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The Effects of Education and Health on Wages and Productivity

Productivity Commission Staff Working Paper

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Abbreviations

Abbreviations

AME	average of the marginal effects
BMI	body mass index
COAG	Council of Australian Governments
CURF	Confidentialised Unit Record File
DSP	Disability Support Pension
GAD	generalised anxiety disorder
GDP	gross domestic Product
HILDA	Household, Income and Labour Dynamics in Australia
MCS	mental component summary
MDD	major depressive disorder
MEM	marginal effect at the sample mean
MER	marginal effect at a representative value of the independent variables
MOS	Medical Outcomes Survey
NESB	Non-English speaking background
NHS	National Health Survey
NRA	National Reform Agenda
PC	Productivity Commission
PCS	physical component summary
SDAC	Survey of Disability, Ageing and Carers
USGP	United States General Population
VET	Vocational Education and Training

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
Human capital	The set of attributes that makes it possible for individuals to work and contribute to production
Labour force participation	A participant in the labour force is a person aged 15 years or over, and who is either employed or unemployed
Labour productivity	An indicator of output per hour worked
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
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
Self-assessed health	A summary measure of a person's overall health status, as determined by that person
SF-36	A self-reported measure of physical and mental health designed for comparing functional health and wellbeing and the relative burden of diseases, across diverse populations
Subjective health	A summary measure of a person's overall health status, as

measure	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

- Human capital theory supports the view that people with higher levels of education and lower incidences of chronic illness should have higher labour productivity.
- Hourly wages can be used as an indicator of labour productivity. While wages are likely to be a reasonable indicator of the effects of education on labour productivity, statistical issues and the way that labour markets function in practice mean that using wages as an indicator could lead to results that under- or overstate the negative effects of ill health on labour productivity.
- In this paper, higher levels of education are estimated to be associated with significantly higher wages. Compared to a person with a year 11 education or less, on average:
  – a man with a year 12 education earns around 13 per cent more, and a woman earns around 10 per cent more
  – a man with a diploma or certificate earns around 14 per cent more, and a woman earns around 11 per cent more
  – a university education adds around 40 per cent to men's and women's earnings.
- People in the workforce who suffer from chronic illnesses are estimated to earn slightly less than their healthy counterparts (between 1.0 per cent and 5.4 per cent less for a range of conditions).
  – It is possible that these results understate the impact of ill health on productivity, because of the impact that one person's illness can have on other employees.
  – It is also possible that 'endogeneity bias' and unobserved heterogeneity in the data lead to results that overstate the positive effects of education and good health on labour productivity.
- A second objective of this paper is to estimate the potential productivity of people who are not employed or not in the labour force. These people tend to have characteristics that are systematically different to people who are employed. For example, they tend to have less education and work experience, and also to be in worse health. Because of this, they are more likely to be targeted by government programs.
  – Comparison of the characteristics of people in employment with those not in employment found that, depending on their age, gender and whether they receive the Disability Support Pension, the average potential wage of people who are not employed or not in the labour force is between 65 and 75 per cent of the wage of people who are employed.

Overview

In 2006 the Productivity Commission published a report on the potential benefits of the National Reform Agenda (NRA). The NRA is a program of reforms that were proposed by the Council of Australian Governments (COAG) to address impediments to productivity growth and to achieve higher levels of workforce participation and productivity. In March 2008 COAG announced a 'COAG Reform Agenda' that focuses on many of the areas that were part of the NRA, including productivity, education, skills and early childhood (COAG 2008).

The NRA includes a 'stream' of reforms to address human capital development. 'Human capital' refers to the set of attributes that makes it possible for individuals to work and contribute to production. It encompasses skills, work experience, health and intangible characteristics such as motivation and work ethic. Human capital is a key driver of workforce participation and labour productivity and, at the aggregate level, gross domestic product, consumption and community wellbeing. Measures to maintain and enhance the community's stock of human capital are likely to increase standards of living.

As part of its report on the potential benefits of the NRA, the Commission was asked to estimate the potential future benefits to the community of increasing education levels and reducing the incidence of chronic illnesses. In particular, the Commission investigated six 'target' conditions: heart disease, cancer, diabetes, arthritis, mental illness and serious injury. The Commission's task included estimating the effects of NRA reforms on labour force participation and labour productivity. To do this, the Commission undertook an extensive review of the literature, drawing from Australian and overseas sources to estimate the effects of education and chronic illness on labour market outcomes. Results from the literature indicated that increasing levels of education and reducing the incidence of illness are associated with higher levels of workforce participation and labour productivity.

Although the Commission relied on the best evidence available at the time, the information obtained was 'often limited or speculative' (PC 2006, p. 339). To address the gaps in the literature, the Commission has undertaken further quantitative work to enhance and refine estimates of the effects of chronic illness and education on labour market outcomes. A previous paper (Laplagne et al. 2007) estimated the effects of education and health on labour force participation. This paper estimates the effects on hourly wages, which are used as an indicator of labour productivity.

A second objective of this project was to estimate the potential wages of people who are unemployed or not in the labour force. The NRA includes reforms to work incentives that were intended to increase the workforce participation of people who are not working. To estimate the economy-wide effects of such reforms it is necessary to estimate the potential productivity of the people who would be brought into the workforce as a result of the reforms. The model that was developed to estimate the effects of education and health status on wages is used to estimate the wages that these people would receive if they were to enter the labour force. This can give an indication of their potential productivity, assuming that there is no change to their level of education or health status.

Modelling approach and data

The effects of education and health status on wages were estimated using a wage model based on Mincer (1974). In this model the natural logarithm of wages is expressed as a function of education and health status. The model includes variables to account for labour market and demographic characteristics such as age, work experience, marital status and living in a regional area. These factors have all been observed in other studies to have a statistically significant effect on wages.

Hourly wages were chosen as the best available indicator of labour productivity. Labour productivity could not be directly measured, because to do so would require detailed data on individuals and their employers, including their access to capital and other inputs. However, according to standard economic theory, under certain conditions a person's wage would be an accurate reflection of their productivity (the value of their 'marginal product'). This, however, requires a number of assumptions about the actual functioning of labour markets, some of which do not fully apply. Nonetheless, as long as wages are set in reasonably competitive markets, differences in wages should provide a useful indication of the effects of education and health on labour productivity.

In the case of education, it is likely that on average across the community, the effect of a person's level of education on their wage gives a reasonable indication of the contribution of education to labour productivity. The effects of illness on labour productivity are more complicated, and wages may be a less reliable indicator of how illness influences productivity. For example, if a person who works as part of a team is absent due to illness, the cost to their employer is not only the cost of the absentee's forgone labour, it is also the cost of the loss of production from other members of the team who rely on the absent worker in their own work (Pauly et al. 2002). The implication for the current project is that using hourly wages as an indicator of labour productivity might tend to understate the extent to which ill health reduces productivity.

However, statistical issues including 'endogeneity bias' and 'unobserved heterogeneity' could lead to the opposite effect — overstating the benefits to labour productivity of good health. It is not possible to determine the net effect of these issues, and whether the results systematically understate or overstate the benefits of education and good health. For that reason, the results should be interpreted with caution.

Controlling for sample selection bias

On average, employed people have higher levels of education and better health than people who are unemployed or not in the labour force, and they tend to have different labour market and demographic characteristics. As a result there is potential for bias in the econometric model because only people who report a wage — the employed — are included in the data used to estimate the effects of education and health on wages. The modelling approach used was developed to account for this possibility of 'sample selection bias', which can arise where the sample that is being used to estimate the model has systematically different characteristics from the rest of the population.

To account for this potential bias, the model was estimated using the approach proposed by Heckman (1979). This involves a two-stage process where the model is adjusted to account for the probability that a person is not in the labour force.

The model was estimated using data from five waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey. HILDA is an annual survey that includes information on the demographic, labour market and human capital characteristics of respondents, including their education and health status. Around 30 000 observations were included in the dataset used for this project.

The HILDA data include reliable information on the educational attainment of respondents. HILDA does not include reliable information on the prevalence of the six COAG target health conditions. To address this, a technique was developed that involved estimating the effect of the target conditions on general physical and mental health (of which there are reliable measures in HILDA) and using that information to estimate the effects of the target conditions on wages.

The marginal effects of education and chronic illness

Empirical estimates in the academic literature — both Australian and overseas — support the hypothesis that high education levels and lower incidence of illness are associated with higher wages and, by implication, higher labour productivity. The results of this project are in line with these findings.

Higher levels of education are found to have a large positive effect on wages (table 1). Relative to the base case of a year 11 education or below, completing year 12 or a diploma or certificate qualification is found to increase wages by between 10 and 14 per cent. Results vary slightly for men and women. Obtaining a university education has a large effect on wages — a 38 per cent increase in men's wages and a 37 per cent increase in women's wages.

Table 1 **Average marginal effects of education on hourly wages**
Per cent increase in hourly wages compared with year 11 or below (standard errors in brackets)

Highest level of education	*Marginal effect of each level of education*			
	Men		Women	
	per cent		per cent	
Degree or higher	38.4	(1.90)	36.7	(1.57)
Diploma or certificate	13.8	(1.50)	11.4	(1.44)
Year 12	12.8	(2.11)	10.1	(1.63)

Source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

An earlier paper (Laplagne et al. 2007) found that the target health conditions have a significant negative effect on workforce participation. Averting or successfully treating chronic illness was estimated to increase the probability that a person would be in the workforce by up to 30 percentage points (for males suffering a nervous condition or poor mental health). The second largest effect on participation was observed for major injury (a reduction in the probability of participation of up to 14 percentage points for males and 16 percentage points for females). Other conditions were estimated to have smaller, but still significant effects on the probability of participation (between around 3 and 10 percentage points).

In this paper, chronic illness is found to have a negative — but often small — effect on wages. Many of the conditions are estimated to reduce wages by less than 2 per cent. The largest effects related to poor mental health and major injury, which are associated with an average reduction in men's wages of 4.7 per cent and 5.4 per cent respectively, and women's wages by 3.1 per cent and 3.5 per cent respectively.

Table 2 **Marginal effects of target health conditions on hourly wages**

Target condition	*Percentage hourly wage reduction attributable to presence of target condition*	
	Men	Women
Cardiovascular disease	-1.9	-1.3
Diabetes	-1.8	-1.2
Cancer	-1.6	-1.0
Arthritis	-2.3	-1.5
Poor mental health	-4.7	-3.1
Major injury	-5.4	-3.5

Source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

Potential wages of people who are unemployed or not in the workforce

The wage model developed in this paper was used to estimate the potential wages of people who are unemployed or not in the workforce, given their existing characteristics. These estimates are useful as inputs into estimates of the economy-wide effects of labour market reforms such as reforms to work incentives.

People who are unemployed or not in the labour force have systematically different characteristics from people who are employed. For example, they tend to have lower levels of education, a greater incidence of chronic illness and a longer experience of unemployment. Human capital theory suggests that given their characteristics, if employed, these people would be expected to be less productive on average than people who are currently working, and earn lower wages.

The potential wages of people who are not working were estimated separately for men and women, and dummy variables were used to estimate the potential wages of different age groups and recipients of the Disability Support Pension (DSP). Potential wages were estimated separately for different age groups and DSP recipients because COAG noted in its agreement to develop a NRA that ‘international benchmarking suggests that the greatest potential to achieve higher participation is among people on welfare, the mature aged and women’ (COAG 2006, p. 4). Women, older workers and DSP recipients were therefore considered ‘target’ groups for the NRA.

The results (table 3) indicate that a person with the labour market and demographic characteristics of the average unemployed person would be expected to earn around 70–75 per cent of the average wage of the average employed person in their age group. The estimated potential wage of DSP recipients is lower, around 64–70 per cent of the average wage of employed people of the same age.

These results suggest that people who are unemployed or not in the labour force are likely to be less productive than people who are employed, were they to enter the labour force. This can have economy-wide implications, including lower average labour productivity.

Table 3 **Predicted potential relative wages for NRA target groups**

Demographic group	*Estimated potential wages of people not currently employed relative to employed people (per cent)*		
	Men	Women	Men and women
15–24 years	75.4	76.6	76.1
25–44 years	67.3	74.8	71.3
45–64 years	72.2	73.7	73.0
55–64 years	72.8	75.2	73.9
Weighted average[a]	70.5	74.7	72.7
Disability Support Pension recipients			
15–24 years	69.7	72.5	71.1
25–44 years	64.0	65.1	64.5
45–64 years	69.1	68.7	68.9
Weighted average[a]	66.6	67.6	67.1

[a] Weighted to reflect sample proportions.

Source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

Concluding remarks

The research in this paper shows that increasing levels of education and reducing the incidence of chronic illness are likely to increase individuals' labour productivity, as reflected in their wages.

Using wages as an indicator of labour productivity could lead to biases in the results. In particular, it might serve to underestimate the negative effects of ill health on labour productivity. Conversely, statistical issues could lead to results that overstate the negative effects of chronic illness on wages and productivity. It is not possible to say conclusively which of these effects will have a greater impact.

While the paper suggests that there is scope for potential productivity pay-offs from education and improved health status, whether such improvements could be achieved in a cost effective way is a separate matter. Any proposed interventions through health or education programs to increase human capital would require careful assessment to ensure that they would deliver net community benefits.

1 Introduction

In this Staff Working Paper, a human capital earnings function and data from the Household, Income and Labour Dynamics in Australia (HILDA) survey are used to estimate the effects of education and health status on wages, which can be used as an indicator of labour productivity. The same model is also used to estimate the potential wages of people who are unemployed or not in the labour force if they were to become employed.

The outline of the paper is as follows: the aims of the research and the analytical approach are described in this chapter; a review of the literature is presented in chapter 2; the analytical approach and the difficulties associated with using this approach to answer the research question are discussed in chapter 3; the data and variables used are described in chapter 4; and the results of the estimation are set out in chapter 5. Three appendices are attached, providing further detail on some of the theoretical and technical aspects of the research.

1.1 Research objectives and the analytical framework

The primary objective for this project is to analyse the impact of health status and educational attainment on labour force productivity. In particular, the focus is on six 'target' health conditions[1] that were identified by the Council of Australian Governments (COAG) in 2006 as priorities for health promotion and disease prevention under the National Reform Agenda (NRA) (PC 2006).

A second objective is to use the model developed in this paper to estimate the wages that could potentially be earned by people who are unemployed or not in the labour force if they were to become employed, assuming no change in their education or health status.

The main motivation for this research is to obtain estimates of the effects of health and education on labour productivity that could be used as inputs for future modelling of the economy-wide effects of reforms to health and education. In 2006

[1] The target health conditions are heart disease, cancer, diabetes, arthritis, mental illness and serious injury.

the Productivity Commission modelled the effects of reforms to health and education policies that were proposed under the NRA. Although the information used was the best available at the time, there were some limitations:

- The Commission relied on published estimates of the effects of health and education on labour force participation and productivity to generate the inputs that were fed into the economy-wide model. Particularly in the case of health, the literature was sparse and the estimates were not all directly relevant to the modelling task.
- Estimates of the potential productivity of people who were not employed were based on a paper from New Zealand (Bryant et al. 2004). Given the structural differences between the Australian and New Zealand economies, these estimates may not be accurate for Australia. (As it turns out, the estimates presented in this paper are consistent with the estimates based on Bryant et al. (2004) that were used in the Commission's 2006 report.)

To address these limitations, the Commission commenced two projects that used a rich dataset (HILDA) to empirically estimate the effects of education and health status on labour market outcomes in Australia. The first (Laplagne et al. 2007) estimated the effects of education and health on labour force participation. This project is the second.

The current study:

- uses Australian data to estimate the effects of a range of chronic health conditions on wages
- addresses theoretical issues arising from using wages as an indicator of labour productivity, particularly when investigating the effects of health on labour productivity
- develops a technique to estimate the effects of a range of chronic health conditions that is based on the Short Form 36 (SF-36) measure of general health
- uses Australian data to estimate the potential productivity of people who are unemployed and not in the labour force if they were to become employed.

Labour productivity and human capital

Productivity can be defined broadly as 'a measure of the capacity of individuals, firms, industries or entire economies to transform inputs into outputs' (IC 1997, p. 3). The relevant measure for this project is the productivity of individuals' labour, which is an indicator of output per hour worked. Simply put, workers who are more productive produce more in a given period than workers who are less productive (assuming they have access to the same capital and other inputs).

'Human capital' refers to the set of attributes that each individual possesses that makes it possible for them to contribute to production. It can include knowledge, skills, health, work experience and intangible characteristics such as work ethic and motivation. Human capital is a key determinant of individuals' labour productivity.

Aside from formal education and health status, there are other human capital characteristics that are significant determinants of labour productivity. Mincer (1974) emphasised the contribution that experience makes to a person's earning capacity, and proposed a model of earnings that included experience as a non-linear variable to account for the possible decline in the rate of accumulation of on-the-job skills that comes with age. Other authors have identified gender as a factor, as men and women tend to follow significantly different paths in their human capital development and earnings growth.

Finally, it should be noted that returns to human capital (and hence labour productivity and wages) also depend on factors outside a person's control. Individuals with high levels of human capital and potentially high productivity may not be able to achieve their full potential if they do not have access to physical capital (equipment or land). (That is, human capital and physical capital are complementary.) If a person lives where they are not able to find a job that takes full advantage of their skills and attributes, their actual productivity may be less than their potential productivity. This means that returns to human capital can depend on where a person lives and the opportunities they have to apply and be rewarded for applying their skills.

The link between productivity and wages in theory

The question of interest is the effects of education and health status on labour productivity. However, individuals' productivity is difficult to observe and measure, requiring data on individuals and their employers such as their access to capital and other inputs. In practice, these data do not exist in large samples. Therefore for this analysis it was necessary to find an observable variable that is correlated with productivity. In investigating questions similar to this one, researchers have often used wages as an indicator of labour productivity. This approach rests on a number of assumptions, some of which might not fully hold in practice. This places limitations on the interpretation and conclusions drawn from studies that use wages as a surrogate indicator of productivity.

The use of wages as a surrogate indicator of labour productivity is supported using economic theory. Standard economic theory assumes that firms seek to maximise profit. This leads them to choose a level of labour hire where the cost of extra labour (wages and other expenses such as superannuation, workers compensation and administration costs) equals the increase in revenue associated with the extra output from that labour.[2] By definition, more productive workers produce more output per hour worked, so a profit-maximising firm would be prepared to pay more for more productive workers. Factors that affect a person's productivity are thereby also likely to affect the wages that firms are prepared to offer them.

In analysing the relationship between wages and labour productivity it is important to consider supply-side factors, including the elasticity of labour supply, which is related to the costs to workers of acquiring new skills and hence increasing their productivity. If the cost of acquiring new skills (including time, effort and money) is low, the supply of labour with the required skills will be more elastic and increases in labour productivity will result in small or no increases in wages. If the cost of acquiring skills is high, labour supply would be expected to be less elastic and wages more responsive to changes in labour productivity that are brought about by skill acquisition.

In a competitive labour market, with perfect information, mobility of labour, no transaction costs and constant returns to scale, equilibrium wages at the margin would just compensate for the costs of acquiring the additional skills, and in turn would equal the additional productivity generated by those skills. However, given these are unlikely to hold, an individual's wages will rarely be equal to their marginal revenue product of labour. Over longer periods, where markets for goods and services and labour are competitive, changes in wages and differences between the earnings of people with different human capital characteristics are likely to be a reasonable indicator of labour productivity. However, it should be noted that at any given time, individuals' wage levels may under- or overstate their labour productivity.

[2] The increase in revenue resulting from output produced by marginal labour is the marginal revenue product of labour (MRP_L) — the extra output multiplied by the price of the product. In a competitive product market, MRP_L equals the value of the marginal product of labour.

The link between productivity and wages in practice

The following sections compare the assumptions in economic theory about the relationship between wages and productivity with the reality of labour markets. In particular, two issues are addressed:

- how education and health status affect workers' productivity
- whether wages reflect the effects on workers' productivity that are attributable to their education and health status.

How is educational attainment expected to influence productivity?

Higher levels of education are expected to be associated with higher levels of labour productivity for two reasons:

- Education leads to the accumulation of skills that make workers more productive. Such skills can be job-specific (for example, skills learned from plumbing or medical qualifications) or broad (for example, literacy and numeracy).
- Employers might choose to employ highly educated workers because education can be a 'marker' of unobservable characteristics such as work ethic and intrinsic motivation. These characteristics are associated with higher productivity. This is referred to as the 'signalling' effect of education.

Are wages likely to reflect education-induced changes in productivity?

The extent to which education-induced productivity is reflected in higher wages depends on the characteristics of the labour market. There are a number of reasons why the productivity-enhancing effects of education are likely to be reflected in higher wages, including:

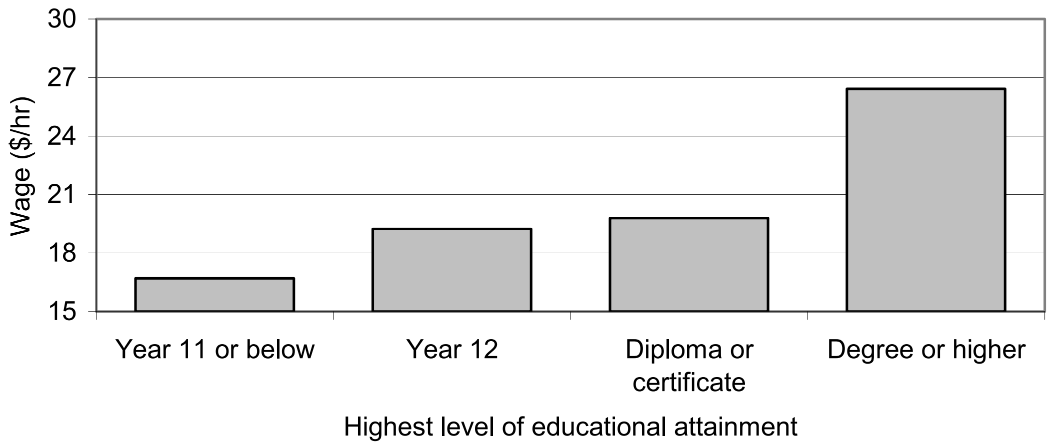
- Although productivity cannot be directly observed by prospective employers, educational attainment can. Where employers perceive that higher levels of education are positively associated with higher productivity, they might reward higher levels of education with higher wages. Over time, employers whose perceptions of employee productivity are most accurate are likely to have an advantage over competitors.
- If employers place a higher value on educated workers and labour markets are competitive, more educated workers are likely to achieve higher wages. This means that even if wages do not immediately respond to changes in individuals' educational attainment, over time they can seek higher wages (either in their current job or elsewhere). Therefore, over the course of their working lives, a

person's wages would be expected to adjust in line with their level of educational attainment.

- One countervailing factor is the possibility that some workers prefer jobs that pay a lower wage than they could earn elsewhere because they gain intangible benefits from the lower-paid job. Characteristics associated with lower wages might include greater flexibility in hours, location or travel time, or some other characteristic that leads them to prefer the job despite the lower wages.
- Along similar lines, some people might face barriers to entry — either real or perceived — into jobs for which they are qualified. This could include linguistic, gender or cultural barriers that prevent them from earning wages that reflect their level of education and productivity.

The link between education and wages is borne out in an established academic literature (both Australian and overseas) and is readily observable in the data used for this project (figure 1.1). This gives support to the assumption that wages are a useful indicator of labour productivity, although it is unlikely that there is a one-to-one relationship between wage variations and education-based differences in productivity.

Figure 1.1 **Mean hourly wages increase with higher levels of education, 2001–2005[a]**



[a] Mean wages are standardised for age and gender.

Source: Household, Income and Labour Dynamics of Australia (HILDA) Survey, Waves 1–5.

How is health status expected to influence productivity?

As a component of human capital, health makes an important contribution to a person's productivity. The literature identifies two channels through which ill health reduces workers output and productivity: absenteeism from work and 'presenteeism'.

Grossman (1972) conceives of health as a 'durable capital stock that produces an output of healthy time'. This healthy time is then allocated between leisure and work, with poor health limiting the amount of healthy time that may be allocated to generating income. This conception of health describes the effects of absenteeism on labour productivity.

As well as influencing the amount of healthy time available for work, health also influences the quality of the time available. The fact that a person is healthy enough to come to work does not necessarily mean that they are working at their potential. The loss of productivity that occurs 'when employees come to work but, as a consequence of illness or other medical conditions, are not fully functioning' (Econtech 2007, p. ii) is referred to as 'presenteeism', and it is a source of health-related productivity loss.

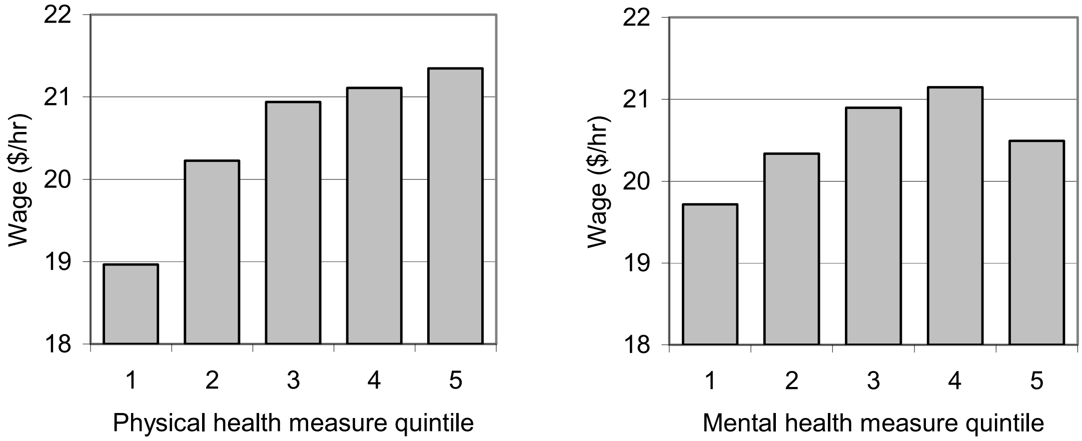
Ill health that leads to absenteeism or presenteeism reduces the output and productivity of affected workers (and also potentially the productivity of co-workers).

Are wages likely to reflect health-induced changes in productivity?

Ill health (including the COAG target health conditions) can lead to lower labour productivity through absenteeism and presenteeism. Figure 1.2 shows that there is a positive relationship between physical and mental health and wages (although people with the highest levels of mental health earn less than people in the third and fourth quintiles).

Although there is evidence of a positive relationship between health and hourly wages, the way labour markets function suggests that wage differentials might not capture all of the effects of ill health on labour productivity.

Figure 1.2 **Mean wages, by physical and mental health measures** [a,b]



[a] Physical and mental health are measured using the SF-36 Physical and Mental Component Summaries. See Appendix B for more information on these health measures. [b] Mean wages are standardised by age and gender.

Source: Household, Income and Labour Dynamics of Australia (HILDA) Survey, Waves 1–5.

One important difference between education and health status is that it is generally possible for employers to observe the education levels of employees (or potential employees). Employers can therefore choose to pay higher wages to more educated employees, if they consider that they are likely to be more productive. It is much more difficult for employers to observe or predict the health status of employees or potential employees, and for employees to predict their own health status.

As a protection against the financial consequences of unpredictable episodes of ill health, most permanent employees are entitled to sick leave. This has the effect of insuring the employee against some of the potential loss of wages due to illness. Employers presumably cover the costs of sick leave by paying somewhat lower wages to all employees. This is likely to lead to more muted responses of an individual's wages to an episode of ill health than if there were no provision for sick leave.

As well as sick leave, there are a number of regulations and conventions that protect unwell workers from wage cuts, provided they are still well enough to attend work. The effect of these regulations is likely to transfer some of the costs of illness onto employers and colleagues. Some of the protection from wage cuts derives from the conditions under which people are employed. For example, many employment agreements stipulate drawn-out procedures for dealing with underperformance. This can make it difficult for employers to change their employees' wages, even if illness leads to significant reductions in their productivity. Like sick leave provisions, such regulations and conventions are likely to lead to muted wage responses to ill health.

A further issue to consider is the effect of illness on co-workers. Pauly et al. (2002) develop a model of the effects of illness on output and labour productivity to analyse the impact of absenteeism on employers and employees. They show that in a simplified model where homogeneous workers produce output individually (not as part of a team) and that output can be stored at zero cost:

> [t]he cost to the firm when a worker is absent due to illness is the worker's marginal revenue product, which is equal to the wage. (Pauly et al. 2002, p. 223)

Pauly et al. then consider a more complex and realistic model of firms that use team production processes. When workers work as a team, the absence of one member can reduce the productivity of the whole team, particularly if the absent worker has skills that can not easily be replaced (that is, where good substitutes are not available). Pauly et al. show that:

> … when there is a team production and substantial team-specific human capital, the value of lost output to the firm from an absence will exceed the wage per day of the absent worker. (p. 226)

This suggests that using wages as an indicator of productivity will tend to understate the negative effects of absenteeism on labour productivity. As well as losing the production of the absent worker, there is a flow-on effect that reduces the productivity of the rest of the team, so the lost productivity exceeds the wage of the absent individual.

Pauly et al. observe that the costs of absenteeism due to illness are likely to vary from firm to firm, and state that the costs are likely to be largest at firms where the inventory is perishable. They give the example of an airline that is forced to cancel a flight because the pilot is absent and will never be able to recoup the lost revenue. The cost to the firm of the pilot's illness would far exceed the pilot's wage.

The model developed by Pauly et al. implies that productivity losses that are caused by presenteeism are also likely to be larger in firms that use team production processes. Presenteeism leads to lower productivity from some workers who remain at work in spite of illness. Workers who are 'present' may produce less output for every hour they attend work (that is, they have a below-normal level of productivity). If they are self-employed, this behaviour reduces their income.[3] For employees the lower productivity reduces the revenue that their employer gains from employing them, but does not necessarily reduce the employee's hourly

[3] Data issues meant that self-employed people were excluded from this study.

wages.[4] At least part of the reduction in workers' productivity is borne by the employer. This reduces the productivity and profitability of the firm, and the aggregate productivity of the labour force — which will affect the overall level of wages — but does not show up in data on individual wages.

The effects of presenteeism on firms are likely to vary depending on the duration of the employee's illness. If it is short-lived, firms may respond by requiring their remaining employees to pick up the slack. This effectively passes the costs of the illness onto the other employees who are required to work harder or longer hours to meet the shortfall due to their colleague's illness. In the longer run, this situation is unlikely to be tenable, and the firm will have to replace the sick worker, or adjust to a permanent fall in output, labour productivity and profits.

The unpredictable nature of illness, provisions for sick leave and labour market conventions mean that the response of individual wages to ill health is likely to be muted. Presenteeism and the effects of team production suggest that some of the costs of a person's ill health might be borne by their employer and by co-workers. Therefore using individuals' wages as an indicator of the effects of health on labour productivity might tend to understate the negative effects of ill health on productivity.

There are also statistical issues that could imply that the results obtained using hourly wages as an indicator of the effects of health on productivity might not reflect the true relationship between health and productivity. For example, if higher wages lead to better health, and at the same time better health leads to higher wages, 'endogeneity bias' might lead to results that overstate the positive effects of good health on labour productivity. Statistical issues are discussed further in chapter 3.

[4] For workers whose employment agreements include the scope for performance bonuses, reductions in productivity due to illness may result in them not receiving bonuses (or receiving less). In this way, some of the effects of health on productivity would be reflected through wages.

2 Literature review

There is an extensive literature in Australia and overseas that investigates the effects of education and health on wages (or other comparable measures such as income or earnings). This chapter briefly describes some of the literature and reports the main findings relating to the effects of education (section 2.1) and health (section 2.2) on wages.

2.1 Education and wages

The influence of education on wages has been investigated extensively. Often this has been done in the context of studying other questions such as male–female wage differentials (for example, Breusch and Gray 2004; Miller and Rummery 1991), comparing full-time and part-time wages (Booth and Wood 2006), and looking at wages across different demographic groups (Creedy et al. 2000). Leigh (2007) used HILDA data to estimate the returns to different levels of education in Australia. He found that education had significant positive effects on participation and productivity. The basic approach to quantifying the effects of education and health conditions in this paper is based on these and other studies that used Australian data, and on overseas studies.

The assumption in each of the papers mentioned above is that higher levels of education have a positive effect on wages. Econometric models were specified to estimate the size and strength of the relationship. Higher levels of educational attainment are consistently found to have a positive and statistically significant effect on wages. The results from these papers suggest that people holding a degree or higher qualification earn wages between 30 per cent and 45 per cent higher than people with otherwise similar characteristics who have not completed year 12. Overseas literature supports the conclusion that higher education leads to higher wages (box 2.1).

Box 2.1 **Some overseas estimates of the effects of education on wages**

Researchers have estimated the effects of education in other countries, finding that education is related to higher wages. For example:

- Pereira and Martins (2001) carried out a meta-analysis to estimate the returns to education in Portugal and to assess the appropriateness of Mincer-style wage equations (the type of equation that was used in this paper) to inform public policy. They estimated that in Portugal in 1995 an extra year of education increased wages by around 9.7 per cent, and supported the use of education coefficients in Mincer equations as an upper bound on the benefits of education for public policy discussions.
- Bonjour et al. (2003) estimated the returns to education for women in the United Kingdom. They estimated that an extra year of education increased hourly wages by 7.7 per cent.
- Kedir (2008) found that education has a positive relationship with wages in Ethiopia, and that women experience higher returns to schooling than men.

2.2 Health and wages

The effects of health conditions on wages in Australia have been the subject of less research than the effects of education on wages. Cai (2007) and Brazenor (2002) point out the relatively small number of studies into the effects of health on labour market outcomes and attempt to fill the gap in knowledge.

Cai (2007) used a self-reported measure of general health to estimate the effect of health on male wages (box 2.2). He found that good health is positively related with wages. For example:

> … compared to persons with poor or fair health, people with very good or excellent health can earn a wage 18 per cent higher. (Cai 2007, p. 17)

Cai used a simultaneous equation model to allow for endogeneity between health and wages.[1]

Brazenor (2002) investigated the effect of disability status on earnings in Australia. He found that men with a nervous or emotional condition earn approximately 35 per cent less than average male income. Men who suffer from chronic pain or

[1] 'Endogeneity' refers to the possibility that as well as better health leading to higher wages, higher wages may lead to better health. The issue is discussed further in chapter 3.

discomfort were estimated to earn 15 per cent less than average, and women 10 per cent less.

Box 2.2 **Measuring the effects of health status for labour market research**

One issue that arises in studies of the effects of health on participation, productivity and wages is the measurement of health status. Some researchers use data based on formal diagnosis of particular medical conditions. For example, the 2003 HILDA survey asked respondents:

> Have you ever been told by a doctor or nurse that you have any of the long-term health conditions listed below? [The list of conditions included arthritis, asthma, cancer, chronic bronchitis, emphysema, diabetes, heart disease and high blood pressure] (AC Nielsen 2003, p. 10)

Other studies rely on individuals' self-reported general health. Self-reported general health can be derived from direct responses to survey questions regarding a person's health status. For example, the HILDA survey asks respondents whether 'in general' they would describe their health as: 'excellent; very good; good; fair; or poor'. In the context of labour market research, this kind of health measure can be prone to 'rationalisation endogeneity', which occurs when a person uses their self-assessed health as a rationalisation for their labour market status. Cai and Kalb (2005) found mixed evidence of rationalisation behaviour in previous studies, and also found that self-assessed health status is highly correlated with diagnosed conditions.

Alternatively, measures of general health can be derived from responses to questions about how well people are able to perform certain tasks (such as climbing stairs and carrying groceries) and how they feel (for example, 'how much bodily pain have you felt during the past four weeks').

Brazenor's study comes closest to providing the estimates of interest in this project. However, Brazenor did not look at most of the chronic conditions targeted by the National Reform Agenda. Specifically, no attempt was made to measure the effects of cancer, cardiovascular disease, diabetes or serious injury on wages. Also, Brazenor used total income (less age and disability pension payments) as the dependent variable rather than hourly labour income. Total income is not a very satisfactory proxy for labour productivity, partly because total income depends on hours worked as well as wages, and includes other (non-labour) income sources.

The results reported by Brazenor (2002) and Cai (2007) are consistent with overseas literature that finds a positive relationship between good health and measures of wages, income and earnings (box 2.3).

Box 2.3 **Overseas estimates of the effects of health on wages**

Gambin (2005) used European data to investigate the relationship between wages and two measures of health: general self-assessed health; and whether the respondent reported having any chronic physical or mental health problem, illness or disability. She found that good health has a significant positive effect on wages throughout Europe, and that self-assessed general health has a larger effect for men's wages, while chronic illness has a larger effect on women's wages.

Jäckle and Himmler (2007) investigated the relationship between hourly wages and self-assessed health (on a 1-10 scale) in Germany. They found that there was no statistically significant relationship between health and wages for women, but that healthy men were estimated to earn between 1.3 per cent and 7.8 per cent more than those in poor health.

Pelkowski and Berger (2004) used US data to investigate the effects of temporary and permanent health conditions on the wages and hours of work of men and women. They found that temporary health conditions have no significant effect on labour market outcomes for men or women. Permanent health conditions are associated with a reduction in wages of between 4.2 per cent and 6.4 per cent (for men) and 4.5 per cent and 8.9 per cent (for women). Hours worked decline by between 6.1 per cent and 6.9 per cent (men) and 3.9 per cent and 4.5 per cent (women).

Andren and Palmer (2004) investigated the effects of past illness on current earnings in Sweden. They found that people who have had a long spell of sickness in previous years have lower earnings than people who have no record of long-term sickness. Andren and Palmer accounted for age in their model, but did not account directly for work experience.

Marcotte and Wilcox-Gök (2001) estimated that in the United States mental illness is associated with a decline in annual income of between US$3500 and US$6000.

Kedir (2008) investigated the relationship between height, body mass index (BMI) and wages in Ethiopia. Height and BMI were used as indicators of nutrition and general health, and were found to be positively correlated with wages (although women at the upper end of the wage distribution were found to suffer a wage penalty related to higher BMI).

3 The model and econometric issues

Human capital literature suggests, and descriptive statistics (figures 1.1 and 1.2) appear to confirm, that higher levels of education and good health have a positive relationship with wages and, by implication, productivity. However, it may also be the case that high wages contribute to better health and higher levels of education as they provide the funding to access related goods and services. This section briefly describes the multivariate model that was used to estimate the effects of education and the target health conditions on wages. It also sets out some of the econometric issues associated with this type of research. More detail is provided in appendix A.

3.1 The basic model

The model used to estimate the effects of education and health on wages is based on Mincer's (1974) specification, in which the natural logarithm of hourly wages is expressed as a linear function of years of schooling and a quadratic function of potential experience. Potential experience was used because of a lack of reliable data on actual labour market experience.[1] The quadratic function of potential experience implies that over time returns to experience diminish and eventually could become negative.

The basic form of the model is:

$$\ln w_i = \beta_0 + \mathrm{S}_{\mathrm{i}}^{'}\beta_1 + \beta_2 e_i + \beta_3 e_i^2 + H_{\mathrm{i}}^{'}\beta_4 + \mathrm{X}_{\mathrm{i}}^{'}\beta_5 + \varepsilon_i$$

where:

- $S_i^{'}$ represents a vector of dummy variables indicating highest level of education;
- e_i is a measure of experience;
- $H_i^{'}$ is a vector of mental and physical health variables;
- $X_i^{'}$ is a vector of control variables denoting labour market and demographic characteristics; and

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[1] Mincer measured experience as a person's age, minus the number of years spent in school, minus the number of years prior to school (generally assumed to be five).

- ε_i is an error term.

The variables are explained in more depth in chapter 4 and appendix B.

The model is estimated separately for women and men, to allow for gender differences.[2]

3.2 Sample selection bias and the Heckman approach

Data on wages are only available for people in employment, which raises the possibility of bias in the data used to estimate the wage model. The potential for bias arises because people with observed wages — the employed — may be systematically different from working-age people without observed wages — people who are unemployed or not seeking employment. If they are systematically different, a model that only uses data from employed people could be biased because it does not account for the potential wages of people not currently working. Regression analysis of wages and their determinants that is restricted to the working population is likely to return coefficient estimates that are inconsistent with their true population values (including those who are working and those who are not currently working) (Greene 2003).

Potential sample selection bias is addressed by applying an approach devised by Heckman (1979). This approach involves estimating two equations: a 'selection' equation that estimates the likelihood that a person with a given set of characteristics will be employed; and a 'principal' or 'wage' equation that includes an adjustment factor based on the selection equation to estimate a wage for everybody in the sample, employed or otherwise.

This approach is well-established and commonly used in labour market research. For example, Breusch and Gray (2004) used HILDA data and a Heckman model to estimate the relationship between wages and a number of individual characteristics, including education. Pelkowski and Berger (2004) estimated the effects of health problems on individuals' labour market participation and wages. They used the Heckman approach to account for the fact that the sample of people who are earning a wage is non-random, and health status has a significant effect on people's decision to participate in the labour market.

[2] An alternative approach was tested in which a single model was estimated for men and women, using dummy variables and interaction. Results showed that there were statistically significant differences between genders in the effects of a range of human capital variables, including education and health status.

The results of econometric estimation carried out for this paper show that there is sample selection bias present for the men in the sample, but not for women (section C.1).

3.3 Other econometric issues

As well as sample selection bias, there are a number of other econometric issues that may lead to bias in the results. Two of the more significant issues are endogeneity bias and unobserved heterogeneity. These issues are briefly discussed below, with further detail presented in appendix A.

Endogeneity bias

'Endogeneity bias' arises where the dependent variable (in this case, wages) has a causal effect on one or more of the explanatory variables. This could occur if higher levels of education and good health lead to higher wages and, at the same time, higher wages contribute to better health and higher levels of education. Failing to account for the feedback effects of wages on health and education can lead to biased estimates of the effects of health and education on wages.

Endogeneity between health and wages can arise because of the feedback between wages and health, or from unobserved factors that affect both health and wages. Cai's (2007) study into the relationship between health and wages found that reverse causality (wages driving changes in health status) was not statistically significant. Cai does find, however, that there is evidence of endogeneity of health resulting from unobserved factors.

A key difference between Cai's study and this study is the measures of health used. Cai used self-reported health (poor to excellent) as a general measure of health status. This study uses summary indexes constructed from a short-form health survey to measure health. This is a similar approach to the construction of a 'health stock' in Disney, Emerson and Wakefield (2006). As Disney, Emerson and Wakefield explain, the construction of such a health measure should 'strip the health term in the labour force participation equation of possible subjectivity and endogeneity in individual response to general health-related questions' (Disney, Emerson and Wakefield 2006, p. 626).

Given the findings by Cai (2007) for the HILDA data, and the construction of the health variable by Disney, Emerson and Wakefield (2006), the model used in this study does not adjust for the possibility of endogeneity between wages and health. This is a similar approach to that taken by Brazenor (2002). If endogeneity were present in the data, it would potentially lead to results that overstate the positive effects of good health on wages.

Endogeneity bias with regard to education remains a potential problem. Card (1999) states:

> [s]ince people with a higher return to education will tend to acquire more schooling, a cross-sectional regression of earnings on schooling yields an upward-biased estimate of the average marginal return to schooling … (p. 1814)

This suggests that the modelling framework used for this project might overstate the positive effects of education on labour productivity. This should be taken into account when interpreting the results of the analysis.

Unobserved heterogeneity

In econometric terms, 'unobserved heterogeneity' describes a situation where some unobserved characteristic (such as a person's innate ability or their work ethic) is related to both the dependent variable (in this case wages) and one or more independent variables (such as health or education). Unobserved heterogeneity can cause endogeneity bias.

Unobserved heterogeneity could arise in the context of the relationship between health and wages. If an unobserved variable (such as self discipline) leads to better health and higher wages, estimated coefficients for the effects of health on wages might be biased and not reflect the true underlying effects of health on wages.

Unobserved heterogeneity is also a potential problem when estimating the relationship between education and wages. 'Ability bias' is a specific form of unobserved heterogeneity that refers to the possibility that some people have innate abilities (such as cognitive ability) that would make it easier for them to complete education. Even in the absence of formal education, these characteristics would be sought after in the labour market and rewarded with higher wages. Therefore, some of the benefits that are associated with education might have more to do with the person's innate characteristics than their level of education, and estimates of the effects of education on wages might be biased.

Laplagne et al. (2007) used HILDA data to estimate the effects of education and health status on labour force participation. They used a series of econometric tests to test for the presence of unobserved heterogeneity, and found statistically significant evidence of unobserved heterogeneity in the data. They concluded that 'unobserved heterogeneity means that the coefficients from the standard multinomial logit model are likely to be biased upward' (Laplagne et al. 2007, p. 45).

To the extent that labour productivity is explained by inherent ability (rather than by education), the ability of governments to increase labour productivity by increasing average education levels is lower than would be implied by estimates of the effects of education on wages (as a proxy for productivity).

Leigh (2007) estimated the returns to education in Australia using HILDA data. As part of his analysis Leigh reviewed Australian and overseas literature on ability bias — that is, the extent to which unobserved characteristics account for both the level of education and the measure of performance. Depending on the method used, Australian estimates of ability bias were between 9 per cent and 39 per cent. Overseas estimates ranged from 10 per cent to 60 per cent. For the purposes of his analysis, Leigh assumed that ability bias meant that estimates of the returns to education were biased upward by 10 per cent.

Based on the literature, including Leigh (2007) and the Laplagne et al. (2007) results, it is likely that endogeneity bias would cause the results estimated for this project to be biased upward. That is, the actual positive effects of education and improved health status on wages might be less than implied by this model. However, the use of wages as an indicator of labour productivity could lead to understatement of the effects of education and health status on productivity. It was not possible to determine which of these biases has a more significant effect on the results, and therefore not possible to determine whether the results in this paper under- or overstate the effects of education and health status on labour productivity.

Some researchers have used panel data models to correct for unobserved heterogeneity. This was not possible in this case because of the adjustment required to address sample selection bias in the data. Techniques to correct for sample selection bias in panel data are experimental and beyond the scope of this study.

3.4 Estimating the potential wages of persons not currently employed

The model required to address sample selection bias has the advantage that it can be used to inform other policy questions. One question of interest to policy makers is the potential effect of labour market reforms on macroeconomic indicators such as unemployment rates, gross domestic product (GDP) and labour force productivity. To determine the macroeconomic effects of policies, it is useful to understand the potential productivity that could be expected of people who are unemployed or not in the labour force if they were to become employed. Estimating the potential wages of these groups — as an indicator of potential productivity — was a secondary objective of this paper.

The potential wages of people who are unemployed or not in the labour force are likely to systematically vary by age and gender (for reasons related to experience, for example). To account for this, the potential wages of men and women were estimated separately. And for each gender the model included binary variables to account for different age groups (15–24 years; 25–44 years; and 45–64 years), and for recipients of the Disability Support Pension[3].

The potential wages of non-working men and women in the various age groups were estimated relative to the average wages of employed men and women in the same age groups. Technical details of the approach to estimating the relative wages of the demographic groups are provided in appendix A.

[3] Recipients of the Disability Support Pension were a target group for the NRA reforms.

4 Data and variables

This chapter describes the data and variables used to estimate the wage model described in chapter 3, and the indirect approach that was developed to estimate the effects of the COAG target health conditions on wages.

4.1 Education and health variables

The database for the regression analysis uses five waves of data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. The data were pooled to form a large, cross-sectional dataset. The construction of the dataset is explained in more detail in appendix B.

The dependent variable is the natural logarithm of hourly wages, derived from gross wage or salary income (from all jobs) and average hours worked per week. Hourly wages are preferred to weekly or annual income because income measures are influenced by the wage rate and hours worked. The wage rate is an indicator of individuals' productivity, while the hours worked relates to individuals' participation in the labour market.

One factor that complicates the analysis is the prevalence of casual employment. Casual employees generally do not receive sick leave or other leave, but are paid a loading as compensation. This may lead them to report higher wages than permanent employees with similar characteristics performing similar jobs. Unfortunately, casual loadings were not available with which to adjust the hourly wages of this group. This may understate the extent to which ill health reduces their productivity (relative to permanent employees).

In total, there are 29 explanatory variables used in the selection equation and 28 in the wage equation.

Education variables

The HILDA survey includes questions on the respondents' level of education. For this project, education is represented by four dummy variables that indicate the highest level of education attained (degree or higher; diploma or certificate; year 12;

and year 11 or below). These variables are relatively straightforward and, for the purposes of this modelling, are considered a reliable indicator of the level of educational attainment.

Health variables

The HILDA survey also includes questions on the individual's health status. However, the data in HILDA are not ideal for the purposes of this project, and the health variables are less straightforward than the education variables.

Two types of health variables were considered. The first option was to use binary variables to indicate the presence of each of the health conditions. It was concluded that the binary variables did not adequately reflect the health status of HILDA survey respondents (see appendix B). Therefore an alternative technique was developed using general measures of physical and mental health to impute the effects of the conditions on wages.

General physical and mental health summary scores

HILDA includes an internationally-used self-completion questionnaire called the SF-36. Responses to this questionnaire are used to assign to each respondent two summary scores, known as the 'physical component summary' (PCS) and 'mental component summary' (MCS) scores. These scores range from zero to 100 and reflect the reported general physical and mental health of the respondent. The summary scores are included as explanatory variables in the model to indicate the effects of general physical and mental health on wages. Using results from other studies, it was possible to estimate the average effect of each of the target conditions on PCS and MCS scores (box 4.1).

As an alternative to the PCS and MCS scores, the model could have used another set of self-reported health variables reported in the HILDA survey (a five-point scale of 'poor' to 'excellent'). The PCS and MCS were preferred for a number of reasons:

- There is a range of studies (Australian and overseas) that estimate the effects of the target conditions on the PCS and MCS scores. Using the PCS and MCS scores in combination with these earlier studies it is possible to estimate the effects of the target conditions on wages.
- The PCS and MCS scores are continuous variables, and are therefore more flexible for this analysis than the discrete variables based on health status.

Box 4.1 Estimating the effects of illness using PCS and MCS scores

Each of the target conditions has an effect on the physical and mental health of sufferers. A review of Australian and overseas literature was used to estimate the average effect of the conditions on physical health (PCS) and mental health (MCS). The preferred estimates are described in greater detail in appendix B. Based on the literature review, the average effects of the conditions on general physical and mental health were estimated to be:

- Cardiovascular disease: reduction of 3.3 points in PCS and 2.1 points in MCS
- Diabetes: reduction of 3.5 points in PCS and 1.0 points in MCS
- Cancer: reduction of 3.6 points in PCS and 0 points in MCS
- Arthritis: reduction of 4.5 points in PCS and 1.5 points in MCS
- Mental illness: reduction of 3.9 points in PCS and 13.9 points in MCS
- Major injury: reduction of 9.9 points in PCS and 4.3 points in MCS.

Sources: Alonso et al. (2004); Surtees et al. (2003); Productivity Commission estimates.

4.2 Developing a two-stage process for estimating the effects of the target conditions

Although using binary variables that reliably indicate the presence of the target health conditions would be the best approach to the research question, suitable binary variables were not available. Instead, an alternative approach was devised that uses the PCS and MCS scores for general health to estimate the effects of the target conditions on wages. This approach involves three steps:

1. Estimate the effect of a change in general health on wages.
2. Estimate the effects of each of the target conditions on general health.
3. Combine the estimates from steps one and two to estimate the effect of each of the target conditions on wages.

There is an academic literature that contains estimates of the effects of different diseases on the PCS and MCS scores (for example, Alonso et al. 2004; Surtees at al. 2003; Ware and Kosinski 2001). These estimates can then be fed into the wage model to indirectly estimate the effects of the conditions on wages.

For example, Alonso et al. (2004) estimated that cardiovascular disease was associated with a 3.3 point reduction in the PCS and a 2.1 point reduction in the MCS (out of 100). The PCS and MCS scores have statistically significant effects on wages, so the coefficients on these scores can be used to indirectly estimate the effects of the conditions on wages. Further detail on this approach is set out in appendix B.

Issues arising from the indirect approach

Using PCS and MCS scores to estimate the effects of the target conditions raises a number of potential problems (see also appendix B):

- It is necessary to assume that the PCS and MCS accurately reflect people's health (including the presence of the target conditions). A number of researchers in Australia and overseas have shown that the PCS and MCS are reliable indicators of the effects that specific health conditions have on general physical and mental health.
- Frijters and Ulker (2008) raised concerns about generalising from the results of one survey-based measure of health (such as the PCS) to another (such as chronic illness). However, personal communication with Frijters suggested that the approach taken for this paper is reasonable for estimating the effects of policy changes.
- There is a limited literature on the effects of the target health conditions on PCS and MCS scores, and most of it is from overseas. Overseas literature might be less relevant to Australia because of different labour market and health policies as well as the incidence of the health conditions.
- There is a wide variation in the estimates of the effects of some conditions on PCS and MCS scores. For example, Chittleborough et al. (2005) estimated the effects of diabetes on Australian PCS and MCS scores. They found that diabetes is associated with a PCS that is 7.8 points lower, and an MCS that is 0.1 points lower than for people with normal glucose levels. Alonso et al. (2004) reported the effects of diabetes in six European countries, Japan and the United States, finding average reductions of 3.5 and 1.0 points, respectively.
- The approach assumes that co-morbidities (that is, people suffering from two or more conditions) have an additive effect on PCS and MCS scores. (Regressions using the Survey of Disability, Ageing and Carers dataset show that this assumption is justified empirically.)
- The approach assumes that the PCS and MCS are linear (for example, that a reduction in physical health from 75 to 72 is equivalent to a fall from 51 to 48).

Although these concerns are real and need to be acknowledged in reporting the results, this approach is judged the best means currently available to estimate the effect of chronic illnesses on wages, given the available data.

5 Results

This chapter presents estimates of the marginal effects of educational attainment (section 5.1) and health status (section 5.2) and the potential wages of people not currently working compared with people who are currently working (section 5.3). The results are discussed, including some caveats on their use for policy formulation. The approach to estimating the marginal effects of education and health status is set out in appendix A. Estimation results for the wage model are set out in greater detail in appendix C.

5.1 Marginal effects of education

The results of this study are consistent with the human capital literature and previous estimates showing that increased educational attainment has a significant positive effect on wages (table 5.1).

Table 5.1 **Average marginal effects of education on hourly wages**
Per cent increase in hourly wages compared with year 11 or below (standard errors in brackets)

Highest level of education	*Marginal effect of each level of education*		
		Men	Women
	per cent		per cent
Degree or higher	38.4	(1.90)	36.7 (1.57)
Diploma or certificate	13.8	(1.50)	11.4 (1.44)
Year 12	12.8	(2.11)	10.1 (1.63)

Source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

Obtaining a university education has the largest effect on wages — a 38 per cent increase in men’s wages and a 37 per cent increase in women’s wages. The implication is that people with a degree have a higher level of productivity than people with lower levels of education. Laplagne et al. (2007) found that university education also has the largest effect on workforce participation — increasing the probability of participation by 15–20 per cent (men) and 8–10 per cent (women).

The marginal effect of completing year 12 is close to that of completing a diploma or certificate. Again, this is consistent with Laplagne et al. (2007), who found the participation effects of these qualifications to be of a similar magnitude. These results suggest that the labour market effects of high school completion and vocational education and training (VET) are similar.

The positive effects of education are between 1.8 and 2.8 percentage points larger for men than the effects for women.

In interpreting these results, it should be noted that endogeneity bias and unobserved heterogeneity (such as due to ability bias) may lead to positive bias in the results. This would overstate the positive effects of education on wages, and by implication labour productivity.

It should also be noted that these estimates represent the average marginal effects of increasing levels of education. The actual marginal effects of additional education would be expected to vary according to individual characteristics. For example, Lattimore (2007) reported results from the literature that suggest that for some people additional education is associated with lower wages and labour market participation:

> … students with traits that imply a low ex ante probability of completing school who nevertheless go onto complete the maximum 12 years have lower real weekly full-time earnings and hourly earnings and higher [unemployment] rates than similar students who left earlier. For the group of children with the lowest 50 per cent predicted likelihood of completing school, two additional years of schooling past year 10 actually increases unemployment by around 3 percentage points. For this group of children, each additional year of schooling reduces real hourly earnings by about 1.1 per cent and real weekly fulltime earnings by 2.4 per cent. The best (on average) that students with such traits can do is to leave school earlier. (Lattimore 2007, p. 210)

This result suggests that programs to increase levels of education will deliver the greatest benefits when targeted toward people who are most likely to benefit from additional education.

5.2 Marginal effects of health status

The wage model was used to estimate the marginal effects of health status. The marginal effects reported are not conditional on employment. The target conditions were found to have a small negative effect on wages (wage reductions of between 1.6 per cent and 5.4 per cent for men and between 1.0 per cent and 3.5 per cent for women) (table 5.2). Of the six health conditions, the most significant effects on wages were associated with mental health conditions and major injury. This is consistent with Laplagne et al. (2007), who found that these conditions had the largest effects on workforce participation.

Table 5.2 **Marginal effects of target health conditions on hourly wages**

Target condition	*Percentage hourly wage reduction attributable to presence of target condition* [a]	
	Men	Women
Cardiovascular disease	-1.9	-1.3
Diabetes	-1.8	-1.2
Cancer	-1.6	-1.0
Arthritis	-2.3	-1.5
Poor mental health	-4.7	-3.1
Major injury	-5.4	-3.5

[a] Percentage wage reduction attributable to a target condition is calculated by multiplying the average marginal effect of a change in the PCS and MCS on wages by the expected reduction in PCS and MCS associated with each target condition (see Appendix B).

Source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

These results, combined with the results presented by Laplagne et al. (2007), suggest that the most significant labour market effects of chronic illness relate to the effects of the conditions on workforce participation. People who contract the target conditions but remain at work tend not to experience large reductions in their wage rates.

The results also suggest that the target conditions have larger effects on men's wages than on women's — for all conditions the reduction in men's wages is around 50 per cent larger compared to women's wages. Again, this is consistent with Laplagne et al. (2007), who found that the negative effects of the target conditions on labour force participation were generally larger for men than for women.

In interpreting these results, there are several factors that should be taken into account:

- Using individual's wages as an indicator of productivity leads to results that are likely to understate the effects of health status on productivity. It is likely that individuals' wages do not adjust fully to changes in their health status, and that some of the reduction in labour productivity caused by illness is borne by firms and co-workers, or collectively by society. The full effects of illness on productivity would therefore not come through in individual wages data, although illness could have a real effect on aggregate productivity and national income. This would suggest that the reductions in productivity arising from health conditions are understated.

- Unobserved heterogeneity and endogeneity may lead to positive bias in the results. This would serve to overstate the positive effects on wages (and labour productivity) of improved health status.
- There are issues associated with using the indirect approach (relating changes in PCS and MCS scores to specific chronic illnesses) to estimating the effects of the target conditions on wages. However, the direction of any potential bias relating to the use of this approach is not clear.

These concerns suggest that the positive effects on labour productivity of reducing the prevalence of the target conditions may be larger or smaller than the effects estimated using this model. It is not possible to determine which of the potential sources of bias is likely to have the largest effect, and therefore whether the results will tend to under- or overstate the negative effects of ill health on wages.

It is worth noting that the results of this study and those found in Laplagne et al. (2007) suggest that the more significant effects of chronic health conditions relate to their effect on labour force participation, and that the effects on the wages of people who remain in the labour force are generally of a smaller magnitude.

5.3 Estimated wages of people not currently working

As a group, people who are unemployed or not in the labour force have systematically different characteristics from employed people. On average, they have less education, are in worse health, have less work experience, more experience of unemployment, and demographic characteristics that are associated with lower wages (such as poor language skills and living outside of major cities). These characteristics mean that they are more likely to be unemployed or not in the labour force, and if they were working, they would be more likely to earn lower wages.

The estimates in table 5.3 are derived based on the human capital, labour market and demographic characteristics of people who are unemployed and not in the labour force. The estimates are based on taking the average of these characteristics for men and women of different age groups. The wage model was used to estimate the wages that a hypothetical person with these characteristics would be likely to receive if they were working. These 'offer wages' are divided by the average wage that is earned by employed persons of the same age and gender to derive an estimate of the potential wages of people who are unemployed or not in the labour force relative to employed persons.

The technique used to estimate the wages of people who are not currently employed relative to the wages of people who are currently employed is described in Appendix A.

The potential wages of people who are unemployed or not in the labour force relative to employed persons are estimated separately for men and women. Binary variables are used to distinguish people in four different age groups and recipients of the Disability Support Pension (DSP).

The estimates of the potential wages of people not currently working show that, on average, people with their labour market and demographic characteristics would be expected to earn around 70–75 per cent of the wages of people who are currently working. These figures are consistent with the assumptions that the Commission used in its reports on the economic implications of an ageing population (PC 2005) and the impact of the NRA (PC 2006).[1]

The results also show that the estimated potential wages of people receiving the DSP are lower than the estimated potential wages of the general non-working population. However, the gap between the estimated wages is not large — between 3 and 6 per cent for men and 4 and 10 per cent for women.

A significant result is that the estimated potential wages for male DSP recipients in the 25–44 and 45–64 age groups (that is, working-age men) are only 3–3.3 per cent lower than the general population of non-working men. This suggests that many male DSP recipients have similar human capital and labour market characteristics to other men who are not working (and not receiving the DSP). The gap for working-age women is much larger, particularly in the 25–44 age group, where the estimated potential wage for female DSP recipients is around 9.7 per cent lower than for other non-working women who are not receiving the DSP.

[1] The relevant comparison with the NRA report is the estimate of the ‘productivity ratio of 75 per cent [that] was adopted for additional workers as a result of changed work incentives’ (PC 2006, p. 299).

Table 5.3 **Predicted potential relative wages for NRA target groups**

Demographic group	*Estimated potential wages of people not currently employed relative to employed people (per cent)*		
	Men	Women	Men and women
15–24 years	75.4	76.6	76.1
25–44 years	67.3	74.8	71.3
45–64 years	72.2	73.7	73.0
55–64 years	72.8	75.2	73.9
Weighted average[a]	70.5	74.7	72.7
Disability Support Pension recipients			
15–24 years	69.7	72.5	71.1
25–44 years	64.0	65.1	64.5
45–64 years	69.1	68.7	68.9
Weighted average[a]	66.6	67.6	67.1

a Weighted to reflect sample proportions.

Source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

A Specifying a wage model

This appendix contains a description of the econometric model used to estimate the effects of education and health status on wages, and sets out the approach used to estimate the potential wages of people not currently employed. Also described are some of the econometric issues associated with estimating wage functions and the techniques that were used to overcome some of those problems, as well as the potential implications of unresolved econometric issues.

A.1 Specifying a human capital earnings function

The effects of human capital characteristics on wages are commonly estimated using a human capital earnings function based on the model specified by Mincer (1974). In Mincer's model, the natural logarithm of wages is expressed as a linear function of years of schooling and a quadratic function of potential experience:

$$\ln w_i = \beta_0 + \beta_1 s_i + \beta_2 x_i + \beta_3 x_i^2 \qquad \text{[A.1]}$$

where: w_i is the wage rate of the *i*th individual; s_i represents years of schooling; and x_i is potential years of work experience. Experience is included as a proxy for the accumulation of human capital that occurs after formal education (such as on-the-job training). The quadratic term is included to allow for a possible decline in the returns to this form of human capital over the individual's life. (For example, technological can change render redundant the skills accumulated early in a person's working life.)

Conveniently, coefficients in the log-linear wage equation can be interpreted as approximations of percentage effects. That is, β_1 can be read as an approximation of the effect on wages of an additional year of schooling in percentage terms.[1]

[1] The larger the value of the coefficient, the less accurate it is as an approximation of the percentage effect — coefficients are converted into actual percentages by taking the inverse natural logarithm of the coefficient and subtracting 1: [exp(coefficient) – 1] x 100.

Augmented specification

To estimate the effects of health and education on wages, and to predict the wages of those not currently employed, a number of adjustments are made to Mincer's basic model:

- The explanatory variables are augmented with a vector of health variables (mental and physical health) (appendix B).
- To allow for different returns across different types of education, the continuous measure of schooling is replaced with a series of dummy variables indicating the highest level of educational attainment (appendix B).
- A measure of actual experience is used in place of Mincer's proxy of potential experience.[2]
- A vector of control variables, denoting labour market and demographic characteristics that can influence wages, is included in the specification. The control variables are outlined below.

The basic form of the model is:

$$\ln w_i = \beta_0 + \mathrm{S}_\mathrm{i}^{'}\beta_1 + \beta_2 e_i + \beta_3 e_i^2 + H_\mathrm{i}^{'}\beta_4 + \mathrm{X}_\mathrm{i}^{'}\beta_5 + \varepsilon_i \qquad \text{[A.2]}$$

where $S_i^{'}$ represents a vector of dummy variables indicating the individual's highest level of education; e_i is a measure of experience; $H_i^{'}$ is a vector of mental and physical health variables; $X_i^{'}$ is a vector of control variables; and ε_i is the error term.

Gender

The very different labour market experiences of women and men require that separate models be estimated for women and men. Miller (1982) shows that women typically earn less than men, the growth of their earnings over their lifetime is much slower, and their age–earnings profile 'dips' in the middle, in contrast to the steadily concave male earnings profile. Gender-wage differences have persisted over time (Le and Miller 2001).

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2 A lack of reliable data on labour market experience led Mincer to use *potential* labour market experience as a proxy for actual experience. That is, an individual's potential labour market experience was equal to their age, minus years spent in school, minus years prior to school (typically assumed as 5). Use of an actual measure of experience removes an upward bias associated with measures of potential experience.

Differences in the wages paid to men and women could result from factors including different reservation wages (for example, the opportunity cost of working might be lower for some women than for men), different human capital investment decisions or different treatment in the labour market (including gender discrimination), or a combination of these factors (Preston 2000).

Nevertheless, Australian research shows that there is a persistent 'gap' of around 12–15 per cent between male and female wages, even after taking into account differences that may affect productivity (Eastough and Miller 2004, Le and Miller 2001, Miller 2005, Preston 1997). This suggests that different labour market outcomes are not due entirely to human capital investment decisions.[3]

The fact that men and women have systematically different labour market outcomes, and that these differences cannot be explained in terms of human capital theory, implies that there is a different structure of wage determinants for each gender. Wage equations were estimated separately for men and women to account for these differences.

Control variables

To estimate the returns to education and health, it is appropriate to further augment Mincer's equation with a number of control variables that relate to characteristics that can affect an individual's earning capacity. Broadly, these can be considered as labour market and demographic variables.

Labour market variables

An individual's previous and current labour market status can affect their wages. A number of variables are included in the model to account for these effects:

- Full-time study is likely to impact on an individual's earning capacity, because students' job opportunities are likely to be constrained and they may be paid wages that are not commensurate with their level of human capital. To account for this, the model includes a binary variable to indicate whether the person is studying.
- Unemployment history is included as a control variable, describing the proportion of time that an individual has spent unemployed since completing

[3] Preston (1997) shows that around 72 per cent of the gender-wage gap is 'unexplained', and this is relatively stable between 1981 and 1991. Le and Miller (2001) estimate that the 'systematic unequal treatment' of women accounts for around 84 per cent of the difference in male and female wages in the late 1990s.

school. This is included to account for possible scarring effects that might limit an individual's ability to find employment (Knights, Harris and Loundes 2002), or limit their earnings capacity when they are employed (Arulampalam 2001, Gregg and Tominey 2005).

- Whether or not a worker is full- or part-time might also affect their wages. Booth and Wood (2006) present evidence of a premium afforded to part-time workers in Australia. In contrast, Hirsch (2005) finds that part-time workers in the United States are penalised. To account for this, an indicator of part-time work is included in the wage equation.
- Some researchers include in their models variables identifying the industry that people are employed in. All else being equal, wages can differ across industries, due to a range of factors, including: the desirability of the work involved; the level of competition; and the capital intensity of the industry. However, excluding industry variables makes it more likely that education coefficients are representative of the average returns to education across the entire labour market (Chapman, Rodrigues and Ryan 2007). Given the economy-wide focus of this project, no industry variables were included. In addition, excluding industry variables makes it possible to estimate the potential wages of people who are unemployed or not in the labour force (one of the objectives of this study).

Demographic variables

In estimating the relationship between human capital and wages, there are a number of demographic factors to be considered:

- Changes in the age-education profile over time are likely to alter the wage-education relationship, and need to be taken into account when considering returns to education. To this end the human capital model is augmented with age dummy variables to account for the possibility of age, cohort and period effects that might cloud actual returns to education.
- An indicator of indigenous status is included to control for different employment opportunities that may result from cultural differences, discrimination, or specific government policies that may apply to Indigenous Australians (such as the Community Development Employment Projects program).
- Language difficulties can affect an individual's ability to participate in the workforce. A non-English speaking background indicator is included to account for this effect.
- Marital status has been found to be related to wages. For example, Cai (2007) found that married men earn approximately 9 per cent more than unmarried men.

- Geography (including state of residence and whether the respondent lives in a regional area).

Sample selection bias

Data on wages are only available for people in employment, which raises the prospect of bias in the sample of persons in the database used to estimate the wage model. The potential for bias arises because people with observed wages — those employed — are likely to be systematically different from those without observed wages — those unemployed or not in the labour force. Restricting the sample to people who earn a wage is likely to introduce biases into the estimation. Regression analysis of wages and their determinants that is restricted to this non-random sample is likely to return estimates inconsistent with their true population values (Greene 2003).

The problem of sample selection bias can be taken into account by explicitly incorporating into the model an adjustment for the risk that certain people will not be included in the sample (that is, they will not be employed). Heckman (1979) devised an approach where two equations are estimated: a 'selection' (employment) equation and a 'principal' (wage) equation.[4]

The Heckman approach begins with a latent variable E_i^* that is a function of each individual's characteristics z_i:

$$E_i^* = \gamma' z_i + u_i \qquad \text{[A.3]}$$

The latent variable can not be directly observed, but if its value exceeds zero the person will be employed:

$E_i = 1$ if $E_i^* > 0$

$E_i = 0$ if $E_i^* \leq 0$

Turning now to the wage equation, the natural logarithm of hourly wages can be expressed as a function of a vector of human capital, labour market and demographic characteristics $\mathbf{x}_i$:

$$\ln w_i = \beta' \mathbf{x}_i + \varepsilon_i \qquad \text{[A.4]}$$

4 This section is based on Laplagne, Glover and Fry (2005) (unpublished).

The error terms in equations A.3 and A.4 have the following properties:

$u_i \sim N(0, \sigma_u)$

$\varepsilon_i \sim N(0, \sigma_\varepsilon)$

$\mathrm{corr}(u_i, \varepsilon_i) = \rho$

In order to correct for the fact that w_i is observed only when $E_i=1$, the expected wage of each individual must be adjusted by the expected value of the error from the selection equation. Thus, the conditional expected wage is given by:

$$E(w_i \mid E_i = 1) = \beta'\mathbf{x}_i + \rho\sigma_\varepsilon\lambda_i(\alpha_u) \qquad \text{[A.5]}$$

where $\lambda_i(\alpha_u) = \dfrac{\phi(\gamma'\mathbf{z}_i / \sigma_u)}{\Phi(\gamma'\mathbf{z}_i / \sigma_u)}$ is the inverse Mills ratio and ϕ and Φ are the normal density function and the cumulative normal distribution function, respectively.

Rewriting $\rho\sigma_\varepsilon$ as ψ allows equation (A.5) to be rewritten as:

$$E(w_i \mid E_i = 1) = \beta'\mathbf{x}_i + \psi\lambda_i(\alpha_u) \qquad \text{[A.6]}$$

λ is the term in the principal (or wage) equation that corrects for self-selection. The coefficient for λ is the covariance between the error term in the selection and principal equations (equations A.3 and A.4 respectively). A positive and significant coefficient for the correction term implies that employees have unobserved characteristics, such as innate ability, that result in their observed wages being higher than wage predictions based on their observed characteristics. It should be noted that the consistency and unbiasedness of the estimators in this model depend on the validity of the assumption that the disturbance term ε_i is normally distributed.

A.2 Predicting wages for those not employed

The wage model developed for this paper is well suited to the task of estimating the wages of people who are not currently employed, relative to those who are employed. The relative wages of people not currently employed is of particular relevance when using economy-wide models to estimate the effects of proposed human capital and labour market reforms.

The productivity (and hence wages) of people who are not currently employed is likely to systematically vary according to age and sex. For that reason, relative wages are estimated separately for men and women of different ages. Specifically, the model is estimated separately for men and women aged 15–24, 25–44 and 45–64. It is also estimated for male and female recipients of the Disability Support Pension, and for the labour force as a whole.

There are three steps involved in estimating the potential wages of people who are not employed relative to the wages of those who are:

1. Estimate the average wage of each demographic group, conditional on them being employed.
2. Estimate the 'offer wage' of each demographic group. The offer wage is a hypothetical wage that would be offered to a person who is not currently working if they were to start work. The offer wage is estimated based on the person's observed human capital and labour market characteristics.
3. Calculate the ratio of the wage (conditional on employment) and the offer wage to estimate the potential wage of people who are unemployed or not in the labour force relative to the employed population in each demographic group.

Estimating wages conditional on employment status is complicated in this application by the log transformation of the dependent variable (hourly wages). Yen and Rosinski (2008) show that, where the dependent variable is in log form, using the functional form specified in equation A.5 to estimate expected log wages and then taking the exponent of the expected log wage can lead to systematic underestimation of the conditional wage. To account for this possibility, Yen and Rosinski derive an alternative approach to estimating the wage (in dollars, not log form):

$$E(w_i \mid E_i = 1) = \exp\left(\beta'\mathbf{x}_i + \sigma^2/2\right)\frac{\Phi\left(z'\alpha + \rho\sigma\right)}{\Phi\left(z'\alpha\right)} \qquad [A.7]$$

Following the same reasoning, the expected wage conditional on the person not being employed (the offer wage) is given by:

$$E(w_i \mid E_i = 0) = \exp\left(\beta'\mathbf{x}_i + \sigma^2/2\right)\frac{\Phi\left(-z'\alpha - \rho\sigma\right)}{\Phi\left(-z'\alpha\right)} \qquad [A.8]$$

The ratio of the two wages is reported as an estimate of the relative wage of people who are not currently working.

B Data and variables

The data used in this study are from the first five waves of the Household, Income and Labour Dynamics in Australia (HILDA) survey. Section B.1 describes the HILDA dataset. Section B.2 discusses the relationship between the target health conditions and the indexes of physical and mental health that are derived from HILDA data.

B.1 Data used in the analysis

The HILDA survey provides a valuable opportunity to examine the returns to health and education in Australia. HILDA is a nationally representative household panel survey containing respondents' information regarding education, health, labour force status and experience, and demographic background. Five waves of data were used for this analysis, covering the period from 2001 to 2005.

Te National Health Survey (NHS) and the Survey of Disability, Ageing and Carers (SDAC) were considered as alternative datasets for this analysis. While the NHS and SDAC have the advantage of more detailed data on the health conditions of interest, HILDA was preferred because it:

- contains detailed wages data — SDAC and NHS only include data about income, an unreliable proxy for wages;
- contains more variables relevant to employment (such as work experience and industry) than are available from SDAC and NHS; and
- is based on a representative sample, in contrast to SDAC, which has relatively few observations from healthy people.

Documentation of the sample design, data collection and derivation of variables for the HILDA survey can be found in Goode and Watson (2006).

Estimation subsample

To maximise the number of observations available, the five waves of HILDA data were combined to form a pooled, cross-sectional dataset.[1] The panel data characteristics of the HILDA dataset were not exploited in this study because it was not feasible to use a Heckman approach to correct for sample selection bias using panel data. People eligible for the aged pension (assets permitting), self-employed workers, those employed by their own business, unpaid family workers and those aged under 18 and still at school were excluded from the dataset. Observations with incomplete responses were also dropped — failure to report a wage and failure to return the self-completion questionnaire component of the survey constituted the majority of incomplete responses.[2] After these adjustments, around 30 000 observations remained.

Problems of non-response and sample attrition also need to be considered when using a panel survey. If attrition is influenced by unobservable factors, then there is little that can be done to ensure unbiased estimators. If attrition can be attributed to observable characteristics — as shown by Watson and Wooden (2004) — then the bias can be adjusted by using weights, thereby ensuring that estimates reflect the population being surveyed (Henstridge 2001). For this project observations were weighted to produce unbiased estimators and to present results that are broadly representative of the Australian population.

Variables used in the estimation

Variables used in the wage and participation equations are defined in table B.1. A brief description of most of these variables follows. More detail is provided for the variables of interest — education and health.

The natural logarithm of hourly wages is the dependent variable in the wage equation, and is derived from gross weekly wage or salary and total weekly hours worked. The dependent variable in the participation equation is a binary indicator of

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[1] This approach requires the assumption that coefficient estimates are constant over the five waves. For example, returns to having a degree (in terms of percentage effect on wages) are assumed to remain the same between 2001 and 2005. Also, the pooled data include up to five responses from the same person, so the assumption of error independence between observations from the same person was relaxed, as per Baum and Ford (2004).

[2] Respondents completing a personal interview are also given a self-completion questionnaire, either to be collected at a later date, or to be submitted by mail. Over the five waves of HILDA, an average of 92 per cent of interviewed respondents returned the self-completion questionnaire (Watson and Wooden 2006).

employment, with individuals designated as being employed if they report having a full- or part-time job, and they report a wage.

Table B.1 **Variables used in wage and participation equations**

Variable	*Definition*
Dependent variables	
Log wage[a]	Natural log of the hourly wage, multiplied by 100. (Hourly wage is calculated as the weekly gross wage or salary divided by hours usually worked per week.)
Employment[b]	1 if employed, 0 if not employed
Independent variables	
Employment history	
Experience	Years in paid work
Unemployment history	Proportion of time since leaving school spent unemployed and looking for work.
Demographic variables	
Age	Binary variables indicating whether aged 15–24, 25–44 or 45–64
State	Binary variables indicating state of residence
Region	1 if not resident in a major city
Indigenous	1 if Aboriginal or Torres Strait Islander
Married	1 if married or de facto
Non-English speaking background (NESB)	1 if born in a non-English-speaking country
Studying	1 if currently studying full time
Part time[a]	1 if working less than 35 hours per week
Children 0–4[b]	Number of resident children aged 0–4 years
Children 5–14[b]	Number of resident children aged 5–14 years
Children 15–24[b]	Number of resident children aged 15–24 years
Highest level of educational attainment	
Degree or higher	1 if Bachelor degree or higher
Diploma or certificate	1 if Advanced Diploma, Diploma, Certificate IV or Certificate III
Year 12	1 if completed Year 12
Year 11 or below[c]	1 if Year 11 or below
Health	
Physical component summary	Score ranging from 0 to 100 indicating level of physical health
Mental component summary	Score ranging from 0 to 100 indicating level of mental health
Other	
Wave identifiers	Binary variables indicating HILDA wave for each observation

[a] Used in wage equation only. [b] Used in participation equation only. [c] Includes those who have completed Certificate I or II, but not Year 12.

Source: HILDA release 5.1, waves 1–5.

Both equations contain other labour market and demographic control variables including experience; unemployment history; part-time status; age; geographic location; indigenous status; language background; and marital status. Number of children was also included in the participation equation. Dummy variables indicating the wave from which observations were drawn were also included in both equations to control for changes in labour market conditions and wage inflation over time.

Education variables

Four categories of educational attainment are included in the analysis: degree or higher; diploma or certificate; year 12; and year 11 or below. These categories are derived from the ten categories of highest educational attainment used by HILDA, as shown in table B.2. In the wage model, year 11 and below is used as the default category for education.

Table B.2 **Aggregation of education variables indicating highest level of education**

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

[a] Observations were also dropped if the question was not completed.

Source: Laplagne et al. (2007), based on HILDA survey, release 4.1.

Health variables

Two types of health variables are available in HILDA — measures of physical and mental health and binary indicators of target illnesses. Both were considered in this analysis, with the measures of general health being preferred.

The physical and mental health measures are continuous variables indicating a level of physical and mental health for each individual in each wave. While these health measures do not provide information about specific target conditions, there is a body of literature describing the relationship between these measures and the target conditions, so it is possible to infer the effect of target conditions on wages. This relationship is discussed in section B.2.

Physical and mental health measures

The measures of physical and mental health — known as physical (PCS) and mental (MCS) component summaries — range from 0 to 100, with a population mean of 50 and standard deviation of 10. A higher score indicates better physical or mental health.

The PCS and MCS measures are both derived from the Short Form 36 (SF-36) questionnaire, a widely used self-reported measure of physical and mental health designed for comparing functional health and wellbeing and the relative burden of diseases, across diverse populations (Ware 2000).[3] The SF-36 has been included in each wave of HILDA. While the SF-36 questionnaire does not include references to symptoms of specific diseases, the measures derived from it have been shown to be highly correlated with the frequency and severity of many health problems (see for example, Alonso et al. 2004; Surtees et al. 2003; Ware and Kosinski 2001).

The SF-36 questionnaire comprises 36 questions relating to different aspects of an individual's health-related quality of life. The 36 questions are used to derive eight subscales of health, each ranging from 0 to 100, and measuring different elements of health: physical functioning; limitations in carrying out usual role due to physical problems; bodily pain; perception of general health; vitality; social functioning; limitations in carrying out usual role due to emotional problems; and mental health. The physical and mental health summary measures are produced by aggregating the most correlated of the subscales.

Use of the PCS and MCS as indicators of health-related quality of life and disease burden is widespread (see Ware and Kosinski 2001), as the aggregated information in the summary measures simplifies analyses while maintaining the bulk of the information gathered in the questionnaire (Schmitz and Kruse 2007). Confidence intervals around the summary indexes have also been shown to be smaller than for the eight subscales (Ware 2000).[4]

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[3] Documentation of the Short Form 36 questionnaire, including scoring procedures and applications of the PCS and MCS, is found in Ware and Kosinski (2001).

[4] For the subpopulation used in this analysis, estimates of the subscale means had a confidence interval of ± 0.36–0.62 points, whereas means of the PCS and MCS had a confidence interval of around ± 0.18 points.

Calculating the PCS and MCS

The PCS and MCS were calculated using the method described in Ware et al. (2004).

The PCS and MCS are not included in the HILDA data, but can be generated from the eight scales that are provided and parameters estimated using HILDA (table B.3). Only the first wave was used to estimate these parameters — because survey attrition might be correlated with one or more of the scales, using later waves to derive parameters could bias the summary measures (Dockery 2006).

The scales are standardised via a z-score transformation, using sample means and standard deviations. The standardised scales are then aggregated into physical and mental components using 'factor loadings' calculated using principal components analysis.[5] The aggregated scales are multiplied by 10 and the product is added to 50 to produce the final PCS and MCS measures. After dropping observations, PCS and MCS means were 51.3 and 49.4, respectively.[6]

Table B.3 **Parameters for calculating PCS and MCS measures**[a]

SF-36 scales	*Mean*	*Standard deviation*	*Physical factor loading*	*Mental factor loading*	*Variance explained*[b]
Physical functioning	82.54	23.68	0.4494	-0.2352	0.72
Role limitations — physical	78.74	35.85	0.3683	-0.1244	0.73
Bodily pain	73.84	25.50	0.3379	-0.0953	0.69
General health	69.72	21.32	0.1958	0.0513	0.62
Vitality	60.63	19.88	-0.0527	0.2992	0.68
Social functioning	81.45	23.92	0.0194	0.2429	0.72
Role limitations — emotional	81.93	33.27	-0.1093	0.3232	0.57
Mental health	73.72	17.48	-0.2707	0.4881	0.82

[a] The means, standard deviations and factor loadings used to produce the PCS and MCS were obtained using the unweighted first wave of HILDA. This is the same approach used in producing previous population norms (ABS 1995). [b] The proportion of variance of each scale explained by the physical and mental factors.

Source: Wave 1 of HILDA.

[5] Principal components analysis is conducted with a varimax rotation, and then scored using the regression method in version 9 of Stata. The factor loadings calculated match those reported in Dockery (2006), and are consistent with the unscored loadings presented in Butterworth and Crosier (2006).

[6] When averaged across the entire first wave, mean PCS and MCS scores were 50.1 and 50.0.

Interpreting the PCS and MCS

Individually, the PCS and MCS measures indicate 'physical and mental function and wellbeing, the extent of social and role disability, and personal evaluation of health status' (Ware and Kosinski 2001, p. 57). As a way of understanding what the measures mean in terms of health, a guide to interpreting values at the extremes of both measures is reproduced from Ware and Kosinski (2004) in table B.4. The relationship between individual health and the PCS and MCS measures is discussed further in section B.2.

Table B.4 **Health status of people with very low and very high PCS and MCS measures**[a]

Summary measure	*Very low*	*Very high*
Physical component summary	Substantial limitation in self-care, physical, social and role activities; severe bodily pain; frequent tiredness; health rated 'poor'	No physical limitations, disabilities or decrements in wellbeing; high energy level; health rated 'excellent'
Mental component summary	Frequent psychological distress; substantial emotional and role disability due to emotional problems; health in general rated 'poor'	Frequent positive affect; absence of psychological distress and limitations in usual social/role activities due to emotional problems; health rated 'excellent'

a 'Role' refers to activities that are carried out in an individual's 'usual role'.

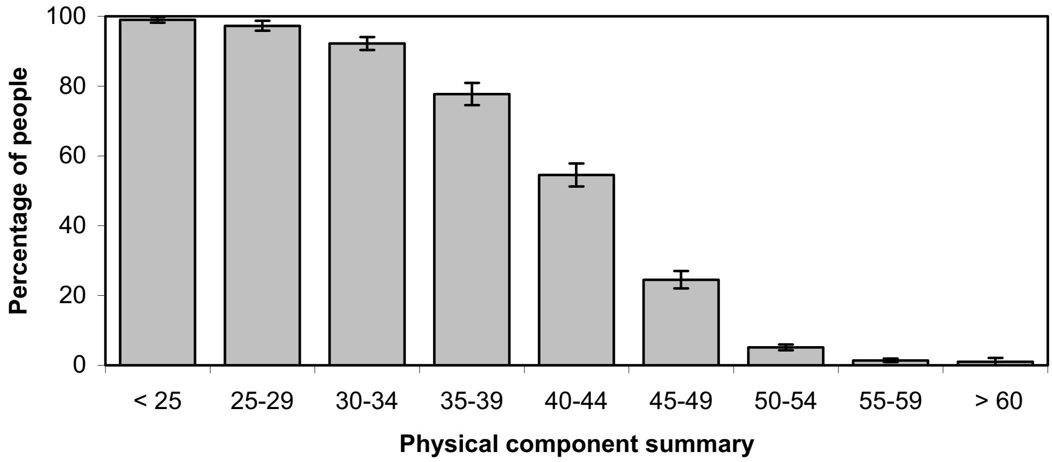
Source: Reproduced from Ware et al. (2001, p. 58).

People with lower PCS scores are significantly more likely to report difficulties in performing work and other activities (figure B.1) Overall, around 20 per cent of people reported some difficulty, but the overwhelming majority of these people have PCS scores below 50. Indeed, the percentage of those experiencing difficulties decreases substantially as PCS scores increase — for example, around 25 per cent of those with a PCS score between 45 and 49 compared to just 5 per cent of people with a PCS score between 50 and 54.

A similar negative relationship is observed between MCS scores and self-declared effects of emotional problems — such as feeling anxious or depressed (figure B.2). The percentage of people who 'didn't do work/other activities as carefully as usual' as a result of emotional problems again decreases substantially as MCS scores increase — 13.1 per cent of those scoring between 45 and 49 to 4.3 per cent of those with a score between 50 and 54.

Figure B.1 **People reporting difficulty performing work or other activities due to physical health, by PCS range[a]**

Percentage of people in each PCS range

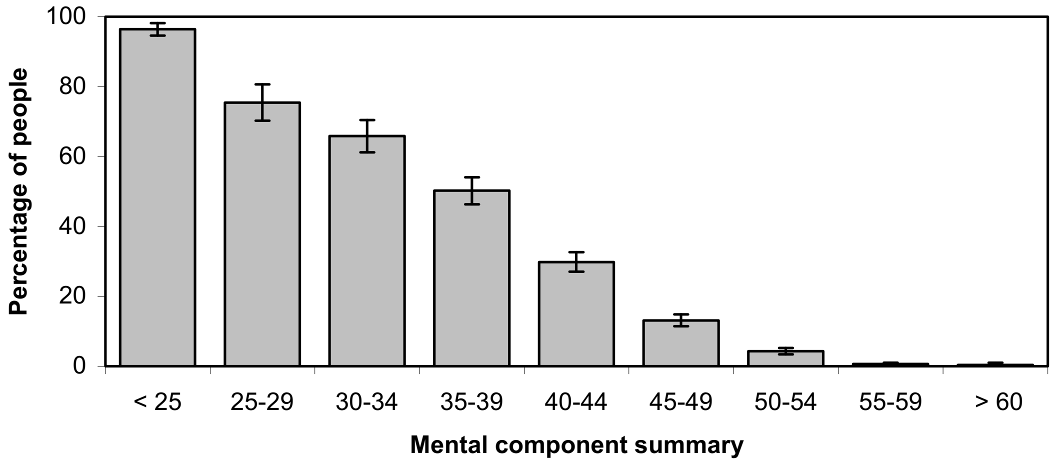


[a] Estimates are population-weighted. Error bars represent 95 per cent confidence intervals.

Data source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

Figure B.2 **People who didn't do work or other activities as carefully as usual as a result of emotional problems, by MCS range[a]**

Percentage of people in each MCS range



[a] Estimates are population-weighted. Error bars represent 95 per cent confidence intervals.

Data source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

Binary indicators of target health conditions

Because the focus of this project is on six specific 'target' health conditions, the most direct approach to the research question would be to use binary variables to indicate whether survey respondents suffer from each of the conditions. Attempts were made to construct binary variables from HILDA data.

Construction of the health condition variables involves combining information contained in waves 3 and 4 of HILDA to impute whether a respondent has a long-term, 'target' health condition across the five waves. Variable construction differs across target health conditions, and is described below.

Cardiovascular disease, diabetes, cancer and arthritis

Variables indicating if an individual has cardiovascular disease, diabetes, cancer or arthritis were constructed using the same approach. In wave 3, respondents were asked if they had been diagnosed with a number of conditions.

Respondents were designated as having cardiovascular disease in 2003 if they indicated in wave 3 that they had ever been 'told by a doctor or nurse' they had either 'heart or coronary disease', 'high blood pressure/hypertension' or 'any other serious circulatory condition (for example, stroke or hardening of the arteries)', and this condition had lasted or was likely to last for more than six months. Similarly, those told by a doctor or nurse that they had diabetes, cancer or arthritis were designated as having that condition for wave 3.

The way that the question was worded means that this approach may overstate the prevalence of the target conditions. The question asked if respondents had 'ever been told by a doctor or nurse' that they had a long-term health condition that had lasted or was likely to last for more than six months. Some of the conditions mentioned in the survey (such as high blood pressure) can be controlled and reversed. This means that somebody who had high blood pressure for six months or more prior to 2003 but got it under control would answer 'yes' to the HILDA question and would be erroneously designated by this process as having cardiovascular disease in 2003.

Respondents are also asked in each wave of HILDA if they have a long-term health condition and the year in which the condition developed.[7] Responses to this question were used to impute the presence of the condition in waves 1, 2, 4 and 5.

[7] This question does not refer to any specific conditions, and is used in this analysis to impute the continuation of conditions declared in wave 3.

For example, if a respondent declared that they developed a long-term condition in 2002 and they had cardiovascular disease in 2003, it was assumed that they had cardiovascular disease in 2002, but not in 2001. If the year they developed the condition was 2003, they were classified as not having the condition in either 2001 or 2002. In 2004, people were assigned a target condition if they declared a long-term health condition and had a target condition in wave 3.

Imputing health conditions in this way requires a number of assumptions that may distort the data. People reporting multiple conditions in 2003 and a long-term health condition in another year are assumed to have *all* the conditions they had in 2003 in that year, because the survey question relating to the year the condition developed does not refer to a specific condition. Around 25 per cent of those with cardiovascular disease, arthritis, cancer, or diabetes, are assumed to have more than one of these conditions in each wave.

The number of people with these four target conditions might have been underestimated in waves 1, 2, 4 and 5. It was not possible to assign a target condition to respondents that reported a long-term condition in these waves but did not report a target condition in wave 3, as there was no information about which condition they might have. For waves 1, 2, 4 and 5, around 40 per cent of those who say they have a long-term condition were assigned one of these four target conditions. This is in contrast to wave 3, where around 46 per cent of those with a long-term condition had at least one of these four conditions.

Mental illness

A binary indicator of mental illness was constructed using the mental health measure. Respondents were designated as being of ‘poor mental health’ if their MCS score was equal to or below 39. This approach is the same as that employed by Jofre-Bonet et al. (2005).[8] Sanderson and Andrews (2002) report that such a variable is likely to capture: 80 per cent of those with moderate depression; 92 per cent of those with severe depression; 75 per cent of those with any affective disorder; 58 per cent of those with anxiety disorder; and 60 per cent of those with psychosis.

Using this approach to construct an indicator of mental health was preferred over indicators based on diagnosis or use of health services, as not all people with mental illness seek treatment for their condition (Frank and Gertler 1991). Such ‘utilisation’ measures are likely to result in biased estimators if the selection of

8 Ware (2000) considers a MCS cut-off point of 42 as an effective screen for psychiatric disorders.

treatment for mental illness is correlated with other determinants of wages, such as education.

Major injury

Information regarding major injury in the HILDA dataset is limited, but a variable can be constructed to gain some insight into the effect it might have on wages.

In waves 2, 3, 4 and 5, respondents were asked if they have suffered a 'serious personal injury or illness'. Those who had another target condition, or had declared a long-term health condition, were assumed not to have suffered a serious injury. For those in wave 1, the likelihood of major injury in wave 1 was conditionally imputed, as advised in Allison (2001). The probability of a person having a major injury in waves 2, 3, 4 and 5 was regressed using a probit model over other independent variables used in the wage equation. This estimated equation was used to generate predicted values of major injury for those in wave 1.[9]

The imputed binary variables were not considered reliable enough to use in this project

Accurate binary variables indicating the presence of the target health conditions would enable reliable estimation of the effects of the conditions on wages. Unfortunately, there are a number of problems with the imputed binary variables that make them unsuited for the current task. Problems include:

- There are only a small number of employed respondents suffering target conditions in the HILDA data.
- The method of imputing the target conditions means that the data are 'noisy'.
- Each year respondents were asked whether they had any long-term health condition. Because the survey question relating to the year the condition developed does not refer to a specific condition, people who reported in 2003 that they suffered from multiple conditions (for example, arthritis and cancer) and reported in another year that they suffered from a long-term health condition were assumed to have all the conditions they had in 2003 in that year. This may

[9] Use of conditional mean imputation is likely to lead to underestimated standard errors (Allison 2001), although bias introduced by this approach tends to be lower than that resulting from unconditional means (Liehr 2003). To examine the effect of imputing major injury on the standard errors for this variable, the wage equation was also estimated using waves 2, 3, 4 and 5 only. This produced standard errors for major injury of a similar magnitude to those resulting from all five waves.

have resulted in persons being assigned health conditions in years when they did not actually have them.

- It is not possible to say with certainty that every person who was imputed to have a certain health condition actually had it. Nor is it certain that the imputed variables have captured every occurrence of the health conditions in the sample.
- Preliminary estimation found — contrary to a priori expectations based on human capital theory — that the binary indicators of target conditions do not have a statistically significant effect on wages, positive or negative, after controlling for the likelihood of participation.[10]

Instead of using the imputed binary variables, an alternative approach was devised that uses the relationship between the target conditions and the PCS and MCS summary scores. This approach is described in section B.2.

It should be noted that these binary health status variables were used by Laplagne et al. (2007), who were aware that this approach could potentially lead to biased estimates of the effects of illness and injury. Sensitivity tests indicated that there was 'no consistent or large bias in the marginal effects of injury [on labour force participation]' (Laplagne et al. 2007, p. 59). Possible biases associated with the other conditions were not accounted for.

Data could be improved by including in the HILDA survey specific questions about whether respondents suffered from any chronic health condition, and when they had developed each condition.

Descriptive statistics

The survey-weighted means and standard errors of variables used in this analysis are shown in table B.5. This table includes means for variables used in all specifications of both the wage and participation equations. Many of these variables are binary (having a value of 1 or 0). The means of these variables represent the percentage of the population for which the variable takes the value of 1.

Differences in human capital and demographic characteristics between those who are employed and those who are not in paid employment are generally as expected. Those who are not employed tend to be older, and so have greater levels of experience. They have also spent a greater proportion of their working life

[10] Target conditions were found to have no significant effect on male wages. If the likelihood of participation is not controlled for — that is the wage equation is run as a simple OLS regression rather than using a two-stage Heckman procedure — then the effects of both mental illness and major injury on wages are both significant and negative at the 5 per cent level.

unemployed (unemployment history). Around 13 per cent of people who are employed are of a non-English speaking background (NESB), in contrast to about 20 per cent of those who are not employed.

The different labour market circumstances and experiences of men and women are captured in the descriptive statistics, giving support to the estimation of separate wage equations. For example, there are noticeable differences between men and women in the levels of part-time employment, wages paid and experience accrued. There are also substantial differences in the marital status and age distribution of men and women who are not employed. In terms of human capital, mean levels of education and physical and mental health measures are noticeably larger for those who are employed.

Table B.5 **Descriptive statistics, by gender and employment status**[a]

Survey-weighted means (standard errors in brackets for non-binary variables)

	Employed				Not employed			
	Male		Female		Male		Female	
Dependent variables								
Log wage[b]	297.49	(0.706)	285.01	(0.60)				
Wage[b]	21.91	(0.182)	18.97	(0.15)				
Independent variables								
Employment history								
Experience	18.70	(0.214)	15.76	(0.19)	21.35	(0.49)	12.23	(0.25)
Unemployment history	0.033	(0.002)	0.025	(0.00)	0.100	(0.01)	0.05	(0.00)
Demographic variables								
Age 15–24	16.94		18.48		17.68		12.11	
Age 25–44[c]	52.78		50.23		26.51		46.72	
Age 45–64	30.28		31.29		55.81		41.17	
NSW[c]	31.59		31.73		31.59		33.07	
Vic	25.55		25.22		25.00		23.78	
QLD	20.26		20.28		20.72		20.27	
SA	7.37		7.57		7.36		7.72	
WA	10.08		9.32		9.33		10.71	
NT	0.88		0.89		0.57		0.63	
ACT	2.04		2.15		0.98		1.38	
Tas	2.23		2.82		4.44		2.44	
Region	30.00		29.19		37.34		35.22	
Indigenous	1.28		1.40		2.64		3.07	
Married	64.36		63.63		53.77		70.83	
NESB	12.97		13.56		19.81		18.92	
Studying	4.50		5.83		10.25		6.23	
Part time[b]	12.83		46.29					
Children 0–4	19.58		12.98		8.37		37.49	
Children 5–14	33.99		40.03		17.43		51.94	
Children 15–24	20.63		28.72		14.03		24.58	
Highest level of education								
Degree or higher	22.89		27.07		10.58		12.35	
Diploma or certificate	36.18		22.93		33.34		18.92	
Year 12	17.09		20.39		16.48		17.53	
Year 11 or below[c]	23.83		29.60		39.61		51.20	
Health								
Physical component summary	52.97	(0.096)	53.01	(0.107)	45.24	(0.37)	48.52	(0.23)
Mental component summary	51.23	(0.131)	49.48	(0.143)	46.93	(0.34)	47.35	(0.23)
Wave identifiers								
Wave 1	19.16		19.39		21.04		19.10	
Wave 2	18.73		19.06		19.78		18.88	
Wave 3	20.71		20.30		20.45		20.72	
Wave 4	21.26		21.02		19.45		21.08	
Wave 5	20.14		20.22		19.28		20.22	
Number of observations	13451		13351		3634		7325	

[a] Means of binary variables represent the percentage of the population with the relevant characteristic. [b] Applicable only to those employed. [c]Default category in regression analyses.

Source: HILDA release 5.1, waves 1–5.

B.2 Target conditions and measures of physical and mental health

Because of the deficiencies in the imputed binary variables, an alternative approach was devised, that draws on the relationship between the target conditions and the measures of physical and mental health. The approach essentially involves:

- determining (based on a literature review and econometric analysis) the effects of the target conditions on the PCS and MCS scores. For example, the literature shows that the PCS score of a person suffering from diabetes is on average 3.5 points lower and the MCS 1 point lower than a similar person without diabetes.
- using the estimated effects of the conditions on PCS and MCS scores combined with the results of econometric estimation to estimate the marginal effect on wages of such a decline in the PCS and MCS scores.

The comparison of disease burden across conditions is a stated purpose of the SF-36 survey (Ware 2000). As patients with target conditions experience a burden of disease that negatively impacts their health-related quality of life, the PCS and MCS can be used to quantify the impact of these conditions on a person's health (Schlenk et al. 1998). This information has been used for the purposes of this study to infer the impact of target conditions on wages. The following sections set out:

- the assumptions about the relationship between the PCS and MCS and the target conditions; and
- estimates of the effects of the target conditions on the PCS and MCS scores, drawing on the literature and regression analysis using the 1998 Survey of Disability, Ageing and Carers (SDAC).

Assumptions about physical and mental health measures

In using the relationship between target conditions and the PCS and MCS to estimate the effect of the conditions on wages, it is necessary to make four key assumptions. These assumptions, and the justification for using the indirect approach, are set out below.

The PCS and MCS accurately reflect people's health

First, it is necessary to assume that the two measures of the relative burden of disease — the PCS and MCS — accurately reflect the effect of conditions on the health of the sufferer. The SF-36 survey — and the measures derived from it — are designed to profile health and wellbeing and to enable comparison of disease burden. To the extent that they do not address impairments particular to specific conditions, the PCS and MCS are a limited reflection of an individuals' heath status (Sprangers et al. 2000).

Internationally, Ware and Kosinski (2001) show the PCS and MCS to be reliable indicators of the impact of chronic conditions. The validity of using the PCS and MCS as a measure of the relative burden of disease in an Australian context is demonstrated by Butterworth and Crosier (2004) and Sanson-Fisher and Perkins (1998). Both studies show that the physical and mental health measures are consistent, reliable and differentiate between individuals of differing health status. Importantly, Butterworth and Crosier conclude that 'results obtained using the SF-36 in the HILDA Survey can be interpreted by reference to published SF-36 normative data and comparison with previous research findings' (2004, p. 44).

Frijters and Ulker (2008) investigated the robustness of different survey-based measures of people's health, where 'robust' is taken to mean that one obtains the same research findings under different circumstances. If the survey-based measures are robust, it may be reasonable to generalise from one measure to another (such as from the PCS to specific health conditions).

Based on econometric estimation of the robustness of different measures of self-reported health, Frijters and Ulker (2008) concluded that:

> … our findings imply a lack of robustness in survey-based health research. Even when controlling for the same variables and using people from the same survey, we find large discrepancies in coefficients across different methodologies. The implication is that care should be taken not to generalise the findings of one health outcome to any other health outcome. (p. 22)

In this context, Frijters and Ulker's conclusions can be taken as a warning against generalising PCS and MCS scores to measure the impact of specific conditions. However, in personal communication, Paul Frijters stated that his 'gut reaction' was that 'as a policy piece, the approach you sketch is quite reasonable and will get you believable (low) estimates' (pers. comm. 19 January 2009). So while the indirect approach to estimating the effects of the target health conditions may not be entirely robust, it is likely to be a reasonable guide for the purposes of the analysis.

Conditions have an additive effect

The second assumption is that the influence of any target condition on the PCS and MCS is independent of the impact of other conditions. That is, the combined effect of two or more conditions is assumed to approximate the sum of the independent effect of each condition. Wee et al. (2005) find this to be the case in terms of the relationship between diabetes and a number of other chronic conditions (see also Ware and Kosinski 2001). However, Gaynes et al. (2002) find the combined effect to be greater than the sum of the individual effects. That is, they assert that co-morbidity has a multiplicative rather than additive effect.

An analysis of Australian data supports the assumption that multiple conditions have an additive effect. The PCS and MCS were regressed on the target conditions, individually and as a set of interaction terms, using the SDAC dataset.[11] The interaction terms were not significant — either individually or jointly — confirming the additive nature of the relationship between the target conditions and the physical and mental health measures.

The effects of the target conditions are similar across countries

Third, it is assumed that relationships between the target health conditions and the measures of physical and mental health are similar across countries. It is necessary to use results from different countries to estimate the relative burden of target conditions because of the lack of analysis of this issue for Australia.

The use of PCS and MCS scores from other countries is supported by Ware et al. (1998), who used principal component analysis to test whether results from the SF-36 could be generalised across countries. They concluded that the SF-36 and the summary measures derived from it (the PCS and MCS scores) are similar across cultures and that the scores can be compared internationally.

The use of estimates from international sources is also supported by comparing the impact of different conditions across countries. For example, Alonso et al. (2004) found that the impact of a range of chronic conditions — including four of the six target conditions — is 'fairly consistent' across the eight developed countries included in their study, despite differences in the incidence of these target conditions across countries (Alonso et al. 2004, p. 294). Effects of target conditions in Australia are also observed to be of a similar magnitude to those observed in other countries (table B.6).

[11] Annex B.1 contains details on estimating the effect of target conditions using SDAC. Estimations with the interactive terms are not included in this annex, but are available on request.

The SF-36 and SF-12 produce comparable results

Finally, it is assumed that PCS and MCS health measures derived from an abridged version of the SF-36 questionnaire — the SF-12 — capture the effects of target conditions to the same extent as those based on the longer version. Studies using the shorter questionnaire are included to provide more information on the relationship between target conditions and summary scores.

Inclusion of these studies is justified on the grounds that PCS and MCS scores drawn from the SF-12 survey explain at least 90 per cent of the variance in the measures derived from the SF-36 survey (see Ware et al. 1998; Müller-Nordhorn et al. 2004). The correlation between the PCS and MCS from the full and abridged questionnaires holds for both the general population (see, for example, Sanderson and Andrews 2002) and for patients with specific conditions such as arthritis (Hurst et al. 1998), stroke (Pickard et al. 1999) and coronary heart disease (Müller-Nordhorn et al. 2004).

Effects of target conditions on the PCS and MCS

The effects of each target condition on PCS and MCS scores were estimated based on a literature review and regression analysis using the SDAC. The literature review focused on studies that were based on large samples that compared the effects of multiple chronic conditions on both the PCS and MCS, and controlled for the effect of demographic characteristics on the health measures. Examining the literature identified three such studies:

- Alonso et al. (2004) examined the impact of multiple chronic conditions — including cardiovascular disease, diabetes and arthritis — using pooled, representative samples from Denmark, France, Germany, Italy, Japan, the Netherlands, Norway and the United States.
- Surtees et al. (2003) compared the effect of generalised anxiety disorder and major depressive disorder with the effect of cardiovascular disease, diabetes and cancer in a large sample (around 20 000) aged 40–74 in the United Kingdom.
- Ware and Kosinski (2001) reported the effects of a large range of chronic conditions as observed in two samples — a sample of patients with chronic medical and psychiatric conditions (Medical Outcomes Survey (MOS)) and a representative sample of the US General Population (USGP).

The effects of target conditions reported in these studies are detailed in table B.6. In addition to already published results, table B.6 includes the effects of target conditions on the PCS and MCS, estimated using the 1998 SDAC. Definitions of variables, descriptive statistics and the results from these estimations are presented in Annex B.1.

Preferred estimates of the effects of target conditions

In order to quantify the effects of target conditions on wages, a preferred estimate of the effect of each target condition is drawn from the available literature, and is used to estimate the impact of each illness on individuals' general health.

As no single study includes estimates of the effects of all six target conditions, different sources are used to provide estimates for different conditions. Where available, multiple sources are sought to ensure that results are not extreme in nature. Preferred estimates, drawn from the summary (table B.6), are presented in table B.7.

Where possible, estimates of the effects of target illnesses are taken from Alonso et al. (2004), a large, recent study bringing together results from a number of countries. The results in Alonso et al. control for the influence of age, gender, marital status and education, which is important for this study.

Estimates from Alonso et al. are preferred to other estimates because they provide a general characterisation of the burden of these diseases, rather than one specific to a particular population. Effects of target conditions from this study are used for cardiovascular disease, diabetes and arthritis. These estimates are preferred to estimates obtained from SDAC because the subjects of the SDAC tend to have more severe conditions. For that reason, the SDAC is not considered a representative sample.

Table B.6 Effects of target illnesses on measures of physical and mental health, selected sources

	Denmark, France, Germany, Italy, Japan, Netherlands, Norway, and United States (Alonso et al. 2004)		*United Kingdom (Surtees et al. 2003)*		*United States, Medical Outcomes Survey (Ware and Kosinski 2001)*		*United States, General US Population (Ware and Kosinski 2001)*		*Australia (Survey of Disability, Ageing and Carers 1998)*	
	PCS	MCS	PCS	MCS	PCS	MCS	PCS	MCS	PCS	MCS
Cardiovascular disease[a]									-3.0 ***	-0.9 **
Myocardial infarction			-6.3 ***	-2.5 ***	-3.2 ***	-0.9	-2.8 **	-2.4		
Angina	-3.3 ***	-2.1 ***			-4.0 ***	-0.4	-3.7 ***	0.2		
Congestive heart failure	-4.4 ***	-1.6 ***			-5.4 ***	-1.0	-6.7 ***	-1.4		
Stroke			-6.6 ***	-3.2 ***						
Hypertension	-1.5 ***	-1.2 ***			-1.9 ***	0.6	-1.5 ***	-0.1		
Diabetes	-3.5 ***	-1.0 **	-4.9 ***	-2.5 ***	-3.5 ***	0.6	-3.4 ***	0.3	-3.5 ***	-0.6
Arthritis	-4.5 ***	-1.0 ***					-2.8 ***	-0.9	-9.3 ***	-0.5
Osteoarthritis					-5.2 ***					
Rheumatoid arthritis					-7.6 ***					
Cancer			-3.6 ***	-1.0					-7.3 ***	-4.3 ***
Mental illness			-3.9 ***	-13.9 ***			-0.4	-9.3 ***	-0.4	-11.0 ***
Major depressive disorder			-3.9 ***	-14.0 ***	-2.3 **	-12.7 ***				
Generalised anxiety disorder			-6.3 ***	-15.7 ***						
Major injury									-9.9 ***	-4.3 ***

*** significant at 1 per cent; ** significant at 5 per cent; * significant at 10 per cent.

[a] Alonso et al. (2004) do not control for mental illness in their published results, and note that the effect of congestive heart failure, hypertension and arthritis on the MCS may be overstated between 0.5 and 1 point. Accordingly, 0.5 has been subtracted from the effects stated above for these illnesses.

Sources: Alonso et al. (2004); Surtees et al. (2003); Ware and Kosinski (2001); Productivity Commission estimates.

Table B.7 **Preferred estimates of the effects of target conditions on physical and mental health summary measures[a]**

Target condition	*PCS*	*MCS*	*Source*
Cardiovascular disease	-3.3	-2.1	Alonso et al. (2004)
Diabetes	-3.5	-1.0	Alonso et al. (2004)
Cancer	-3.6	0	Surtees et al. (2003)
Arthritis	-4.5	-1.5	Alonso et al. (2004)
Mental illness	-3.9	-13.9	Surtees et al. (2003)
Major injury	-9.9	-4.3	Survey of Disability, Ageing and Carers (1998)

a Effects are considered to be 0 if they are not statistically significant in the studies from which they are sourced.

Sources: Alonso et al. (2004); Surtees et al. (2003); Productivity Commission estimates.

Cardiovascular disease and diabetes

There is a general consensus on the size of the effects of cardiovascular disease and diabetes. Although Alonso et al. (2004) reported effects of different types of cardiovascular disease that are of differing magnitudes, the effect of angina is in the middle of the range of effects and can be viewed as representative. This is supported by the fact that angina effects reported by Alonso et al. (2004) are similar to those observed in both the USGP and the MOS (Ware and Kosinski 2001) and the SDAC. Effects of diabetes reported by Alonso et al. (2004) are also consistent with results from those studies, and are adopted as the preferred estimate.

Cancer

The effect of cancer on the PCS and MCS is drawn from Surtees et al. (2003). Cancer is not considered in either Alonso et al. (2004) or Ware and Kosinski (2001). The preferred estimates from Surtees et al. (2003) are supported by Sprangers et al. (2000), who find similar sized effects for cancer in the Netherlands. The SDAC estimates are considerably larger than Surtees et al. (2003), and are viewed as extreme.

Athritis

The estimate from Alonso et al. (2004) is used as the preferred estimate of the effect of arthritis, as it is indicative of the effect arthritis is likely to have on those working, and is comparable to that found in the USGP sample. The impact of arthritis is considerably larger in both the MOS and SDAC samples, which both contain large numbers of people with chronic medical conditions.

Mental illness

Preferred estimates for the effect of mental illness are taken from Surtees et al. (2003), who identify subjects as having either major depressive disorder (MDD) or generalised anxiety disorder (GAD). These estimates are similar to, but slightly larger, than those observed in SDAC and MOS. It is important to note that Goldney et al. (2004) and Sanderson and Andrews (2002) both report Australian effects of depression comparable to those reported by Surtees et al. (2003).[12]

Major injury

The preferred estimate of the effect of major injury is drawn from SDAC, and relates to those who have suffered an injury and are profoundly or severely disabled. There is a limited literature with which to compare these effects, although Haran et al. (2005) report respective PCS and MCS scores of around 17 and 5 points less than the normative population for Australians with spinal cord injury.

12 Sanderson and Andrews (2002) only report the effects of mental illness on the MCS.

Annex B-1: Estimated effects of target conditions on measures of physical and mental health

The 1998 Survey of Disability, Ageing and Carers (SDAC) was used to estimate the impact of the target conditions on both the physical (PCS) and mental (MCS) component summaries.

SDAC is a national survey of people with disabilities, persons over the age of 60 and those who provide care for people with a disability. It can be used for estimating the effects of chronic illness on the component summaries because it contains detailed information on the health conditions and limitations of people with a range of conditions and disabilities, as well as the required physical and mental component summaries. SDAC also contains detailed demographic data. Individual data from survey respondents are accessed using a Confidentialised Unit Record File (CURF).

Only observations that have both a physical and mental component summary are included in the regressions. As most carers do not complete the SF-12 section of the survey, this means that about 90 per cent of the estimation sample report a disability.

Binary indicators of whether or not a respondent has a disease or disorder which has lasted, or is likely to last, for six months or more are included in the regressions.[13] Target conditions and key variables are described in table B.8 and descriptive statistics presented in table B.9.

To estimate the effect of an illness on each health index, the component summaries are regressed over age, sex and illnesses. It is assumed that the effect of an illness on an index is completely additive, with the occurrence of an illness reducing a person's index score by the same amount, regardless of whether or not they have other illnesses. Results from the two regressions are presented in table B.10.

The impact of target conditions is broadly in line with other international studies considered in Appendix B. Possible exceptions are the impact of cancer, which is noticeably larger.

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[13] The disease classification system used in SDAC is based on the International Statistical Classification of Diseases and Related Health Problems-10th Revision (ICD-10), as presented in the SDAC Technical Paper (ABS, 1999). Disease classifications have been adjusted to the needs of the study in the case of diabetes and serious injury.

Table B.8 **Definition of variables used in regression analysis**

Variable label	*Description*
PCS and MCS	Physical and mental component summary indices, derived from SF-12 questions.
Age	Age of respondent, included as five-year cohorts.
Female	A dummy variable that takes a value of 1 if the respondent is female.
Mental illness	Mental and behavioural disorders. These include: psychoses and depression/mood affective disorders; neurotic, stress-related and somatoform disorders; intellectual and developmental disorders; and other mental and behavioural disorders.
Diabetes	All types of diabetes. Other endocrine, nutritional and metabolic disorders are included as a separate condition.
Serious injury	All injuries, poisoning and certain other consequences of external causes where respondent has a 'profound or severe disability'. Other injuries where the respondent does not have a profound or severe disability are included as a separate condition.
Cardiovascular	Diseases of the circulatory system. These include: heart disease; rheumatic fever/chorea with heart disease; hypertension; stroke; arterial or aortic aneurisms; hypotension; and other diseases of the circulatory system.
Cancer	All neoplasms (tumours/cancers).
Arthritis	Diseases of the musculoskeletal system and connective tissue. These include: arthritis and related disorders; back-related problems; repetitive strain injuries; synovitis/tenosynovitis; other soft tissue/muscle disorders; osteoporosis; and other disorders of the musculoskeletal system and connective tissues.
Other conditions	Other ABS broad categories of long-term health conditions.[a]

[a] The ABS coding of conditions is outlined in ABS (1999).

Source: ABS (1999).

Table B.9 **SDAC descriptive statistics**[a]

Population means (standard errors in brackets for non-binary variables)

	Mean	*SE*
Dependent variables		
Physical component summary	41.52	(0.81)
Mental component summary	47.86	(0.27)
Demographic variables		
Female	51.78	
Age 15–19	2.92	
Age 20–24	5.54	
Age 25–29	6.43	
Age 30–34	8.17	
Age 35–39	10.44	
Age 40–44[b]	11.88	
Age 45–49	12.90	
Age 50–54	15.02	
Age 55–59	13.32	
Age 60–64	13.37	
Target conditions		
Mental illness	21.80	
Cardiovascular	19.11	
Diabetes	4.96	
Serious injury[c]	4.49	
Cancer	2.31	
Arthritis	54.19	
Other conditions		
Infectious and parasitic diseases	1.53	
Blood diseases	0.61	
Endocrinal, nutritional and metabolic disorders (excluding diabetes)	4.31	
Diseases of the nervous system	9.09	
Diseases of the eye and adnexa	3.52	
Diseases of the ear and mastoid process	17.89	
Diseases of the respiratory system	14.27	
Diseases of the digestive system	5.40	
Diseases of the skin and subcutaneous tissue	2.37	
Diseases of the genitourinary system	2.56	
Congenital malformations, deformations and chromosomal abnormalities	2.08	
Symptoms, signs and abnormal clinical and laboratory findings	5.01	
Other injury[d]	13.11	
1998 codes with no ICD–10 equivalent	2.02	

[a] Means of binary variables represent the percentage of the population with the relevant characteristic. [b] Default category in regression. [c] Includes people reporting injury, poisoning and certain other consequences of external causes who are profoundly or severely restricted in their core activities. [d] Includes people reporting injury, poisoning and certain other consequences of external causes but who are not profoundly or severely restricted in their core activities.

Source: Productivity Commission estimates based on 1998 Survey of Disability, Ageing and Carers.

Table B.10 **Physical and mental component summary regressions**[a]

	Physical Component Summary		*Mental Component Summary*	
	Coefficient	*SE*	*Coefficient*	*SE*
Constant	49.628***	(0.566)	50.597***	(0.617)
Demographic variables				
Female	0.514	(0.336)	-1.197***	(0.363)
Age 15–19	3.768***	(0.917)	3.598***	(1.107)
Age 20–24	2.462***	(0.819)	2.709***	(0.932)
Age 25–29	0.775	(0.812)	-0.926	(0.896)
Age 30–34	1.270*	(0.744)	0.672	(0.817)
Age 35–39	0.937	(0.679)	-0.740	(0.768)
Age 45–49	-1.066	(0.667)	0.487	(0.714)
Age 50–54	-1.637**	(0.640)	1.326*	(0.694)
Age 55–59	-2.584***	(0.671)	2.883***	0.706)
Age 60–64	-1.566**	(0.682)	3.519***	(0.700)
Target conditions				
Mental illness	-0.376	(0.401)	-11.032***	(0.469)
Cardiovascular	-3.024***	(0.452)	-0.901*	(0.468)
Diabetes	-3.479***	(0.746)	-0.574	(0.859)
Serious injury[b]	-9.910***	(0.776)	-4.280***	(0.941)
Cancer	-7.329***	(1.247)	-4.253***	(1.413)
Arthritis	-9.274***	(0.337)	-0.486	(0.362)
Other conditions				
Infectious and parasitic diseases	-3.959**	(1.574)	-2.133	(1.641)
Blood diseases	-4.113**	(2.095)	0.119	(2.993)
Endocrinal, nutritional and metabolic disorders (excluding diabetes)	-0.730	(0.784)	1.014	(0.867)
Diseases of the nervous system	-4.484***	(0.629)	-0.733	(0.652)
Diseases of the eye and adnexa	0.642	(0.851)	0.237	(0.874)
Diseases of the ear and mastoid process	1.938***	(0.410)	0.165	(0.433)
Diseases of the respiratory system	-4.130***	(0.494)	-0.890*	(0.515)
Diseases of the digestive system	-2.794***	(0.719)	-1.951**	(0.790)
Diseases of the skin and subcutaneous tissue	-3.226**	(1.287)	-0.803	(1.144)
Diseases of the genitourinary system	-3.571***	(1.092)	-1.277	(1.155)
Congenital malformations, deformations and chromosomal abnormalities	-0.186	(1.226)	3.414***	(1.138)
Symptoms, signs and abnormal clinical and laboratory findings	-2.841***	(0.803)	-1.956**	(0.858)
Other injury[c]	-1.551***	(0.485)	0.886*	(0.499)
1998 codes with no ICD–10 equivalent	-2.611**	(1.261)	-1.581	(1.438)

*** significant at 1 per cent, ** significant at 5 per cent, * significant at 10 per cent.

a Regressions are survey-weighted. **b** Includes people reporting injury, poisoning and certain other consequences of external causes who are profoundly or severely restricted in their core activities. **c** Includes people reporting injury, poisoning and certain other consequences of external causes but are not profoundly or severely restricted in their core activities.

Source: Productivity Commission estimates based on 1998 Survey of Disability, Ageing and Carers.

C Results

This appendix presents, in section C.1, the results of estimation of the model described in appendix A. In section C.2 the possible approaches to estimating the marginal effects of education and health are described and a preferred approach is selected.

C.1 Regression results

This section presents estimates of the coefficients for the participation and wage equations, estimated separately for men and women. Table C.1 sets out the estimated coefficients for the Heckman selection equation.

Table C.2 sets out the estimated coefficients for the wage equation, including λ, the coefficient that accounts for sample selection bias (appendix A). The estimated coefficients show that there is no sample selection bias present for women in the sample (because the estimated value of the sample selection coefficient λ is not significantly different from zero).

Table C.1 **Probit selection equation coefficient estimates**[a]

	Male			*Female*		
Variable			*Standard error*			*Standard error*
Age 15–24	0.243	***	0.083	0.674	***	0.062
Age 45–64	-0.992	***	0.078	-1.026	***	0.056
Vic	-0.068		0.060	0.032		0.050
Qld	-0.027		0.065	0.006		0.051
SA	0.018		0.079	0.030		0.072
WA	-0.008		0.081	-0.081		0.064
Tas	-0.240	**	0.115	0.257	**	0.105
NT	0.089		0.232	0.305		0.310
ACT	0.032		0.166	0.112		0.121
Region	-0.108	**	0.049	-0.080	**	0.041
Indigenous	-0.353	**	0.138	-0.207	*	0.117
Married	0.247	***	0.056	-0.148	***	0.042
Unemployment history	-2.194	***	0.191	-0.880	***	0.158
Experience	0.062	***	0.008	0.102	***	0.007
Experience^2	-0.001	***	0.000	-0.001	***	0.000
Degree or higher	0.350	***	0.071	0.708	***	0.054
Diploma or certificate	0.159	***	0.055	0.342	***	0.048
Year 12	0.257	***	0.073	0.421	***	0.052
PCS	0.045	***	0.002	0.034	***	0.002
MCS	0.022	***	0.002	0.012	***	0.002
NESB	-0.259	***	0.067	-0.270	***	0.056
Studying	-0.864	***	0.076	-0.570	***	0.066
Children 0-4	0.007		0.056	-0.769	***	0.033
Children 5-14	0.007		0.035	-0.199	***	0.023
Children 15-24	0.259	***	0.043	0.146	***	0.033
Wave 2	0.077	**	0.034	-0.002		0.027
Wave 3	0.167	***	0.039	-0.009		0.030
Wave 4	0.212	***	0.040	0.024		0.032
Wave 5	0.190	***	0.042	0.035		0.033
Constant	-2.960	***		-2.546	***	

*** significant at 1 per cent; ** significant at 5 per cent; * significant at 10 per cent.

a The dependent variable is a binary indicator of employment.

Source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

Table C.2 **Wage equation coefficient estimates**[a]

	Male			Female	
Variable			*Standard error*		*Standard error*
Age 15–24	-15.567	***	2.130	-11.127***	1.776
Age 25–44	-1.682		2.318	-0.619	1.542
Vic	-4.379	***	1.581	-6.012***	1.405
Qld	-6.611	***	1.730	-8.975***	1.432
SA	-10.926	***	2.224	-9.027***	2.018
WA	-4.094	*	2.283	-9.099***	1.869
Tas	-7.294	**	3.449	-4.776*	2.626
NT	5.279		8.598	2.032	5.180
ACT	7.024	**	3.556	1.230	3.967
Region	-9.439	***	1.359	-6.393***	1.170
Indigenous	2.005		5.021	8.060**	3.573
Married	10.790	***	1.386	4.530***	1.092
Experience	1.556	***	0.224	2.027***	0.213
Experience^2	-0.019	***	0.005	-0.038***	0.005
Degree or higher	38.373	***	1.900	38.180***	1.573
Diploma or certificate	13.668	***	1.497	11.992***	1.436
Year 12	12.402	***	2.111	10.743***	1.636
PCS	0.329	***	0.094	0.328***	0.065
MCS	0.158	***	0.060	0.162***	0.047
NESB	-6.087	***	1.928	-6.130***	1.940
Studying	0.465		2.901	2.575	2.497
Part time	-2.945		2.038	-0.162	1.048
Wave 2	2.873	***	0.958	3.265***	1.065
Wave 3	7.791	***	1.018	7.854***	0.932
Wave 4	12.878	***	1.015	10.971***	0.981
Wave 5	17.242	***	1.050	15.726***	1.016
λ	-7.637	**	2.666	2.00	1.301
ρ	-0.194	**	0.067	0.055	0.036
Constant	234.396	***		224.402***	

*** significant at 1 per cent; ** significant at 5 per cent; * significant at 10 per cent.

[a] The dependent variable is the natural logarithm of hourly wage multiplied by 100.

Source: Productivity Commission estimates based on HILDA release 5.1, waves 1–5.

C.2 Estimating marginal effects

Because the model is not a simple linear regression, estimating the marginal effects of changes in education and health status on wages is not simply a matter of reporting the estimated coefficients.

Cameron and Trivedi (2009) describe three common methods for the evaluation of the marginal effects of independent variables in nonlinear models:

1. The average of the marginal effects at each observation (AME)
2. The marginal effect at the sample mean (MEM)
3. The marginal effect at a representative value of the independent variables (MER).

Cameron and Trivedi state that the marginal effects that are calculated using the different approaches 'can differ appreciably' (p. 340). Bartus (2005) prefers the AME approach to evaluating marginal effects. He states:

> The main argument in favour of AME is based on a demand for realism: the sample means used during the calculation of MEM might refer to either nonexistent or inherently nonsensical observations, a problem typically encountered when there are dummies among the regressors. (Bartus 2005, pp. 309–310)

Cameron and Trivedi argue that for nonlinear models, using the MEM approach is:

> … better than doing nothing, because it does provide a rough gauge of the magnitude of the [marginal effect]. However, for policy analysis, one should use either the MER for targeted values of the regressors … or the AME … (Cameron and Trivedi 2009, p. 340)

Greene (2003) states that:

> … in large samples [the MEM and AME approaches] will give the same answer. But that is not so in small or moderate-sized samples. Current practice favours averaging the individual marginal effects when it is possible to do so. (Greene 2003, p. 668)

In the empirical literature in this area there are examples of the MEM and MER approaches.

Breusch and Gray (2004) used the MEM approach to estimate the marginal effects of education on male and female wages in Australia. Their model (a Heckman model similar to that used in this study) used HILDA data, and included educational attainment through four binary variables ('incomplete high school', 'year 12', 'trade' and 'degree') that are analogous to the variables used in this study.

To estimate the marginal effects of continuous variables, the variable of interest was increased from just below the sample mean to just above the sample mean, while all other variables were held at their sample means. For binary variables (including level of education attained), the marginal effect was measured by changing the value of the variable from 0 to 1, and comparing the change with the base case of incomplete high school education.

Creedy et al. (2000) used the MER approach to evaluate marginal effects. They used data from the Income Distribution Surveys for 1995 and 1996 and a model that was similar to the model used for this project to estimate the wages of different demographic groups in Australia. Creedy et al. presented a sample of 'case studies' that demonstrated how their model could be used to estimate the wages of various demographic groups. For example:

> … consider an unemployed married female: aged 40 to 44 years; with one dependent child aged over 15 years; European born; residing in Perth; with no formal educational qualifications; partner has vocational qualification but is currently not employed; other income is $25 per week; owns home outright. The basic imputed wage is $13.49 per hour. (Creedy et al. 2000, p. 313)

Following the arguments put forward by Greene (2003), Bartus (2005) and Cameron and Trivedi (2009), the AME approach was chosen as the most suitable for evaluating the marginal effects of education and health status on wages.[1] The results are set out in chapter 5.

[1] Marginal effects were estimated using the Stata program 'margeff' version 8. Bartus (2005) describes the program.

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