\right) \qquad \text{(B.12)}$$

$$= \frac{\gamma_1}{1 - \gamma_1 \gamma_2} \cdot \sigma_2^2 \qquad \text{(B.13)}$$

where $\sigma_2^2 = Var(\varepsilon_2) > 0$

If the expression in equation (B.13) is non-zero, then the true health variable in the labour force participation equation (B.5) is correlated with the error term of that equation, resulting in endogeneity bias affecting the estimated coefficient for health, γ_2, in a single equation model.

That bias has the same sign as $\dfrac{\gamma_1}{1 - \gamma_1 \gamma_2}$. Unfortunately, it is not possible to be definite about the sign of this ratio. While γ_2 (the influence of health on participation) is expected to be positive, γ_1 could be positive or negative, given that it measures the effect of participation on health (see chapter 2). If γ_1 is negative, the bias is negative also, meaning that the effect of true health on labour force participation is underestimated by assuming health to be exogenous. If γ_1 is positive, the direction of the bias cannot be known in advance.

Note that, in practice, ε_1 and ε_2 might be correlated in equation (B.11). This correlation is accounted for in a simultaneous equations model, but not in a single equation model. The direction of the simultaneity bias becomes even more uncertain when error terms are correlated. However, it remains the case that single-equation estimators are biased if the relationship between health and labour force participation is one of simultaneous determination.

B.3 Endogeneity bias in the presence of rationalisation endogeneity

This section discusses the effects rationalisation endogeneity can have on coefficient estimates produced by the SE model for the education and (objective) health condition variables of interest. This exposition is adapted from Cai and Kalb (2006) and Cai (2007).

Initially, both the true health and labour force equations are as modelled in the previous section:

$$h = \gamma_1 l + \eta' \mathbf{y} + \varepsilon_1 \tag{B.14}$$

$$l = \gamma_2 h + \beta_2' \mathbf{x} + \varepsilon_2 \tag{B.15}$$

However, only self-assessed health (H) is now observed, which is assumed to be related to true health and to labour force participation in the following way:

$$H = h + \alpha l + \omega \tag{B.16}$$

$$\Rightarrow h = H - \alpha l - \omega \tag{B.17}$$

where ω is a normally distributed disturbance.

Note that, if $\alpha \geq 0$, then people in the labour force overstate their health and those not in the labour force understate their health (Cai and Kalb 2006). Substituting (B.14) into (B.16):

$$H = \theta l + \eta' \mathbf{y} + \varepsilon_H \tag{B.18}$$

where $\theta = (\gamma_1 + \alpha)$, and $\varepsilon_H = (\varepsilon_1 + \omega)$

Substituting (B.17) into (B.15) gives:

$$l = \lambda H + \beta' \mathbf{x} + \varepsilon_l \tag{B.19}$$

where $\lambda = \gamma_2/(1+ \gamma_2\alpha)$, $\beta = \beta_2/(1+ \gamma_2\alpha)$, and $\varepsilon_l = (\varepsilon_2 + \gamma_2\omega)/ (1 + \gamma_2\alpha)$

Equations (B.18) and (B.19) are those estimated in the Cai and Kalb simultaneous equations model. Note that these equations are in the same form as (B.4) and (B.5), but are now expressed in terms of self-assessed health H instead of true health h.

Distinguishing between rationalisation endogeneity and true endogeneity

From (B.18), if θ is not equal to zero, then endogeneity occurs, because labour force participation affects health. However, the source of this endogeneity cannot be known: either γ_1 differs from zero, or α differs from zero, or they both do.

From (B.16), because α relates labour force participation to *self-assessed health*, it can measure the degree of *rationalisation* endogeneity. Rationalisation means that a person first 'decides' whether to participate or not, then self-reports a health status to justify that work decision. For example, a person unwilling to work might report a low level of health to justify non-participation. For rationalisation endogeneity to occur, α must be positive. In contrast, true endogeneity (γ_1) can be positive or negative.

Cai (2007) demonstrates that the sign of the estimated value of θ can provide some insight into whether true endogeneity or rationalisation endogeneity is more dominant. First, consider the case when $\theta < 0$. Because α is positive, true endogeneity must be negative ($\gamma_1 < 0$) and dominate any rationalisation endogeneity.

Alternatively, if $\theta > 0$, there are two possible explanations: (i) true endogeneity has a positive effect ($\gamma_1 > 0$) (and may be reinforced by rationalisation endogeneity); or (ii) true endogeneity has a negative effect, but is dominated by the positive effect of rationalisation endogeneity. Particularly when the latter is true (rationalisation endogeneity is present and is the dominant factor influencing θ), it is of interest to examine the consequences of rationalisation endogeneity on estimated results.

Rationalisation endogeneity can bias coefficient estimates

If labour force participation affects *true* health ($\gamma_1 \neq 0$), then health and participation are simultaneously determined. The simultaneity bias arising from using a single equation in that case was discussed in section B.2. In the remainder of this section, it is shown that rationalisation endogeneity can still bias coefficient estimates, even if a simultaneous equations model is used to correct for simultaneity.

The focus is now on how rationalisation endogeneity influences the effects of education and objective health conditions on labour force participation in the SE model. In that model, exogenous variables can have two types of effects: direct and indirect.

From (B.19), the *direct effect* on labour force participation of the education variables contained in the **x** vector is given by: $\beta = \dfrac{\beta_2}{(1+\gamma_2\alpha)}$

Note that this expression is a coefficient, not a marginal effect.

When no rationalisation endogeneity exists and α equals zero, $\beta = \beta_2$, and their expected value is equal to the 'true' coefficient. However, if α is positive, the estimate of β decreases (recalling that γ_2 is assumed to be positive), so that its expected value is lower than the true value.

Turning to the exogenous health condition variables, they do not influence labour force participation directly because they do not appear in the participation equation. They do, however, influence labour force participation indirectly (as does education) because they appear in the self-assessed health equation (in the **y** vector).

The *indirect effect* of education and health conditions on labour force participation is the product of:

1. the individual coefficients of the education and health conditions in the self-assessed health equation (as represented by vector η); and
2. the coefficient for self-assessed health in the participation equation (λ).

From equations (B.18) and (B.19), this is given by: $\eta\lambda = \eta \dfrac{\gamma_2}{(1+\gamma_2\alpha)}$

Here also, if α is non-zero and positive (rationalisation endogeneity), estimated indirect effects will be smaller than if α is zero.

To summarise: the larger the amount of rationalisation endogeneity, the smaller the estimated direct and indirect effects of education on participation. That is, the direct and indirect effects are biased downward. Furthermore, the estimated (indirect) effects of the exogenous health conditions on labour force participation are also biased downwards in the presence of rationalisation endogeneity.

C Model estimation results

This appendix provides the coefficient estimates for the explanatory variables appearing in the three models used in this paper. (A definition of the explanatory variables can be found in appendix A.) Marginal effects of the health and education variables, together with their standard errors when available, are also reported.

C.1 Multinomial logit models

The factors influencing a person's detailed labour market state are modelled using the multinomial logit models. These states — employed full-time, employed part-time, unemployed, not in the labour force — form the dependent variable of the models, with 'not in the labour force' chosen as the reference state. The coefficient estimates of the explanatory variables used in the standard multinomial logit model are reported in table C.1, and those used in the panel multinomial logit model in table C.2. The estimation methods used are:

- For the standard multinomial logit model, maximum-likelihood estimation (Greene 2003) using the Stata computer program.
- For the panel multinomial logit model, simulated maximum-likelihood estimation (Greene 2003) using the Limdep computer program.

For the panel multinomial logit model, supplementary estimates are reported, in the form of the value and the significance of the standard deviation of the random constant terms (table C.2), and the correlation coefficients between those constant terms (table C.3).

Table C.1 Coefficients of explanatory variables in the standard multinomial logit model[a]

	Males			Females		
Explanatory variable	*Full-time*	*Part-time*	*Unemployed*	*Full-time*	*Part-time*	*Unemployed*
Demographic characteristics						
Age1524	1.0674***	0.9348***	1.5876***	1.3208***	1.0426***	0.4488
Age50plus	-1.9061***	-1.5356***	-1.1424***	-1.9224***	-1.3271***	-1.2448***
Married	0.5498***	0.1072	0.0324	-0.3282***	-0.0056	-0.7526***
Children04	0.2057	0.2302	-0.0016	-1.9249***	-0.6395***	-0.7449***
Children514	-0.0147	-0.0528	-0.1328	-0.6652***	-0.0210***	-0.0855
Children1524	0.4179***	0.2714**	-0.0510	-0.0025	0.1974	-0.0161
Indigenous	-0.7519*	0.1638	0.4822	-0.5911**	-0.4397**	-0.3664
NESB	-0.7105***	-0.4579***	0.0269	-0.6012***	-0.6772***	0.1678
Region	-0.2350****	-0.0094	-0.2013	0.0819	0.2040***	-0.0333
Education						
Degree or higher	1.5076***	1.5049***	0.6512**	2.0631***	1.3181	0.5778***
Year 12	0.8641***	1.2161***	0.1821	0.9045***	0.4715***	0.0371
Diploma/Certificate	0.7727***	0.5974***	0.0649	1.0347***	0.5478***	0.2820
Health						
Cardiovascular disease	-0.5738***	-0.4797***	-0.8395***	-0.5382***	-0.4142**	-0.6624**
Diabetes	-0.5248**	-0.2413	0.2453	-0.3473	-0.5718***	-1.0152**
Cancer	-0.6485***	-0.3523	-0.8430**	-0.1296	-0.4723***	0.0622
Mental/nervous	-2.5977***	-1.2564***	-1.3937***	-1.9552***	-1.2870***	-0.1785
Arthritis	-0.8610***	-0.4483***	-0.5568***	-0.6436***	-0.3310**	-0.0305
Major injury	-0.8620***	-0.8315***	-0.2041	-0.7211***	-0.6617***	-1.1661**
Employment history						
Experience	0.0752***	-0.0037	0.1168***	0.1840***	0.1846***	0.0357
Experience squared	-0.0008**	0.0011**	-0.0022***	-0.0022***	-0.0025***	-0.0003
Unemployment history	-4.0416***	0.3264	3.5523***	-2.0765***	0.7043	3.5626***
Interactive variables						
Degree x age1524	-1.3861***	-0.6299	-1.1050	-0.3932	0.0761***	-0.6776
Diploma/Certificate x age1524	0.3663	0.3834	0.3732	0.3107	0.6537	0.5629
Year 12 x age1524	-0.2896	-0.0441	-0.2547	-0.0501	0.7069**	0.6975
Degree x age50plus	-0.5899*	0.0486	-0.0152	-0.8040***	-0.6942**	-0.1810
Diploma/Certificate x age50plus	-0.6996***	-0.5523*	-0.0138	-0.5496**	-0.5017***	-0.3514
Year 12 x age50plus	-0.4333	-0.3659	0.3150	-0.3474	-0.5005**	0.2142
Other						
Constant	1.3166***	-0.5411*	-1.9903***	-0.8208***	-1.5879*	-1.8668***
No. of observations	13 955	13 955	13 955	15 232	15 232	15 232

[a] The reference category for the dependent variable is 'not in the labour force'. For binary or categorical independent variables (for example, NESB or education), the base categories are, in the same variable order as in the table: aged 25 to 49; non-Indigenous; born in Australia or in an English-speaking country; living in a metropolitan centre; Year 11 or lower education; does not have the health condition; surveyed in 2001 (wave 1) *** significant at 1 per cent, ** 5 per cent and * 10 per cent.

Source: Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

Table C.2 **Coefficients of explanatory variables in the panel multinomial logit model[a]**

	Males			*Females*		
Explanatory variable	*Full-time*	*Part-time*	*Unemployed*	*Full-time*	*Part-time*	*Unemployed*
Demographic characteristics						
Age1524	2.2024***	1.6377***	1.6598***	1.6416***	1.3989***	0.9781***
Age50plus	-3.0108***	-2.5928***	-1.7253***	-3.3646***	-2.0982***	-2.0056***
Married	1.0233***	0.2761*	0.0074	-0.4236***	-0.0595	-0.9756***
Children04	0.2056	0.2258	-0.0400	-3.2452***	-1.1574**	-1.2765***
Children514	-0.0580	-0.0891	-0.0727	-1.0542***	-0.0430	-0.2400***
Children1524	0.5283***	0.4172***	0.0969	-0.1267*	0.2171***	-0.0357
Indigenous	-1.7128***	0.0853	0.3799	-0.6628**	-0.5156**	-0.1016
NESB	-1.3679***	-0.7995***	-0.0342	-1.2367***	-1.1687***	-0.2037
Region	-0.3468***	0.0207	-0.2318	0.0371	0.1784**	-0.0968
Education						
Degree or higher	3.3289***	2.6759***	0.8455**	3.3745***	1.9776***	0.6848***
Year 12	2.0345***	2.1164***	0.3668	1.2735***	0.5530***	-0.1219
Diploma/Certificate	1.5412***	0.9134***	0.0359	1.6592***	0.8200***	0.2316
Health						
Cardiovascular disease	-1.2616***	-1.0766***	-1.2959***	-0.8861***	-0.7063***	-0.9224***
Diabetes	-0.9443***	-0.4035	0.2240	-0.6120**	-0.9333***	-1.1447*
Cancer	-1.5524***	-0.9238***	-1.3216***	-0.1510	-0.6050***	-0.0767
Mental/nervous	-4.5705***	-2.2731***	-1.9089***	-3.0229***	-1.9083***	-0.4403*
Arthritis	-1.5213***	-0.9181***	-1.0215***	-1.0522***	-0.6952***	-0.1175
Major injury	-1.2761***	-1.0673***	-0.4694	-0.9853***	-0.7241***	-1.2015**
Employment history						
Experience	20.1961***	2.8771	5.3038*	30.9706***	26.6410***	0.8558
Experience squared	-26.0681***	8.9967*	-13.4449**	-39.1206***	-35.5563***	4.7947
Unemployment history	ne	ne	ne	ne	ne	ne
Interactive variables						
Degree x age1524	-2.6235***	-1.1484	-1.9396**	-0.3523	-0.1605	-1.5921**
Diploma/Certificate x age1524	-0.0265	0.2277	0.0915	1.0987***	1.0218***	0.1667
Year 12 x age1524	-0.8669*	-0.3457	-0.6657	0.4216	1.5054***	0.5396
Degree x age50plus	-1.4093***	-0.0016	0.3883	-1.0364***	-1.0000***	0.0655
Diploma/Certificate x age50plus	-1.5801***	-0.8492***	-0.1020	-0.3695	-0.4753**	-0.1269
Year 12 x age50plus	-1.1115***	-0.6039	0.5299	0.2679	-0.2183	0.7102
Wave identifiers						
Wave 2	-0.0612	0.0444	-0.3446*	-0.1132	-0.0419	0.0926
Wave 3	0.0392	0.0732	-0.5361***	-0.0372	-0.1138	-0.0990
Wave 4	-0.0944	-0.1600	-0.9511***	-0.0767	-0.0293	-0.2145
Other						
Constant	1.6060***	-0.1351	0.8413**	-1.3784***	-1.7537***	-0.9425***
No. of observations	13 955	13 955	13 955	15 232	15 232	15 232

(Continued next page)

Table C.2 (continued)

	Males			Females		
Explanatory variable	*Full-time*	*Part-time*	*Unemployed*	*Full-time*	*Part-time*	*Unemployed*
Standard deviation of constant	3.2403***	2.9221***	2.3408***	2.9642***	2.2819***	1.7407***

a The reference category for the dependent variable is 'not in the labour force'. For binary or categorical independent variables (for example, NESB or education), the base categories are, in the same variable order as in the table: aged 25 to 49; non-Indigenous; born in Australia or in an English-speaking country; living in a metropolitan centre; Year 11 or lower education; does not have the health condition; surveyed in 2001 (wave 1) *** significant at 1 per cent, ** 5 per cent and * 10 per cent. **ne** Not estimated (to facilitate convergence).

Source: Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

Table C.3 **Correlation coefficients of random constant terms in the panel multinomial logit model**

	Full-time	*Part-time*	*Unemployed*
Males			
Full-time	1.0000	0.7131	0.6807
Part-time	0.7131	1.0000	0.7720
Unemployed	0.6807	0.7720	1.0000
Females			
Full-time	1.0000	-0.5994	-0.5305
Part-time	-0.5994	1.0000	0.5595
Unemployed	-0.5305	0.5595	1.0000

Source: Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

C.2 Simultaneous equations model

The simultaneous equations model is estimated for four different age and gender groups. The estimated coefficients for each of these groups are presented in table C.4. Note that some variables are used as explanators (and have corresponding coefficients) in both the labour force participation and health equations.

Table C.4 also contains the correlation coefficient between the error terms of the participation and health equations, denoted by ρ, and the model's estimates of the health cut-off points, denoted by 'bound'.

The SE model is estimated using the FIML method (Greene 2003) and the Stata computer program.

Table C.4 **Coefficients of explanatory variables in the simultaneous equations model**

	Males		*Females*	
Explanatory variable	*15–49*	*50–64*	*15–49*	*50–62*
Labour force participation equation				
Self-assessed health (λ)	1.3061*	0.7286***	0.5249***	0.6322***
Demographic				
Age	0.0442**	ne	-0.0812***	-0.1153***
Age squared	-0.0026***	ne	0.0007*	-0.0019
Married	0.1124	0.3068***	-0.0978**	-0.4206***
Children04	0.0287	na	-0.6920***	na
Children514	-0.0031	na	-0.1082***	na
Children014	na	0.0706	na	0.0095
Children1524	0.0570	0.2938***	0.1555***	0.0107
Indigenous	-0.0792	-0.3248	-0.1174	0.2159
NESB	-0.2818**	-0.2407***	-0.2172***	-0.2625
Region	-0.0284	-0.0760	0.0767*	-0.0465
Education				
Degree or higher	0.3003***	0.0119	0.6261***	0.2820**
Year 12	0.0823	0.0221	0.1855***	0.0193
Diploma/Certificate	0.1074	-0.0595	0.2864***	0.0267
Employment history				
Experience	0.0092	0.0125	0.1049***	0.0583***
Experience squared	0.0019***	-0.0002	-0.0009***	-0.0002
Unemployment history	0.0828	0.4636	0.6926***	1.0920
Constant	1.7961*	-0.3934	0.9265***	-0.0677
Self-assessed health equation				
Labour force participation (θ)	-0.8347**	0.1182	0.0187	0.6997***
Demographic				
Age	0.0428*	ne	0.0092	0.1008***
Age squared	-0.0032***	ne	-0.0007**	-0.0002
Married	0.2029***	-0.2844***	0.1021***	0.3684***
Indigenous	0.0058	0.2510	-0.2636**	-0.3423
Region	-0.0905*	0.0360	0.0540*	0.1117
Education				
Degree	0.8802***	0.5581***	0.2127***	-0.0062
Year 12	0.3918***	0.2657**	0.1300***	0.0849
Diploma/Certificate	0.3473	0.1302**	0.0540	0.0803

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Table C.4 (continued)

Explanatory variable	Males 15–49	Males 50–64	Females 15–49	Females 50–62
Self-assessed health equation (continued)				
Health				
Cardiovascular disease	-0.4859***	-0.3399***	-0.4214***	-0.2318*
Diabetes	-0.6593***	-0.3762***	-0.6620***	-0.2329*
Cancer	-0.1320	-0.0823	-0.3852***	-0.1551
Mental/nervous	-1.1360***	-0.9644***	-1.0707***	-0.5677*
Arthritis	-0.7167***	-0.4267***	-0.4159***	-0.2507*
Major injury	-1.1075	-0.7100***	-0.9432***	-0.6699*
Employment history				
Experience	-0.0094	0.0309	0.0165*	-0.0414**
Experience squared	0.0027***	-0.0001	-0.0001	0.0003
Unemployment history	-0.2735	-1.2394**	-0.6050***	-1.0673
HH disposable income	0.1482***	0.1286***	0.1260***	0.0693**
Other				
Bound0	-2.1204***	-1.2118***	-2.2024***	-2.0011***
Bound1	-1.4662***	-0.1021	-1.0941***	-0.8912***
Bound2	-0.7269**	1.0839***	0.0872	0.2741
Bound3	0.0237	2.3346***	1.3560***	1.5068***
Correlation between error terms (ρ)	0.0681	-0.5924***	-0.4315***	-0.8681***
Number of observations	10 014	3 941	11 654	3 578
Log likelihood	-13 873.30	-6 858.28	-19 032.23	-655.96

*** significant at 1 per cent, ** 5 per cent and * 10 per cent. **HH** Household. **ne** Not estimated (to facilitate convergence). **na** Not applicable. Due to limited observations, children aged 14 and under were grouped together for the estimation of older age groups.

Source: Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

C.3 Marginal effects estimates

The estimated health and education marginal effects for the three models, and the associated standard errors for the standard multinominal logit and SE models, are set out in table C.5. Given its method of estimation, it is not possible to calculate standard errors for the marginal effects of the panel multinominal logit model.

Table C.5 **Marginal effects and standard errors of selected health and education variables**[a]

Variable	*Standard MNL*		*Panel MNL*	*SE model*	
	Marginal effect	*Standard error*	*Marginal effect*	*Marginal effect*	*Standard error*
	ppt	ppt	ppt	ppt	ppt
Health[b]					
Females					
Cancer	4.3	2.9	**3.1**	**5.2**	1.8
Cardiovascular disease	7.4	1.8	**6.9**	6.2	1.2
Mental/nervous condition	24.7	3.7	**21.7**	16.7	3.0
Major injury	11.3	3.3	**7.6**	**15.8**	1.5
Diabetes	7.6	3.6	**7.3**	**9.0**	2.2
Arthritis	6.6	1.7	**6.6**	6.2	1.1
Males					
Cancer	**5.6**	2.4	7.4	1.2	1.6
Cardiovascular disease	5.1	1.4	6.2	**5.2**	1.2
Mental/nervous condition	29.6	4.9	**25.5**	17.0	3.7
Major injury	7.7	2.5	**5.8**	**14.2**	1.5
Diabetes	3.6	2.1	**3.2**	**7.1**	2.3
Arthritis	7.2	1.6	**6.9**	**7.8**	1.5
Education[c]					
Females					
Year 12	9.0	2.6	**7.7**	6.4	2.1
Diploma or certificate	10.2	2.3	**9.1**	7.7	1.9
Degree or higher	19.7	2.5	**15.9**	**16.9**	2.1
Males					
Year 12	**5.7**	2.3	6.7	4.8	2.0
Diploma or certificate	3.4	1.8	**3.2**	3.0	1.5
Degree or higher	8.6	2.1	9.5	**8.7**	1.9

[a] **Bolded numbers** in this table represent the 'preferred' marginal effects, based on the rule illustrated in figure 6.1. When two numbers in a row are bolded, the preferred estimate is equal to the average of these two numbers. [b] The estimated health marginal effects measure the increased probability of labour force participation arising from the prevention or treatment of one of the six specified health conditions. [c] Each education marginal effect measures the effect on the labour force participation rate of a hypothetical individual, who has Year 11 or lower education, of acquiring one of the three specified educational levels. **MNL** multinominal logit. **SE** simultaneous equations. **ppt** percentage points.

Data source: Productivity Commission estimates based on the HILDA survey, 2001–04, release 4.1.

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