Interactions between Health and Labour Market Outcomes over the Life Course

Joanne Maree Flavel
B Ec (Hons) (University of Adelaide)

This thesis is presented for the degree of Doctor of Philosophy of Flinders University of South Australia

National Institute of Labour Studies, Faculty of Social and Behavioural sciences
Flinders University

Date of Submission: August 2015

Abstract

Fifteen per cent of the Australian working age population has some form of work-limiting health condition at any one time. There are many determinants of labour market activity and one of these is health. Health and the capacity to perform in the labour market are linked. This thesis explores the effects of poor health on under-examined labour market outcomes and indicators of accumulating disadvantage in Australia with a specific focus on the cumulative effects of poor health and what this means for lifetime earnings and disadvantage. I use longitudinal data, together with econometric modelling corrected for sources of bias through use of contemporary and tailored methods. The thesis analysed the extent to which health affects individuals' choice of form of employment, their level of occupation and their lifetime earnings. The results suggest that poor health affects the nature and extent of employment over the life course in a way which significantly reduces lifetime earnings. While there is some effect of health on labour market outcomes for those who are employed, the main impact comes from withdrawal from the workforce.

Table of Contents

List of Tables

List of Figures

Acknowledgements

A number of people have been of tremendous assistance in helping me complete my thesis. First, I wish to acknowledge my supervisors, Professor Sue Richardson and Associate Professor Anna Ziersch. I am grateful for their constructive feedback and guidance. They have both been supportive and encouraging and I have learned so much from them.

I also wish to thank Dr Laurence Lester and Dr Stephane Mahuteau for valuable advice. Laurence's enthusiasm for my research has been a great support. Gratitude is extended to the National Institute of Labour Studies and my colleagues who have been wonderful throughout every stage of this study. Particular thanks go to Megan Moskos, Llainey Smith, Lulu Sun, Rupali Saikia and Trish Amee.

This thesis would not have been possible without the financial support offered by the Australian Health Inequities Program (AHIP). I am grateful for the scholarship funding provided by AHIP for enabling me to undertake this research.

On a personal note, I would like to thank my mother and sister for their love and support throughout my study. My mother in particular has been wonderful to discuss my thesis with and has constantly supported and encouraged me throughout the entire process.

Declarations

'I certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.'

This thesis uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this thesis, however, are those of the author and should not be attributed to either DSS or the Melbourne Institute.

List of Abbreviations

ABS Australian Bureau of Statistics

ANZSCO Australian and New Zealand Standard Classification of Occupations

ANZSIC Australian and New Zealand Standard Industrial Classification

AUSEI06 Australian Socioeconomic Index 2006

APRA Australian Prudential Regulation Authority

ATO Australian Taxation Office

BIC Bayesian Information Criterion

CURF Confidentialised Unit Record File

EGP Goldthorpe class measure

GLLAMM Generalised Linear Latent and Mixed Model

GSS General Social Survey (Australia)

GDP Gross Domestic Product

GFC Global Financial Crisis

HILDA Household, Income and Labour Dynamics in Australia Survey

HRS Health and Retirement Study (US)

HUNT Nord-Trøndelag Health Study

LR test	Likelihood ratio test
MCMC	Markov Chain Monte Carlo
MIMIC	Multiple Indicators and Multiple causes model
NHS	National Health Survey (Australia)
OECD	Organisation for Economic Co-operation and Development
PSID	Panel Study of Income Dynamics
SES	Socioeconomic status
SF-36	Short-Form 36 health status questions
WHO	World Health Organisation

1. Introduction

1.1 Background and Significance of the Study

Populations around the world are ageing, particularly in developed countries, due to declining fertility and longer life expectancies. This has increased the focus on population health and specifically, health disparities. The Ottawa Charter for Health Promotion, presented at the First International Conference on Health Promotion in 1986 states that “health is a resource for everyday life… Health is a positive concept emphasizing social and personal resources, as well as physical capacities”. Good health enables participation in all aspects of society while poor health is a source of disadvantage (WHO, 1986).

The prevalence of self-reported fair/poor health (as distinct from ‘good”, “very good” or “excellent”) in the Australian population aged 15 years and older has remained fairly steady over time. In 2007-08, 15.1 per cent of all persons aged over 15 years reported fair/poor health compared with 15.9 per cent in 2004-05, 18.1 per cent in 2001 and 17.2 per cent in 1995 (ABS 2006c, 2009b). The prevalence of fair/poor health in Australia compares favourably with that in most other developed countries (OECD, 2010).

In developed countries, poor health is generally associated with ageing. As people become older and approach retirement, their health typically declines. While prevalence of poor health is highest among older age groups (particularly those aged 65 and over), health also matters for the working age population. In Australia, according to the 2007-08 National Health survey (NHS) CURF data, 12 per cent of people aged between 15 and 64 years of age reported their health to be fair/poor. The prevalence of fair/poor health steadily increases with age from 6.8 per cent of 15-24 years olds to 15.9 per cent of 45-54 year olds and 20.7 per cent of 55-64 year olds.

The decline in health associated with ageing will rise in importance in future years as the proportion of the population aged 50-64 is forecast to rise from 24 percent in

1. Introduction

2002 to 30 percent in 2021 (ABS, 2003). Corresponding with this, the proportion of those aged 15-49 will fall over this same period with the largest decline being among those aged 15-29 (ABS, 2003), this being the group with the best overall reported health. With the ageing of the working age population, prevalence of poor health in the working age population can be expected to rise.

Health is distributed unevenly, with low education, low income and low socioeconomic status associated with worse health (Turrell *et al.* 2006; Marmot, 2004). Poor health has both aggregate impacts and individual impacts. On an aggregate level, socio-economic differences in health have been estimated to reduce GDP through reduced labour productivity. Mackenback *et al.* (2010) conservatively estimated that reduced labour productivity in Europe arising from poor health reduced relative GDP by 1.4 per cent per annum. On an individual basis, poor health is associated with labour market disadvantage (Marmot and Wilkinson, 2005) and this leads to broader disadvantage. Poor health can result from disadvantage but it also perpetuates the cycle of disadvantage by leading to further poverty and social exclusion (Burchardt, 2003; Buddelmeyer and Cai, 2009). People with disabilities or long term health conditions experience high poverty levels linked to their low rate of participation in employment and are also more likely to experience social exclusion in other areas of life (Fitzgerald, 2007).

The relationships between health and labour market activity and the broader disadvantage resulting from effects of poor health make it important for researchers to fully understand interactions between health and labour market outcomes and ways in which effects of health related labour market disadvantage may be cumulative over the life course. This is relevant given health matters even for younger persons but it becomes particularly relevant given the ageing of the population and likely effects this will have on the health of the working age population.

Policies aimed at promoting employment for those experiencing health conditions will be more effective if they take into consideration the impact of health on labour market outcomes. Policy makers also need to consider the degree to which health impacts in this area may be cumulative in order to formulate the most effective policies to address the broader disadvantage resulting from health related labour market disadvantage. A more in depth analysis of impacts of health on labour market outcomes and cumulative effects arising from this is needed to allow consideration of these relationships to devise the most effective strategies.

1.2 Purpose of the Research and Statement of the Research Questions

This thesis examines the relationship between health and some under-examined labour market outcomes and indicators of accumulating disadvantage in Australia. Through conducting detailed analyses of these relationships the thesis aims to determine the extent to which poor health during working age is associated with accumulating disadvantage. By determining the degree of health related labour market disadvantage, we can better understand how to effectively target assistance to those vulnerable to health related labour market disadvantage.

Some forms of employment, namely part time and casual employment, have negative implications for lifetime earnings. Calculations using Australian labour market statistics show that part time and casual workers are concentrated in lower skilled occupations (ABS, 2012). Occupational segregation, lower pay, limited career progression and effects on human capital formation via fewer training opportunities have also been identified in the literature as associated with these forms of employment (Arumpalam and Booth, 1998; Draca and Green, 2004; Prowse, 2005; O'Dorchai *et al.* 2007).

Occupational segregation is found for those in poorer health, with poor health associated with employment in lower skilled and physically demanding occupations (ABS, 2012). Occupation affects income and career prospects (Yamaguchi, 2010). Occupation can also have an impact on exposure to health hazards and risk of unemployment. This too has implications for lifetime earnings.

Identification of the relationship between health and labour market outcomes leading to disadvantage adds to the knowledge of the degree to which health during working age is associated with accumulating disadvantage. Likewise, examination of indicators of accumulating disadvantage will add to what is known about the effects of health disparities and implications of this for broader disadvantage later in life.

In particular, the thesis addresses the following questions:
1. Are those in poor health more likely to be in part time or casual employment?
2. What level of occupation are those in poor health employed in and what effect does a change in health (for better or worse) have on level of occupation?
3. Is health related labour market disadvantage cumulative and if so, to what degree?

These questions are addressed by undertaking detailed econometric analyses using longitudinal data in order to identify causal effects. The answers to these questions identify whether there are cumulative effects of health related labour market disadvantage and if so, provide some information on the size of these effects.

1.3 Structure of the Study

There are 8 chapters in this thesis. Apart from the introduction and conclusion chapters, the thesis is organised into two parts. The first part contains the background and justification and lays down the groundwork with regard to methodological considerations. It is comprised of Chapters 2 through 4. Chapter 2 discusses the development of the theory and sets out the theoretical framework. It reviews issues surrounding measurement of health and highlights the focus with regard to causal relationships and issues to keep in mind in doing this. It also reviews the empirical literature on relationships between health and labour market outcomes and analyses of cumulative disadvantage identifying limitations of the literature.

The review finds that the current literature is not uniform in its application of methodology. There has been limited use of panel data methods (particularly over longer time periods) and of health measures which account for bias, measurement error and issues with establishing causality. Until recently the availability of suitable data allowing complex modelling of these relationships has been limited. Empirical work has also focused mainly on a subset of the population, namely older workers. It also focuses mainly on relationships between health and select labour market outcomes and there is a scarcity of evidence on the degree to which the effect of health on labour market outcomes results in cumulative disadvantage over the life course.

Chapter 3 describes data used in the thesis and why the specific data sources were chosen. It then uses these data to profile some key relationships between health and labour market outcomes and provides some cross sectional indicators of accumulating disadvantage. This profile suggests that health influences the type of employment contract that people are on (form of employment) and their occupation. Health is also found to affect labour force experience and wealth over time.

Chapter 4 focuses on the particular issues which must be taken into account when conducting empirical analyses of the relationships identified in the descriptive analyses. It begins by further considering concerns surrounding measures of health, outlines the method used in this thesis to address these concerns then moves on to set out more broad methodological issues. Using the example of employment participation, this chapter identifies issues involved in modelling relationships between health and labour market outcomes and illustrates the preferred modelling approach to be used in terms of addressing econometric issues.

The second part of the thesis provides the empirical analysis and findings to answer the research questions set out in the previous section. It is comprised of Chapters 5 through 7. These three chapters conduct econometric investigations for the working age population using appropriate panel data methods aimed at disentangling the causal effects behind the relationships identified in the descriptive analysis.

Chapter 5 conducts an econometric examination of the effect of health on form of employment (type of employment contract). It specifically tests the hypothesis that individuals in poor health are more likely to be in part time or casual employment. The results presented in this chapter find evidence supporting this hypothesis. Given that there are likely to be adverse effects of persistence in these forms of employment on lifetime earnings this suggests that the effect of health on form of employment is one avenue by which the relationship between poor health and labour market outcomes results in cumulative disadvantage. It is however important to note that more people experiencing impaired health are likely to be not employed at all if part time and casual employment were not available, and the only option were full time permanent employment.

Chapter 6 provides an empirical analysis of the effect of health (and changes in health) on the occupation individuals are employed in. The chapter presents econometric findings from estimating models of determinants of occupation and occupational change. Findings from the analyses suggest that persons experiencing poor health are more likely to leave employment than to change jobs. After controlling for selection into employment, health (and changes in health) was not found to have a significant effect on occupation amongst persons who are employed.

Chapter 7 conducts econometric analyses aimed at determining whether there are cumulative effects of health related labour market disadvantage. It specifically hypothesises that there is a cumulative effect and that early onset of persistent poor health during working life results in greater cumulative disadvantage. The results of the analyses in this chapter suggest that there is evidence of health related cumulative labour market disadvantage operating through lifetime earnings. A quantitative measure of the degree of the cumulative effect supports the hypothesis that earlier onset of poor health results in greater disadvantage compared with persons in continuous good health.

Throughout the three econometrics-based chapters 5 through 7, it is found that in order to obtain reliable estimates and eliminate sources of bias, modelling must take into account methodological issues. Panel data techniques are required in order to estimate causal relationships and within the panel modelling framework there is a need to control for unobserved heterogeneity, state dependence and the initial conditions problem. Aside from this, selection into employment must be accounted for along with addressing concerns surrounding choice of health measure. This is addressed in this thesis by constructing an index of health through estimating a latent variable model of health in order to address concerns with using subjective measures**.** This methodological approach is found to be important in conducting analyses of health and labour market outcomes.

1. Introduction

The summary and conclusion of the thesis is given in Chapter 8. In this chapter, the major findings of the dissertation are discussed. The chapter also provides an evaluation of the research undertaken and identifies limitations. The chapter and thesis concludes by identifying policy implications and providing directions for future research.

PART I: Background, Justification and Groundwork

2. Theoretical Framework and Literature Review

This chapter begins by setting out theory and economic background on the relationship between health and labour market behaviour (section 2.1). It then discusses causal relationships and reviews issues surrounding measurement of health (section 2.2). The chapter then presents a review of the empirical literature, beginning with the evidence on interactions between health and labour market outcomes in section 2.3 and concluding with a review of evidence of accumulating disadvantage with respect to health in section 2.4. A summary of the chapter is presented in section 2.5.

2.1 Theory and Economic Background

Theory has linked health and labour market behaviour. In this section, the historical development of theory and the economic background behind the relationship between health and labour supply (and the demand for health for its own sake) is discussed. There is also reverse causation between health and employment outcomes (work affects health). This is acknowledged and will be discussed in further detail in the next section. The focus of this section and of the thesis itself is how health affects labour market outcomes.

This section begins by outlining the origins of theory in the area and how it has developed over time. It then sets out the main model linking health and labour market behaviour. The section concludes with a discussion of more recent theoretical literature and the current state of theory surrounding analysis of the relationship between health and labour market outcomes. The implications drawn from the theory and this model inform much of the literature in this area and lay the groundwork for later discussion of the empirical relationships found thus far between health and labour market outcomes.

2.1.1 Outline of theory and development of ideas

2. Theoretical Framework and Literature Review

The main theory informing the literature on links between health and labour market behaviour is derived from human capital theory. The origins of human capital theory can be traced back to the work of Adam Smith, however, the extension of this theory to encapsulate the links between health and labour market behaviour originated in the 1960s.

Mushkin (1962) was the first to explicitly link health and labour market behaviour by distinguishing between the effects of investment in health and the effects of investment in education on people as productive agents. People as productive agents were said to be improved by investment in health and education and the outlays on these investments yield a continuing return in the future, that is, there is human capital formation through investing in both education and health services. Mushkin (1962) claimed that health services, as with education, become a part of the individuals' 'effectiveness in field and factory'. It was noted that the return on investment in health is often attributed to education however health has an effect independent of education, for example, labour force participation is not possible unless the individual is well enough to attend work in the first place. The effectiveness of investment in education is also reduced if there is a loss of days of schooling due to poor health. Linked with this, increased life expectancy through improved health increases the return to education.

Mushkin (1962) also alluded to the direct utility effects of better health-when an individual is well, life can be more satisfying which facilitates more effective performance in the labour market. Mushkin noted the difference between health and education as investments: education chiefly affects the quality of labour (i.e. productivity) while health programs can increase both numbers (and hours) in the work force as well as the quality of labour.

Becker (1964) in his detailed examination of human capital, expanded on the earlier claims made by Mushkin. Human capital consists of the attributes of an individual that are productive and can be used to create economic value. While use of the term commonly refers to educational attainment, the meaning has also been broadened to include other attributes and investments which add to the productivity of an individual including experience, training and health. In this way, in economics, a person’s stock of health can also be referred to as their health capital and health capital is one component of the stock of human capital.

Becker noted that earnings are linked with health, with reduced death rates in the population during working years extending the period during which earnings can be received. Increased strength and stamina associated with better health also increases individual earning capacity. Better health was observed to increase investment in other aspects of human capital by increasing returns to those investments. Increased returns result from increased time in which a person is capable of spending in the labour force -either increased days (fewer lost work days resulting from lower morbidity) or increased years (resulting from lower mortality) - which allows benefits of investing in human capital such as education or training to be reaped over a longer period of time.

Becker set out a detailed analysis in which he derived the relationships between earnings, investment costs and rates of return for investment in human capital and outlined the implications of costs and returns for the degree of investment in human capital. The analysis, while generally assumed to apply to investment in education and training (which is more easily measured), is extended by him to ‘any type of investment’ in human capital, including health. Thus, Becker drew an analogy between investment in health and investment in other forms of human capital such as education.

Grossman (1972) extended prior work by Mushkin (1962) and Becker (1964) by constructing a model of the demand for ‘good health’ or health capital. While it had been suggested previously by others (including Becker and Mushkin) that health can be viewed as a form of human capital, until Grossman, no one had constructed a model of demand for health capital. This model explicitly linked investment in health with labour market behaviour, further adding to the understanding of the relationship between health and labour market outcomes (see the next section for more details on the model).

Grossman’s work also distinguished health capital from other forms of human capital. He proposed that health can be viewed as a durable capital stock that produces an output of healthy time. The model enabled a life cycle view of investment in health and its implications for labour market activity.

The work by Mushkin (1962), Becker (1964) and Grossman (1972) laid out the theoretical framework that is currently used in economics in analysing the relationship between health and labour market behaviour (referred to as the Grossman model from hereon). A more recent paper by Becker (2007) presented a synthesis of the theory of health as human capital, integrating the various contributions made. He highlighted the Grossman model as a major step forward in research into the concept of health as human capital. The original article by Grossman (1972) is noted by Becker to have stimulated a large literature and he also states that analysis of optimal investments in health by individuals follows on from Grossman's analysis.

In their review of the theory, Cai and Kalb (2006) observed that under the approach developed by Becker and Grossman:

> 'Both employers and employees value health like they value education because health and the capacity or ability to perform a job adequately are closely related' (p. 242).

This emphasises the continued importance of these seminal papers on current research on interactions between health and labour market outcomes.

The next section discusses in more detail the Grossman model linking health and labour market behaviour because the basic assumptions underlining the model continue to form the foundations of the theory informing analysis of health and labour market behaviour.

2.1.2 Outline of Model Linking Health and Labour Market Behaviour

In the decades following Grossman's 1972 work on health as human capital, the notion that individuals invest in themselves became widely accepted in economics. Increases in a person's human capital are assumed to raise their productivity in paid work (leading to higher earnings) and also in the non market or household sector (leading to higher utility). Grossman argued that while health can be viewed as one form of human capital, the demand for health capital requires a separate model to that used to measure investment in other forms of human capital. While health can affect productivity as with other forms of human capital, an individual's stock of health also determines the total amount of time they can spend producing money earnings and commodities in paid and unpaid work. It is this difference which justified Grossman's model of the demand for health.

Grossman's framework assumes that individuals inherit an initial stock of health that depreciates over time. The depreciation occurs at an increasing rate (at least after some stage in the life cycle) and the stock of health can be increased by investment. The primary focus in research until recently has been on physical health and the assumption with respect to the depreciation of the health stock reflects this. It should be noted that there is some debate over whether this is the case for mental health (see discussion in section 2.2). Incorporating mental health within the measure of the health stock is discussed in section 2.1.3.

Gross investments in health capital are produced by household production functions. Direct inputs into these production functions include time, medical care, diet, exercise, recreation, housing and other market goods. The production function also depends on the individuals' level of education which influences the efficiency of the production process (more educated persons may be more efficient in producing health).

Grossman argued that an individuals' level of health is not exogenous. It depends in part on the resources allocated to production of health. Health is demanded for two reasons. It yields direct satisfaction and utility (as a consumption good) and indirect satisfaction through increased productivity, fewer sick days and higher wages (as an investment good).

Health directly enters preference functions as a consumption commodity, with sick days being a source of disutility. It also determines the amount of time available for market and non market activities, with the monetary value of the reduction in time lost due to an increase in the stock of health being an index of the return to an investment in health (in addition to its direct contribution to wellbeing, or utility).

The law of the downward sloping demand curve led Grossman to conclude that the quantity of health demanded should be negatively correlated with its marginal cost. He stressed that the marginal cost depends on many other variables besides the price of medical care. The optimal amount of health is altered by shifts in these variables. Grossman shows that the marginal cost rises with age if the rate of depreciation on the health stock rises over the life cycle and falls with education if those with higher education are more efficient producers of health.

An abbreviated version of Grossman's model drawn from Grossman (1972) follows. First, let the intertemporal utility function of a typical consumer be:

$$U_t = U(Q_t, C_t, L_t; X_t, u_1, \varepsilon_{1t}), \qquad (1)$$

where Q is the stock of health, C is consumption of other goods, L is leisure, X is a vector of exogenous taste shifters, u_1 is a vector of permanent individual specific taste shifters, and ε_1 denotes a shock to preferences.

Net investment in the stock of health equals gross investment minus depreciation:

$$Q_{t+1} - Q_t = I_t - \delta_t Q_{t,} \qquad (2)$$

where I is gross investment and δ is the rate of depreciation. The rates of depreciation are assumed to be exogenous, but they may vary with age. Investments in health and other commodities in the utility function are produced according to a set of household production functions:

$$I_t = I_t(G_t, V_t; E_t), \qquad (3)$$

$$D_t = D_t(X_t, T_t; E_t), \qquad (4)$$

In these equations, G and V are material and time inputs into health production, X and T are the goods and time inputs into production of commodity D, and E is the stock of human capital.

For a given individual, as both market goods and own time are scarce resources, the goods budget constraint equates the present value of outlays on goods to the present value of earnings over the life cycle plus initial assets:

$$\sum \frac{P_{1t}G_t + P_{2t}X_t}{(1+r)^t} = \sum \frac{w_t H_t}{(1+r)^t} + A_0. \qquad (5)$$

Here P_1 and P_2 are the prices of G and X, w is the wage rate, H is hours of work, A_0 is initial assets and r is the interest rate. The time constraint requires that Ω, the total amount of time available in any period, must be exhausted by all possible uses:

$$H_t + S_t + V_t + T_t + L_t = \Omega \qquad (6)$$

where S is time lost from market and non market activities due to illness or injury. Grossman's model assumes that S is inversely related to the stock of health, i.e. that $\partial S_t / \partial V_t < 0$. If Ω were measured in days (with Ω=365 if we take a year as the relevant period), and h equals the number of healthy days in a given year then

$$S_t = \Omega - h_t \qquad (7)$$

Grossman noted that it is important to draw a distinction between sick time and the time input in the gross health investment function. If the rate of depreciation were held constant, an increase in V_t, the time input into health production, would increase I_t and Q_{t+1} and would reduce S_{t+1}. Thus, time input into health production in one period and sick time in the next period would be negatively correlated.
By substituting for hours of work from equation (6) into equation (5), the "full wealth" constraint is obtained:

$$\sum \frac{P_{1t}G_t + P_{2t}X_t + w_t(L_t + H_t + T_t)}{(1+r)^t} = \sum \frac{w_t \Omega}{(1+r)^t} + A_0. \qquad (8)$$

According to equation (8), full wealth equals initial assets plus the present value of the earnings an individual would receive if they spent all their time at work. Some wealth is spent on market goods and nonmarket production time and part is lost due to illness. This equation has intuitive appeal and is of particular relevance to the research questions addressed in this thesis.

This thesis is concerned with the extent to which poor health during working life (represented by S in the Grossman model) results in accumulating disadvantage. Lifetime earnings and measures of wealth reflect advantage or disadvantage over the life course with otherwise similar persons in poor health having lower wealth in equation (8) compared with persons who do not experience poor health. This indicates that equation (8) gives a simple illustration of how poor health might affect wealth and over time result in accumulating disadvantage.

The equilibrium quantities of H_t and D_t can be found by maximizing the utility function in equation (1) subject to constraints given by equations (2), (3) and (8). The inherited stock of health Q and the rates of depreciation δ are given, therefore in the Grossman model the optimal quantities of gross investment determine the optimal quantities of health capital.

In order to obtain equilibrium conditions, first order optimality conditions must be set out. Utility is derived from healthy days (with marginal utility of healthy days given by $Uh_t = \partial U / \partial h_t$) and utility is derived from wealth (with marginal utility of wealth given by λ). The optimum gross investment in period *t-1* is where the marginal product of the stock of health in the production of healthy days ($q_t = \partial h_t / \partial Q_t = -(\partial L_t / \partial Q_t)$) is equal to the marginal cost of gross investment in health (given by π_{t-1}).

First order optimality conditions in the Grossman model are:

$$\frac{\pi_{t-1}}{(1+r)^{t-1}} = \frac{w_t q_t}{(1+r)^t} + \frac{(1-\delta_t) w_{t+1} q_{t+1}}{(1+r)^{t+1}} + \ldots + \frac{(1-\delta_t)\ldots(1-\delta_{n-1}) w_n q_n}{(1+r)^n} + \frac{Uh_t}{\lambda} q_t + \ldots + (1-\delta_t)\ldots(1-\delta_{n-1}) \frac{Uh_n}{\lambda} q_n \tag{9}$$

According to equation (9), the present value of the marginal cost of investment in period t-1 must equal the present value of marginal benefits. The marginal product of health capital q_t is the increase in the number of healthy days caused by a one-unit increase in the stock of health.

The model presented in this section can be solved to yield a conditional labour supply function in which labour supply (*H*) depends on the endogenous health variable. Currie and Madrian (1999) noted that the main implication of the model is that health must be treated as an endogenous choice (within the range made possible by Q). Health is determined endogenously with wages and labour supply however wages and labour market activity may have a direct effect on health (see later discussion). Endogeneity of health can result in bias in empirical estimations. This arises for a number of reasons: unobserved heterogeneity, justification bias (where a particular health status is reported to justify an individuals' situation, particularly with regards to welfare benefits), simultaneity between health and labour market outcomes and measurement error. These can bias estimates of relationships between health and labour market outcomes.

Health differs from the stock of education (which can also be treated as an endogenous choice). Most investment in education occurs early in the lifecycle (as this is the optimal investment profile). This is not the case for health (or at least physical health) where an initial large stock depreciates and must be continually replenished, with many investments in health occurring later in life. For this reason Currie and Madrian suggest that endogeneity of health may be a greater potential source of bias than endogeneity of other forms of human capital (specifically education), however they note that health is still similar to general human capital in more traditional models. It is valued by employers and employees take it with them when changing jobs.

2.1.3 Theoretical Critiques Post Grossman

The Grossman model linking health and labour market behaviour constituted a major breakthrough in health economics (Zweifel, 2012). Forty years after the original publication of the model, it still forms the foundation for much of the theoretical framework used in analysing the effect of health on labour market behaviour in economics. Nevertheless, the model is constrained in a number of respects and has been subject to criticisms.

There are a number of assumptions built into the model. Unlike Becker's model of human capital, in the Grossman model health (as a form of human capital) does not affect productivity (Podor and Halliday, 2012). In Grossman's health capital model, better health relaxes the time constraint and has an income effect. It also assumes a long and fixed planning horizon, a fixed ratio between expenditure on investment in health and cost of health enhancing efforts regardless of the individual's state of health and it presumes the ability to restore the state of optimal health at a speed which is not dependent on state of health (Zweifel, 2012). Health has also been found to decline faster for individuals with lower socioeconomic status and the model does not predict this (Galama *et al.* 2013).

The model also assumes forward-looking rational agents however the solutions to the model do not depend on past or future values of endogenous variables or initial health and wealth. Structural and reduced form equations for health depend on present time conditions such as current wage and current prices (Galama *et al.* 2013). Of most concern amongst criticisms of the model is the claim that the model does not have a unique solution (Galama and Kapteyn 2011; Galama *et al.* 2013). If this is the case it would invalidate many theoretical and empirical analyses based on the model (Galama *et al.* 2013).

This claim has been disputed and a review and rebuttal of other limitations mentioned was set out in Grossman (2000). Further to this, Laporte (2014) recently undertook an analysis of the empirical and theoretical criticisms of the Grossman model. They showed that even the criticisms which cannot be discounted can be considered more as simplifying assumptions rather than fatal structural flaws. Most of the criticisms of the Grossman model are suggested to arise from looking at an intrinsically dynamic model through static eyes (Laporte 2014). Laporte contends that when dynamic economic analysis is applied to the Grossman model, its status as the cornerstone of modelling individual related health behaviours is justified.

There have been empirical extensions to the original 1972 model. These have centred around modelling investment in health but still have some relevance to analysing effects of health on labour market outcomes. Wagstaff (1986) used the 1976 Danish Welfare Survey to estimate the structure and reduced form of Grossman's pure health investment model. He obtained four health indicators reflecting physical mobility, mental health, respiratory health and presence of pain. He then used a MIMIC (multiple indicators-multiple-causes) model employing maximum likelihood procedure. The main unique extension offered by Wagstaff (1986) was a method accounting for the multidimensional nature of good health at both conceptual and empirical levels (Grossman, 2000).

Wagstaff concluded that, broadly speaking, the coefficients derived from estimating the reduced form of the investment model are similar to those reported by Grossman and are consistent with the model's structural parameters being of the expected sign. He did however find that good health and the demand for physician visits are negatively related (the opposite of the prediction in the model).

Erbsland *et al.* (1995) apply a MIMIC model to the 1986 West German Socio-economic Panel. They use self reports of degree of handicap, self-rated health, duration of sick time and number of chronic conditions as four indicators of the unobserved health stock. Their results are again consistent with the predictions made by the investment model with the exception of replicating the finding of a negative relationship between good health and demand for medical care. Both Wagstaff and Grossman argue that the sign of the correlation between medical care and health can be reversed if medical care is treated as endogenous when estimating health production functions.

Wagstaff (1993) made empirical extensions to the Grossman model using longitudinal data. Wagstaff uses the Danish Health Study and as with his 1986 study, he uses a MIMIC model. Physician assessed health (self-reported), self-assessed health and a dichotomous indicator of the presence of a health limitation are used as indicators of health in 1982 and 1983. The desired health stock in period *t* is a linear function of age, schooling, family income and gender. The lagged health stock enters the demand function for health.

Grossman (2000) notes that longitudinal studies such as the one by Wagstaff can be useful for testing the effects of relaxing assumptions and for taking account of the effect of unmeasured variables. The findings in Wagstaff however with regard to the rate of depreciation of health were noted to be implausible. Grossman attributes this to the methodology used with the MIMIC model placing inordinate demands on the data. He also suggests that cost-of-adjustment models of health investment require at least three data points.

The studies summarised in this section as empirical extensions to the original 1972 theoretical model all suffer flaws. They do nonetheless add to the framework used to analyse health capital and the relationship between this and labour market behaviour. While the series of equations in section 2.1.2 do not specifically acknowledge demographic differences (e.g. gender, class), empirical work has extended the original model both conceptually and empirically to allow these variables to account for these important differences. The use of health indicators to capture the different dimensions of good health extends the concept of the health stock in the model beyond that which originally appeared to focus on physical health.

Aside from the empirical extensions outlined above, there have also been some further theoretical extensions to the original model. A number of authors have extended the model to introduce uncertainty beginning with Cropper (1977) and most recently Chang (1996). Ehrlich and Chuma (1990) and Galama and Kapteyn (2011) extended the model to include a health production process characterized by decreasing returns to scale rather than the constant returns to scale assumed in the standard model. Health production is generally understood to be subject to the law of diminishing returns therefore incorporating decreasing returns may more realistically represent real world processes (Galama *et al.* 2013). Finally, Liljas (1998) extended the Grossman model to take into account health insurance[1].

This thesis is informed by the theoretical relationships between health, labour market activity, earnings and wealth employed in the framework of the Grossman model. While there has been debate surrounding assumptions employed in the model, the basic relationships set out in the series of equations in the previous section make theoretical and intuitive sense. The framework provided by this model continues to form the theoretical basis in the majority of empirical work in the area. The findings from empirical work undertaken in this thesis will be analysed in relation to the basic assumptions underlying the model and conclusions from analyses will be linked to this theory in order to determine any theoretical contributions as well as whether the results meet theoretical expectations.

[1] As modelling of health production (and investment) is not the aim of this thesis, these extensions are not incorporated into the modelling in later chapters. They are set out here to acknowledge the current state of theory on health capital but it is the basic framework set out in section 2.1.2 which informs the analysis in this thesis.

2.2 Measurement of Health and Causal Relationships

2.2.1 Measurement of Health

It is important to clarify at the outset what is meant by ‘health’ in this thesis. There are many ways to define and measure health. Health can be broken down into physical or mental health (and, less commonly for economics, emotional and spiritual health). Either separately or within this physical versus mental health breakdown, health can also be distinguished further between permanent (long term) or temporary (episodic) conditions. Some literature considers certain specific conditions while others use a general measure of health.

The choice of definition(s) has implications for studying effects on labour market outcomes. Key issues discussed in this section with regard to health measures include: lack of comparability between studies, the issues associated with different ways of measuring health, availability of data and theoretical assumptions particularly with regards to mental health.

Each of the measures of health has advantages and disadvantages. The use of different health measures in empirical work has, however, made it more difficult to compare results. While the direction of the effect can be established even through different measures are used, the magnitude of estimated effects is less settled. The ideal measure of health for estimating effects of health on labour market outcomes should be one which captures the aspect of health which affects work capacity. While some measures of health (particularly objective measures) appeal due to their superior performance in capturing ill-health, these measures are not necessarily closely related to work capacity (Bound, 1991).

Currie and Madrian (1999) considered criticisms of health measures, noting (as Bound did) that indicators for specific conditions may not be specifically related to productivity. They also observed that self reported measures of work limiting health conditions may be more subject to reporting biases even though they are more directly related to productivity. Currie and Madrian (1999) cite the main problem with self-reported health measures as non-random measurement error, in particular that attributed to justification bias[2]. Given that survey data relies on self-reports of health this is a concern. The disadvantages associated with particular health measures must be taken into account when choosing which health measure to use in empirical work.

There are theoretical assumptions made with respect to the stock of health declining with age as highlighted in section 2.1.2 when discussing the Grossman model. As mentioned earlier there has been some debate as to whether this is the case for mental health.

Studies have found that rates of certain mental health conditions decrease with age for the working age population. It has been found that rates of depression, psychological distress and anxiety reduce with age (see for example Jorm *et al.* 2005, Scott *et al.* 2008) These findings are not however universal. Stordal *et al.* (2003) find the opposite effect, with prevalence of depression increasing with age. A review paper by Jorm (2000) noted the variable results in studies. Many studies of depressive disorders found an initial rise by age followed by a drop but this pattern is not universal. Studies using depressive symptom scales were noted to give even more variable results, with some showing an increase across age groups and others a decrease (Jorm, 2000). Controlled studies were observed to reveal a more consistent pattern with most studies showing a decrease across age groups.

There is a scarcity of studies in this area which use longitudinal data. Longitudinal studies of the relationship between age and mental health are needed to determine causation and to take account of cohort effects (Jorm, 2000; Brault *et al.* 2012). The few longitudinal studies undertaken to date have only used short panels but a review of these found conflicting results (Jorm, 2000) while a more recent study found that intensity of depressive symptoms increases with age but that cohort effects explain this increase (Brault *et al.* 2012). Given the conflicting findings, arguments about the relation between age and mental health are far from settled.

[2] There are further concerns with using self-reported health measures. These are discussed in more detail in chapter 4.

Given that more work needs to be done to determine the exact effect of age on overall mental health and in the absence of convincing evidence to the contrary, this thesis will work on the existing theoretical assumption that health in general declines with age. In addition to this, the health measure used in this thesis incorporates a measure of mental health as an indicator as part of its construction[3]. This will go some way towards accounting for the multidimensional nature of good health in the empirical work.

Other issues regarding health measures, as mentioned at the beginning of this section, include distinguishing temporary health conditions from permanent conditions or using specific health conditions such as coronary heart disease, arthritis, diabetes and asthma. Suitability of these measures depends on the research question to be answered. Health conditions, for example, might be best used to capture relationships between labour market outcomes and these specific conditions rather than looking broadly at overall health. This is useful particularly in determining costs attributable to burden of certain diseases.

The ability to use the different types of health measures listed in this section also depends on data availability. Most datasets only contain a subset of the types of health measures listed in this section or if they contain comprehensive measures of health, they lack necessary data on labour market activity and demographic characteristics. Even where a range of health measures are available, these measures are still subject to certain criticisms as set out earlier in this section.

A method used recently, particularly in health economics, involves generating a general measure of health which takes into account more objective measures of health and is purged of justification bias. Given the issues with many health measures available and the advantages associated with this method, this approach will be adopted for the empirical work in chapters 5, 6 and 7. The method used to generate the health measure is explained in detail in chapter 4.

2.2.2 Causal Relationships

[3] See chapter 4 for the method used to construct the health measure.

The literature on health and work covers a wide research area. It includes factors such as the role of health insurance and the incentive effects of disability insurance. The thesis will not focus on these issues given that in Australia- the setting for the research undertaken- health and disability insurance is not tied to labour market status. Surveys on these have been undertaken by Currie and Madrian (1999), Gruber and Madrian (2002) and Bound and Burkhauser (1999).

Within the remaining literature, aside from concerns surrounding the measure of health in analysing relationships between health and labour market outcomes over time there is the additional issue to consider of determining causal relationships. While health has an effect on labour market outcomes, labour market outcomes and work characteristics have also been found to affect health. There is some overlap within the literature but there also exists a separate area concentrating on the causal effects of work on health as opposed to the causal effects of health on work.

The focus of this thesis is on the causal effects of health on labour market outcomes. As such, the literature on the effects of work characteristics on health will not be reviewed in great detail. An extensive discussion of this literature would require more space and move beyond the scope of the research questions of interest but a brief discussion is warranted in order to highlight the different ways in which health and labour market outcomes interact.

The literature in this area is drawn from a number of disciplines. Virtanen *et al.* (2005) have reviewed the relationship between temporary employment and health. They find evidence of an association between temporary employment and psychological morbidity but that health risks may depend on instability of employment and the context of temporary employment. Stansfeld and Candy (2006) conducted a systematic review to determine associations between psychosocial work stressors and mental ill health. Their survey used longitudinal studies to undertake a meta-analysis. They find robust and consistent evidence that psychosocial work environment is important for mental health. Combinations of high demands and low decision latitude and combinations of high efforts and low rewards are risk factors for common mental disorders.

Benach and Muntaner (2007) in setting out a research agenda also undertook a brief review of the ways in which flexible work (the preferred broad term capturing temporary, precarious and other nonstandard forms of employment) can affect health. They repeated the finding that flexible work has adverse effects on health but acknowledged that current conception and empirical work on flexible employment and health is still limited. This is illustrated in a recent paper by Richardson *et al.* (2012) which found that flexible employment has no effect on (mental) health in Australia in contrast with the previously discussed papers which studied the case in other countries.

There has been a focus and a large literature on the effects of unemployment on health, with surveys on the literature undertaken by Jin *et al.* (1995), Dooley *et al.* (1996) and Mathers and Schofield (1998). The earlier reviews by Jin *et al.* (1995) and Dooley *et al.* (1996) find that unemployment is associated with adverse health outcomes but that further research is needed to test evidence of causal relationships. Mathers and Schofield (1998) acknowledge the issues with identifying causal effects but find that longitudinal studies show reasonably good evidence that unemployment itself is detrimental to health and has an impact on health outcomes. More recent papers have focused further on identifying causal effects and two recent economic papers using longitudinal data suggest that much of the relationship can be explained by health selection into unemployment (Böckerman and Ilmakunnas, 2009; Schmitz, 2011).

This brief review of the literature on the effects of labour market outcomes and work characteristics on health by no means covers all the outcomes studied. It is a brief overview of the main research areas within a large literature. Nevertheless, the findings from the papers reviewed serve to highlight the issues surrounding the determination of causal effects, that labour market outcomes affect health just as health affects labour market outcomes and that longitudinal data is required in order to determine causal effects. This highlights the importance of keeping the extent and direction of causal effects in mind when setting out to analyse the relationship of interest.

This section has established ways in which health can be defined and has clarified what is meant by ‘health’ in this thesis. It also reinforced that the causal relationship of interest is the effect of health on labour market outcomes. Causal effects and methods to estimate these will be discussed in more detail in the following chapters including methods used to address the endogeneity of health discussed at the end of section 2.1.2.

The next section provides a review of the current empirical evidence on relationships between health and labour market outcomes, focusing on the causal effects of health. With regards to measures of health, it was stated at the beginning of this section that empirical work has used a range of different health measures. The next section of this thesis, in reviewing empirical evidence, will reflect this.

2.3 Interactions between Health and Labour Market Outcomes-The Evidence

The availability of better data in recent decades has allowed improved empirical testing of the relationship between health and specific labour market outcomes as set out in the theoretical framework described in section 2.1. Based on this theoretical framework, empirical work has focused on investigating links between health and labour market outcomes. The following areas have been of particular interest:

- Health and labour force participation
- Health and the probability of gaining and retaining employment
- Health and wages, earnings and hours worked
- Health and the retirement decision

Research has also been conducted on other labour market outcomes however other outcomes have received less attention in comparison with those set out above. The review in the next sections concentrates on the main areas of research, with the empirical work undertaken in these main areas canvassed and critically assessed. The empirical chapters in Part II of the thesis conduct a more detailed review of under-examined research outcomes.

2.3.1 Health and Labour Force Participation

A number of studies have considered the relationship between health and participation in the labour force. These can be separated into those studies which analysed the connection between health and participation for the working age population (Cai and Kalb, 2006; Cai, 2010; Oguzoglu, 2010; García-Gómez *et al.* 2010; Polidano and Vu, 2015; Webber and Bjelland 2015) and those which focused on older working age people (see for example Bound *et al.* 1999; Au *et al.* 2005; Disney *et al.* 2006; Cai and Kalb 2007; Zucchelli *et al.* 2010; Bound *et al.* 2010). The effect was found to differ by age groups, with health having a larger effect on older peoples' participation than younger people's (Cai and Kalb, 2006). Many of these studies focus primarily on physical health and its effects on participation.

There are few longitudinal studies within the economics literature which analyse the effect of mental health on labour force participation. The results of cross-sectional studies such as Ettner et al. (1997), Chatterji et al. (2007, 2011) and Zhang et al. (2009) found that mental illness is associated with lower labour force participation for both men and women. Frijters et al. (2014) recently built upon these studies by using the HILDA survey to conduct panel data analysis of the extent to which poor mental health affects employment outcomes. They used a time-varying instrumental variable model to overcome the known econometric issues of obtaining causal health effects and to account for unobserved heterogeneity and measurement error in mental health. Frijters et al. (2014) found that a one-standard-deviation decline in mental health reduces the probability of employment by 30 percentage points. The effect is large for both men and women and is larger for older workers than younger workers.

Table 1 summarises the findings of key studies of the effect of health on participation in employment, highlighting methods and data used. The papers included in this table are those which illustrate methodological issues in analysing the effect of health on labour market behaviour, those which highlight the concerns surrounding the health measure to be used and in particular papers which use panel data methods.

Table 1: Studies of the Effect of Health on Labour Force Participation

Study	**Age range studied**	**Data, methods, health measure**	**Findings**
Bound *et al.* (1999)	50 to 62 in the first wave	Health and Retirement Study (3 waves), dynamic panel data modelling, constructed health index	Poor health is strongly associated with labour force exit. Changes in health are important
Au *et al.* (2005)	≥50	Canadian National Population Health Survey (4 waves), dynamic modelling, constructed health index	Health has an economically significant effect on employment probability for those aged 50-64. Changes in health are important. The effect is underestimated by estimates using self- assessed health.
Cai and Kalb (2006)	15 to 49 50 to 64 (men) 50-60 (women)	HILDA Survey, first wave, simultaneous equation, self assessed health	Better health increases the probability of labour force participation. The effect is larger for older groups and women. Health is found to be endogenous to labour force participation
Disney *et al.* (2006)	50-65 (men) 50-60 (women)	British Household Panel Survey (1991-1998), dynamic panel data modelling, constructed health index	Health shocks predict retirement behaviour among workers aged 50 until state pension age. Use of the constructed health index seems superior, in terms of explanatory power, to models using disability type health measures.
Cai and Kalb (2007)	51-64 (men only)	HILDA Survey, three waves, panel data modelling, self assessed health	Health has a significant effect on labour supply. Controlling for unobserved heterogeneity and the correlation between the health and labour force status equations is important.
Bound *et al.* (2010)	50-62 in the first wave, men only	Health and Retirement Study (4 waves), dynamic panel data modelling, constructed health index	Poor health has a large impact on work decisions. Estimates are substantially smaller than in models treating self-assessed health as exogenous
Cai (2010)	25-64 (men) 25-59	HILDA Survey, four waves, simultaneous	Health has a positive and significant effect on labour force participation

Study	**Age range studied**	**Data, methods, health measure**	**Findings**
	(women)	equation, self assessed health	for both men and women. There is evidence of justification bias in self assessed health for women and self-assessed health is found to be endogenous to labour force participation
García-Gómez *et al.* (2010)	16-64 (men) 16-59 (women)	British Household Panel Survey (1991-2002), panel data modelling, constructed health index	Health affects entries into and exits out of employment. The effects are higher for men than for women.
Oguzoglu (2010)	24-64 (men) 24-60 (women)	HILDA Survey, five waves, dynamic panel data modelling, work limiting health	Persistence and unobserved heterogeneity play an important role in work limitation reporting and its effect on labour force participation.
Zucchelli *et al.* (2010)	50-64 (men) 50-61 (women)	HILDA Survey, six waves, panel data modelling, constructed health index	Health shocks are key determinants of early exit from the labour market.
Frijters *et al.* (2014)	21-64	HILDA Survey, ten waves, panel data modelling, uses instrumental variable model and constructed index of mental health	A one-standard-deviation decline in mental health reduces the probability of employment by 30 percentage points. The effect is large for both men and women and is larger for older workers than younger workers

The estimated effects of health on labour force participation are of different magnitudes across studies. As discussed in section 2.2, this is primarily because different health measures were used although differences in methodology have also contributed to differences in estimates. The way in which health is modelled can have a substantial effect on the conclusions about the behavioural effects of poor health (Bound *et al.* 2010).

Likewise, failure to account for unobserved heterogeneity and endogeneity can bias results of empirical analysis. Bound *et al.* (1999) noted that modelling health in a dynamic, longitudinal framework is important in order to determine insights into behaviour. Aside from allowing control for unobserved heterogeneity, panel data enables analysis of changes in health. Cai and Kalb (2006) and Cai (2010) emphasise the importance of accounting for endogeneity of health. They find health to be endogenous in estimating the effect of health on labour supply. The different methods used in empirical work makes comparisons between studies difficult, however, all studies found a positive relationship between health and participation, that is, better health is associated with a higher likelihood of labour force participation.

Health, as a form of human capital, affects productivity. Ill health is linked with lower work performance and this will lead to lower productivity. Low productivity is known to decrease individuals' earning potential. Cai (2009b), Disney *et al.* (2006), Bound *et al.* (1999) and Chirikos (1993) suggest that poor health is associated with lower earnings. This decreases the opportunity cost of leisure and correspondingly decreases willingness to participate in the labour force (via a substitution effect of leisure for work). Thus, health and labour force participation are positively correlated with better health linked with a higher probability of labour force participation.

Even if an individual's productivity is unaffected by the onset of a health problem, their relative utility derived from income and leisure may change. It has been argued that poor health may increase the value of leisure because individuals require more time to care for their health (Cai and Kalb, 2006; Lumsdaine and Mitchell, 1999; Chirikos, 1993). Also, if the health problem is such that it reduces life expectancy, poor health may make withdrawal from the labour force more attractive by altering the time horizon over which economic decisions are made (Cai and Kalb, 2006; Chirikos, 1993). Another argument is that rather than increasing the relative utility of leisure, poor health may cause an individual to experience disutility from work. While the individuals' health problem may be such that non work time does not bring enjoyment, they may suffer such a degree of stress from their work due to their reduced physical or mental capacity that they experience increased disutility from work. As with the theory of productivity effects discussed above, these arguments predict that poor health is associated with a lower probability of labour force participation or, if the individual does participate, a lower number of hours supplied.

Cai and Kalb (2006) note that the literature has not been able to discriminate between productivity effects and the role of preferences in the effects of health on labour market behaviour. While the theory generally argues that poor health reduces the probability of labour force participation, it is possible that lower earnings associated with lower productivity may have an income effect. If the income effect dominates, the individual could increase their labour supply in response to the onset of poor health. It has also been argued that increased demand for health services following onset of poor health may result in individuals needing to work more to earn additional income (Cai and Kalb, 2006). While this implies that theoretically the direction of the effect of better health on labour supply is not clear, as already stated earlier, empirical studies find a positive impact.

2.3.2 Health and the Probability of Gaining and Retaining Employment

Aside from poor health reducing the probability of participating in the labour force, applicants with ill health are less likely to be hired than applicants with better health holding other factors constant (Schuring *et al.* 2007; Korpi 2001). This makes a distinction between voluntary and non-voluntary unemployment and economic inactivity amongst persons in poor health[4].

LaPlagne *et al.* (2007) highlight the possible role of signalling and statistical discrimination in the likelihood of mentally ill persons gaining employment. They said:

> ‘People with depression might also face limited employment opportunities if an episode of impaired motivation is interpreted by employers as reflecting a low overall motivation level (Waghorn and Lloyd 2005), or if employers ascribe low motivation to everyone who suffers from depression (statistical discrimination)’ (p. 31).

[4] Withdrawal from the labour market or inactivity based on grounds of ill health is arguably involuntary regardless. Obstacles to employment for those with poor health who choose to seek employment adds another layer to the degree to which their exclusion from employment is involuntary.

This analysis can be extended to those with physical impairments. Provided that the physical impairment is observable (or if not, that the applicant discloses the existence of a physical impairment), poor physical health could be interpreted by employers as reflecting lower productivity.

Of course, the converse could be true. A mental or physical impairment which is not disclosed and which is not observable could result in the applicant presenting as in better health than is actually the case. The employer could infer that the applicant has high productivity when in actual case they could well be less productive than a person in good health.

Anti-discrimination legislation renders it illegal for employers to discriminate on grounds of disability however legislation has been found to have no impact on the employment rate of disabled people in both the US and the UK (Bell and Heitmuller 2009). The low rate of employment amongst the disabled cannot of course be solely attributed to discrimination. Work limiting health impairments can mean employment is simply not possible. Inability to gain employment for those where it might be possible is an area of concern because it adds to the hardship faced and can contribute to cumulative disadvantage for those with poor health. Poor health, whether it be actual disability or a more transitory impairment, can therefore be associated with not just voluntary absence from employment but an involuntary absence where individuals seek employment or seek to retain employment and cannot find or keep employment.

A number of studies have found evidence of health based selection both into and out of employment (see for example Korpi 2001; Schuring *et al.* 2007; García-Gómez *et al.* 2010; Virtanen *et al.* 2013). This reflects both voluntary and involuntary transitions based on the theory outlined in the previous section regarding productivity and utility effects. While these transitions can be linked with the relationship between health and participation discussed in the previous section, analysis of health effects on entry and exit from employment rather than solely identifying (the still very important) relationship between health and participation has the potential to shed light on other obstacles faced by individuals with poor health.

The literature cited in the previous paragraph mostly focused on physical health. The limited employment opportunities for persons with mental illness are illustrated in the findings of Baldwin and Marcus (2014). They studied the impact of serious mental illness on employment transitions using two waves of the US National Epidemiologic Survey of Alcoholism and Related Conditions. Their methods do not account for potential endogeneity of mental illness but their findings, consistent with previous research and the recent study by Frijters *et al.* (2014), do suggest that serious mental illness reduces the probability of gaining employment and for those who are employed, increases the probability of transitions out of employment. The higher probability of transitioning out of employment is highlighted as a concern for disadvantaged groups, with the authors stressing the need for stable employment.

One way in which persons experiencing health impairment may retain employment is to change jobs. Likewise, employer accommodation can assist in both gaining and retaining employment. The literature on both job change and accommodation as a means to encouraging employment for those with a health limitation is limited but it does find that people with health problems who are not accommodated in their current job select into less physically demanding jobs **(**Daly and Bound, 1996; Krause *et al.* 2001**).** Job change is also said to allow a worker to adapt to their health problem by adjusting the demands of their employment (Daly and Bound, 1996; Bound *et al.* 1999). The degree to which these tactics are feasible and effective is limited however, resulting in many opting out of work altogether. Polidano and Vu (2015) note that those without post-school qualifications are particularly vulnerable, being more likely to be out of work and on income support after onset of disability.

2.3.3 Health and Wages, Earnings and Hours Worked

The discussion of the empirical work on employment participation and entry and exit from employment highlights the important issue of the degree to which persons with poor health are able to obtain and retain employment. There are however people with poor health engaged in work and this prompts the question of how poor health affects other labour market outcomes such as wages, earnings and hours worked.

In an early empirical study on the economic effects of poor health, Chirikos and Nestel (1985) used US National Longitudinal Survey data to provide evidence that health problems in the past have an adverse effect on current earnings. They found race differences, with whites (but not blacks) with a history of ill health having lower wages than those in continuous good health. This effect of previous poor health on earnings has also been found more recently, with childhood health found to affect earnings later in life (Smith, 2009; Lundborg *et al.* 2014). While their findings are suggestive (with childhood health being retrospective and an imperfect measure), the interactions between health and education also play a part, with health and education being interdependent (Gan and Gong, 2007). Health affects academic success and this exacerbates the effect of early life health on earnings later in life.

Chirikos and Nestel (1985) noted that empirical work on the economic consequences of health problems focused mostly on white men. Currie and Madrian reviewed literature on the links between health, wages, earnings and hours worked and they acknowledged the same limitation. Their extensive literature review found that a glaring limitation in empirical work 'is the intense focus on elderly white men, to the virtual exclusion of most other groups'. They did find that health has a greater effect on hours worked than on wages. There is evidence in the literature that health affects earnings but this is unsurprising in light of poor health being linked with fewer hours of work. The link between health and hours worked fits with the theory on the effects of health on labour supply. People with worse health may want part-time work via the productivity effects and utility effects outlined earlier in relation to the link between health and participation.

Differences in effects across groups are important. The intense focus on older white men is likely to miss important differences in effects for certain groups. Effects of health on labour market outcomes may differ by gender, race, occupation and other characteristics. Chirikos (1993) noted that interaction studies that do look at women and other race groups find that poor health compounds even further the well-known labour market disadvantages of women and minorities. Chirikos (1993) suggests that as more is known about older white men than about any other group, new research should focus on health differences across groups in the work force. These differences have implications for interactions between health and labour market outcomes over the life course and for the degree of inequality faced by disadvantaged groups later in life. A failure to consider these differences presents an incomplete picture of links between health and labour market outcomes.

Pelkowski and Berger (2004) focused on the effect of health on labour market outcomes for a broader sample. They used the Health and Retirement Study (HRS) to examine the effect of health problems on employment, annual hours worked and hourly wages for both men and women. The HRS data were used to compile employment and health experience profiles over the lifetimes of respondents. Their analyses also extended previous work by distinguishing between permanent and temporary illnesses and considering the impact of age of onset of illness.

Permanent illnesses were found to have a negative and significant effect on labour market outcomes while there was no significant effect for temporary illnesses. Pelkowski and Berger found that poor health has different consequences for men and women. Illness was found to affect both wages and hours worked, with women experiencing larger reductions in wages while men experienced larger decreases in hours worked. It is likely that the larger reduction in hours worked for men can be attributed to the fact that men, on average, work longer hours than women. After adjusting for selection bias, Pelkowski and Berger (2004) noted that while permanent health conditions do affect wages and hours worked, they actually have far greater effects on the likelihood that an individual works in the first place. Taking into account their findings on reduced probability of participation, wages, and hours worked, Pelkowski and Berger (2004) also calculated what their estimates implied about total lifetime earnings. While the method they used was crude, they found that permanent health conditions lowered lifetime earnings by just over 50 percent for both men and women.

One limitation of this study is the failure to account for endogeneity between health and labour market outcomes. Pelkowski and Berger estimated the effect of health on labour market outcomes but they did not take account of the reverse causation effect-that labour market outcomes such as wages and hours worked can affect health. If there is endogeneity and is not accounted for, the estimates will be biased. This study does, however, extend the finding that poor health is linked with fewer hours of work from Currie and Madrian (1999) to a broader sample.

Cai (2009b) also examined the effect of health on wages for Australian men aged 25 to 64 using the third wave of the longitudinal Household, Income and Labour Dynamics in Australia (HILDA) survey. They used a simultaneous equation model to account for the endogeneity of health. Good health is found to have a positive and significant effect on the wages of Australian men but only when measurement error and endogeneity are accounted for. This is the first study to estimate the effect of health (rather than disability or alcohol consumption) on wages in Australia. While it confirms the common finding of the effect of health on wages, the cross sectional nature of the study (with analysis limited to only the third wave of HILDA) and restricted sample (men only) are limitations.

More recently, Cai *et al.* (2014) estimate the effect of health on working hours. They use the Australian HILDA data and dynamic panel data modelling to estimate the joint effect of health status and health shocks on working hours. A Tobit model is used in recognition of the fact that a health shock does not necessarily result in one leaving the workforce, the individual may just reduce hours worked. Predicted health is used to account for possible measurement error and endogeneity. Lower health status is found to result in fewer working hours and health shocks lead to further reductions in working hours. The study does take into account gender differences, finding that men who suffer a health shock reduce hours worked more than women but women who suffer a health shock are more likely to leave work altogether than men.

There are also studies which look at part time work rather than hours worked. Pagán (2009) does this for a sample of people with disabilities in Europe but the study is cross sectional and focused on older workers. It does find that older people with disabilities are more likely to have a part time job but the cross sectional nature of the study does not allow any determination of the causal nature of this relationship. Zucchelli *et al.* (2012) consider evidence on labour market transitions amongst older individuals in Australia using the HILDA survey. They do find some evidence that poor health could push older workers into part time employment but poor health increases the probability of transition out of work from all forms of employment.

The studies reviewed in this section provide empirical support for the expected relationships between health and wages, hours worked and earnings. Most of the literature however only analyses a subset of the population and/or suffers from methodological limitations. This suggests that further research is needed to fully settle the question of the effect of health on these labour market outcomes.

2.3.4 Health and the Retirement Decision

Aside from research into the labour market outcomes discussed in the previous sections, there has been a focus on the effect of health on age of retirement and the decision to retire. Of all the labour market outcomes listed at the beginning of this section, the effect of health on retirement has received arguably the most attention and understandably so given the ageing population in the developed world and the changing age profile of the workforce.

There is an overlap between research into the effect of health on retirement and the effect of health on labour market participation discussed in section 2.3.1. The earlier section observed that research has considered the effect of health on the employment participation of older workers. This is closely linked with the retirement decision as older persons face a different time frame for making decisions compared with younger persons and this affects preferences for consumption and leisure.

Lazear (1986) noted that the retirement models all considered the retirement decision in the context of the life-cycle. The decision of what age to retire was assumed to depend on the life time utility maximization problem. People generally work in their younger years and then choose to take their leisure in a bunch representing retirement. It is assumed that workers consider foregone earnings as well as foregone retirement income (superannuation and the age pension in Australia) when deciding to retire. The opportunity cost of retirement will be the wage as well as foregone fringe benefits such as retirement benefits (Lazear, 1986). It is expected that a person will retire once their retirement income (in the form of superannuation and/or the age pension) reaches a level where the trade-off or benefit to continuing in paid employment, the utility derived from working (or utility derived from consumption levels corresponding with the wages earned), no longer exceeds the cost of forgone leisure.

Corresponding with this theory, policy initiatives aimed at encouraging older workers to remain in the workforce have looked at the retirement decision as predominantly a financial decision (Jackson *et al.* 2006). The literature has found that financial incentives are very important in the retirement decision but health is also important. In a large number of studies, health has appeared to be the most important determinant of older peoples' labour supply, however this result is not undisputed due to the difficulties in measuring health and the joint determination of work and health (Lindeboom, 2006). Henkens and van Dalen (2003) outline policy makers' tacit assumptions and, citing a number of studies, show that financial incentives explain only a small part of long run retirement trends.

Empirical studies into effects of health on the retirement decision have, until recently, suffered from a number of limitations. These echo those limitations acknowledged in the previous sections of this review with regards to focusing on only a subset of the population and issues with methodology. Firstly, most literature tended until recently to focus on men's retirement due to both a lack of data and because retirement was thought of as more of a concern for men. Secondly, early literature on the subject tended to rely on cross-sectional data, self reported health and did not control for endogeneity of health. This review will begin by discussing early advancements in empirical work before focusing on the evidence from more recent literature where efforts have been made to address many of the concerns which might affect empirical results.

Sickles and Taubman (1986) is an early example of a paper using panel data to estimate the effect of health on retirement status for men. Their contribution was to jointly model health and retirement status using the US Retirement History Survey and they found that retirement decisions are strongly affected by health status. Sickles and Taubman advanced the empirical work in this area but while they allowed health to affect labour force status, the effect of labour force status on health is assumed to be zero. This failure to account for endogeneity of health limits their findings as does the focus on men only.

Bound (1991) identified different sources of bias in measures of health resulting from measurement error and endogeneity. Bound *et al.* (1999) expanded on this by using a latent variable model to construct an index of health to account for measurement error and some sources of bias in self assessed health[5]. They used the Health and Retirement Study to examine the interplay between health and labour market behaviour later in life for men and women. Their analysis of the dynamic relationship between health and alternative labour market transitions (labour force exit, job change and applications for disability insurance) included controls for lagged and current health. Bound *et al.* (1999) find that it is not only poor health but declines in health which help explain retirement behaviour and that dynamics and a longitudinal framework offers important new insights into the labour force behaviour of older workers. Results for women were broadly similar to those for men, adding value to the literature focusing predominantly on men. They did however only have a short panel containing three waves of data.

The method used by Bound *et al.* (1999) has been applied to Canadian data by Au *et al.* (2005) and to British data by Disney *et al.* (2006). Au *et al.* (2005) uses four waves of the Canadian National Population Health Survey and finds that changes in health are important in the work decision of older workers. Disney *et al.* (2006) use eight waves of the British Household Panel Survey (1991-1998) and they show that adverse shocks to individual health predict retirement behaviour amongst workers aged 50 until state pension age. They also find that lagged health as well as current health affects decisions to retire. Both studies confirmed the results of Bound *et al.* (1999).

More recently, Jones *et al.* (2010) and Bound *et al.* (2010) extended the findings of these studies using similar methods to address the issues with measurement error and endogeneity in the health measure. Bound *et al.* (2010) analysed the interplay

[5] This is the method referred to in section 2.2.1 and is discussed in more detail in chapter 4.

between health, financial resources and labour market behaviour of men late in their working lives. They used four waves of the HRS and find large impacts of health on work decisions but that impacts estimated are smaller than those using self reports of health. In relation to financial resources, men in poor health base their decisions less on financial resources available. They are quite likely to leave the workforce even if not currently eligible for pension benefits. Men in poor health are estimated as ten times more likely than a man in average health to retire before becoming eligible for a pension.

Jones *et al.* (2010) use twelve waves of the British Household Panel Survey to explore the existence of reporting bias and use a constructed health index, as with the previous studies following on from Bound *et al.* (1999), as a measure purged of this bias. Their model takes into account that anticipated retirement might influence reporting of health and also considers the relative effect of health on retirement compared to other factors including private pensions. They find that health shocks are a determinant of retirement age for both men and women and for two different health measures, health limitations and the health index. The size of the health effect varies depending on health measure used.

Whichever way health is measured, Jones *et al.* (2010) show it is a key determinant of early retirement for both men and women. The size of the relative effect is large compared to other significant variables and in particular when compared to the effect of private pensions. The findings of Bound *et al.* (2010) and Jones *et al.* (2010) support the earlier claim that health effects are stronger than financial incentives in influencing the retirement decision.

There are two recent studies using methods derived from Bound *et al.* (1999) using Australian data. Zucchelli *et al.* (2010) uses six waves of Australian HILDA survey to analyse the relationship between ill-health, health shocks and early labour market exits among older working individuals. Their results show that health shocks are key determinants of early exit from the labour market for both men and women. The findings were confirmed using four different health measures-two measures of health shocks, a measure of health limitations and a constructed health index.

Zucchelli *et al.* (2012) likewise use the HILDA survey but in this study they consider retirement as a multi-state process. They analyse the effect of health on labour market transitions among older individuals and find that ill health and health shocks increase the probability of transitioning into inactivity from full-time employment. There is also evidence of health-driven paths into inactivity from part-time and self-employment. If previously employed, health shocks can, to a smaller degree, enhance the probability of switching to part-time and self-employment especially for women. Their model took into account dynamics and state dependence as well as controlling for endogeneity.

With the effect of health on retirement and retirement decisions being a research area receiving much attention, methodology has evolved in an attempt to account for sources of bias in results and to provide reliable findings. The recent papers reviewed in this section take account of many previous weaknesses in empirical work, using more representative data (within the subset of the population containing older people), panel data covering longer time frames and methods to account for unobserved heterogeneity, endogeneity, justification bias and measurement error in the health measure. Addressing these methodological issues provides more reliable results which account for bias and produces findings which reflect the relationships of interest with a much higher degree of confidence.

Nonetheless, some recent research still suffers one or more of the highlighted limitations. Christensen and Kallestrup-Lamb (2012) estimated the impact of health shocks on retirement in Denmark. They used objective measures of health from a large, register-based longitudinal data set. The use of objective measures aimed to mitigate justification bias and they find a strong impact of health changes on retirement. While they do contribute to the literature, their results do not control for the endogeneity arising from reverse causation.

Jiménez-Martin *et al.* (2006) noted that panel data in Europe combining detailed information on both health and labour are very scarce in general, with the European Community Household Panel a notable exception, having (severely limited) health data. They then had to rely on cross-sectional data using retrospective information in order to study older workers' labour force transitions following a health/disability shock. More recently, the Survey of Health, Ageing and Retirement in Europe has collected longitudinal data but this is a rather new development, only commencing in 2004 and currently consisting of four waves of data. Even with advances in data collection and methodology there are still improvements to be made in many areas and these limitations are reflected in current research.

The literature has clearly established that poor health and health shocks have a strong impact on the retirement decision. Poor health is an important determinant of early retirement. As stated earlier however, leaving the labour force is only one response to deteriorating health and is often a response of last resort. Both Bound *et al.* (1999) and Pelkowski and Berger (2003) considered the role of job change in extending working life following the onset of health problems. They found that the earlier in life a health shock occurs, the less likely it is to lead to immediate withdrawal from the labour force.

While job change occurs at all ages and is therefore is not relevant only to the retirement decision, it is the decline in physical health at older ages which is likely to create a mismatch between an individuals' capabilities and their job requirements (Bound *et al.* 1999). Poor health is more likely to result in withdrawal from the labour force for older workers than younger workers. Changing jobs is one way to adapt to declining health and to delay retirement.

Bound *et al.* (1999) found that among older individuals with ill health who continued to work, more than 20 per cent changed jobs after onset of ill health. Pelkowski and Berger (2003) extended the analysis to consider the types of job change which occurred. They found that workers with health problems (among those who do continue working), are more likely than healthy workers to remain with the same employer. However, among those who switch employers, those with health problems are more likely to change broad occupational categories than are healthy workers (the change in occupation being to one which is less physically demanding). Pelkowski and Berger (2003) noted that employer accommodation of health problems is likely to have influenced the choice to change jobs or not.

Despite job change being an avenue through which individuals suffering poor health might adapt and remain employed, it must be acknowledged (as was stated in section 2.3.2) that this is not always feasible. It might be difficult to find employment suited to declining physical health and/or employers willing to accommodate such limitations. The choice to continue in employment amongst older workers also differs in relation to that of younger workers with the different time frame they face in making their decisions (as acknowledged at the beginning of this section) having an effect on how they might allocate their time in the face of health impairments which also have an effect on the decision making process.

The choice to change jobs in order to extend working life is likely to depend in part upon preferences. The onset of a health problem may change the relative utility derived from income and leisure. Differing preferences for income and leisure can explain differing retirement ages. There is also the trade-off suggested by Lazear (1986) in terms of forgone earnings and utility derived from consumption as opposed to forgone utility derived from leisure. Both age and health combine to affect this choice.

Health can play a role in these preferences as it could be argued that worsening health strengthens the preference for leisure, or non-work (Lumsdaine and Mitchell, 1999). Individuals requiring more time to care for their health may put increased value on leisure and may even experience increased disutility from paid work depending upon the difficulties associated with their health problems. Those who choose to change jobs rather than retire must still derive some utility from work (and income) which prolongs their time in the labour force.

The theory explaining the importance of health in the retirement decision is very similar to that described earlier in relation to the choice to participate in the workforce. Ill health can have an effect on the budget constraint by affecting employee wage opportunities. Ill employees are generally less productive in the short run, have been found to suffer more absenteeism in the medium run and are less likely to invest in long-term skills in the long run (Lumsdaine and Mitchell, 1999). It can be argued that if older workers experience greater health problems than younger workers (which is generally assumed), then poor health could reduce employability and compensation offers for older workers (Lumsdaine and Mitchell, 1999).

This argument is merely an extension of the productivity effect explanation of the relationship between health and labour supply discussed earlier. Lower pay could contribute to early retirement for those suffering ill health as it reduces the opportunity cost of leisure. If the substitution effect dominates the income effect when pay falls, (Lumsdaine and Mitchell (1999) suggest this is the case among older workers) then older workers may respond to lower pay by leaving their jobs, reducing their hours or retiring. Unemployment and disability benefits play an important role in the decision to retire, even if health has been found to have a greater effect than *retirement* related financial incentives. If poor health results in lower pay, the replacement rate of these benefits rises, further reducing the opportunity cost of leisure and making withdrawal from the workforce more appealing. Henkens and van Dalen (2003) highlight the availability of these benefits as an important factor in the retirement decision-they provide an alternate route into early retirement, particularly for those in poor health.

As stated towards the beginning of the review of empirical work, the way in which health is measured can have a substantial effect on conclusions about the effects of poor health on behaviour. In recent years there have been a growing number of studies of the effect of health on retirement using comparable health measures based on the method applied in Bound *et al.* (1999). The review in this section shows that these studies find comparable results across a number of countries, with poor health having a strong impact on the retirement decision.

2.3.5 Summary

The studies of the relationship between health and labour market outcomes indicate that poor health has a negative effect on the outcomes studied. It is associated with reduced likelihood of labour force participation, reduced chances of gaining and retaining employment, lower wages, lower hours of work, lower earnings and early retirement. While the literature reviewed shows that empirical work has advanced, particularly in recent years, there are still limitations.

In terms of measuring health, the effects of mental health have received far less attention compared with physical health. Focusing purely on measures of physical health does not fully capture the ways in which health impacts labour market behaviour. One advance in methodology has involved using a measure of mental health as an indicator along with other health measures in constructing a health index to measure general health. This method can be argued to better capture the dimensions of good health.

Aside from the emphasis on physical health, there are other concerns about health measures in terms of bias and measurement error related to self reports as well as the issues with establishing causality (due to labour market outcomes affecting health). Recent studies have attempted to control for these methodological issues but the application of methodology is not uniform across empirical studies.

The need to control for endogeneity and unobserved heterogeneity was also emphasised early in the review. This illustrates the importance of having suitable data and in particular use of panel data. The availability of data (particularly panel data covering longer time frames) is continually improving, allowing for more reliable analysis but there are still improvements to be made. This is reflected in the state of the literature. Failure to address these methodological issues risks overestimates of the effect of health on labour market outcomes. The use of more econometrically appropriate methods and data provides more robust results which give far greater confidence that findings accurately reflect the relationships of interest.

Apart from issues with methodology, the review found that empirical work has, until recently, focused on a subset of the population. Research has concentrated on older white men and use of more representative data is a relatively new development. Even so, the majority of the literature on health and labour market outcomes focuses on older people, specifically the role of health in transitions to retirement. While this is important, particularly in the context of the ageing populations in developed countries, there is some evidence also of health affecting labour market outcomes of younger individuals (García-Gómez *et al.* 2010)**.** This reinforces the importance not only of encouraging older persons to continue working but also to retain younger workers in the labour force if they suffer a health impairment but still have capacity to work.

Poor health, while more common amongst older persons, also afflicts a lesser but still significant proportion of younger persons (see chapter 3). The focus in this thesis is the causal relationship of the effect of health on labour market outcomes and disadvantage arising from this, not just for older workers but for the whole working age population. This is analysed using a general measure of health as described briefly above and in further detail in chapter 4.

The literature reviewed to date provides a snapshot of interactions between health and labour market outcomes. While the findings from these studies, taken together, can provide a picture of many of the dimensions through which health affects labour market experience, it does not show the full extent to which health differentials may result in accumulating disadvantage through the full range of outcomes which might be affected by poor health.

The next section reviews the available evidence on accumulating disadvantage arising from health differentials.

2.4 Evidence of Accumulating Disadvantage with respect to health

The adverse effects of poor health on labour market outcomes established in the previous section suggest that poor health is associated with labour market disadvantage. The nature of the disadvantage experienced also points to a likelihood of accumulating disadvantage, with poor health not only affecting the likelihood of employment but also affecting labour market outcomes amongst those who are employed. These adverse effects might have repercussions in terms of levels of training, human capital appreciation and chances for promotion. Even if this were not the case, effects of health on labour market outcomes might persist over time and this suggests that accumulating labour market disadvantage as a result of poor health is a real possibility.

If poor health results in accumulating labour market disadvantage then this will exacerbate the disadvantage experienced relative to those in continuous good health. This is likely to be especially the case for those suffering ill health soon after reaching working age, or at mid age. Disadvantage associated with early onset of poor health has the potential to accumulate over the duration of working life, with the implication being that those in poor health during early to mid working age in particular, will suffer added disadvantage post retirement due to lower accumulation of wealth and superannuation through lower earnings over the life course.

There has been limited study of accumulating labour market disadvantage resulting from poor health. Even in the labour economics literature there are few studies. This section reviews the available evidence on accumulating disadvantage, drawing on literature from other disciplines in order to present the available knowledge of this area.

Research into socioeconomic inequalities in health (the SES-health gradient) finds that inequality increases with age (Ross and Wu 1996; Deaton and Paxson 1998; Sacker *et al.* 2005; Chandola *et al.* 2007; Haas 2008; van Kippersluis *et al.* 2009). While the contribution of health related labour market disadvantage has not been isolated within this research, some studies explicitly state support for this accumulating disadvantage hypothesis in the context of the SES-health gradient (see for example Singh Manoux *et al.* 2004; Willson *et al.* 2007).

Those in poorer health are also more likely to be disadvantaged in terms of education, income and socioeconomic status (WHO, 2003; Marmot, 2004; WHO, 2007). Accumulation of exposure to low socioeconomic status is associated with worsening health, suggesting that there are further health effects from prolonged low SES. The health effects are one way in which accumulating disadvantage can manifest, this thesis is interested in identifying cumulative disadvantage arising from health effects on labour market outcomes.

Labour market disadvantage itself has been found to result in labour market disadvantage later in life. Altonji, Smith and Vidangos (2013) use the Panel Study of Income Dynamics (PSID) to jointly model earnings, employment, job changes, wage rates and work hours over a career. They find that unemployment shocks have a large impact on earnings in the short run as well as a long term effect on the wage rate. Shocks associated with job change and unemployment explain a large amount of the variance of career earnings. Their sample is confined to male heads of households but the findings do make theoretical sense and are likely to be applicable beyond this group.

Dewilde (2011) also studied the effect of labour market experience, analysing the impact on household income for older people in the UK and Belgium using the Panel Study of Belgian Households and the British Household Panel Study. They find a “scarring effect” of unemployment on income which persists even into retirement and that occupation affects income post retirement. They draw on the conceptual framework of cumulative disadvantage. Use of household income (not including assets) for older persons is a noted limitation, with this being a rather imperfect measure of resources available at older ages. Also, while they use panel data, the degree to which they exploit these data is limited. They use OLS regression and do not appear to account for unobserved heterogeneity, dynamics or endogeneity.

The effect of early non-employment on subsequent employment status has also been studied. Luikx and Wolbers (2009) used five retrospective life-history surveys collected in the Netherlands to analyse whether non-employment in the beginning of the career damages workers’ later employment opportunities. They applied panel data analysis and find that longer duration of non-employment in the first 3 years after leaving full time education increases the likelihood for both men and women of subsequently exiting employment (up to 15 years after leaving education). They also find negative effects of early non-employment on the likelihood of re-entering employment after job loss for men. This suggests a scarring effect of early life non-employment on later employment chances in the Netherlands. It also adds to the earlier findings of Arulampalam *et al.* (2001), a review paper which finds that the best predictor of future risk of unemployment is past history of unemployment.

The literature analysing cumulative effects of *health* on labour market outcomes is limited. There are some recent papers analysing the effect of health on life cycle labour supply (Hum *et al.* 2008; Smith, 2009; van der Wel 2011). Health is, unsurprisingly, found to affect individual labour supply over the life cycle. Van der Wel (2011) uses three waves of the Norwegian HUNT study spanning two decades to investigate whether there are cohort differences in the employment consequences of poor health (measured as the likelihood of non-employment).

Adverse consequences of poor health (measured as a limiting longstanding illness) are found to have a stronger effect on younger people compared to middle aged people and especially amongst people with fewer educational resources. The author does note that despite the longitudinal design of the study, analyses do not provide causal interpretations. Many relevant variables are omitted and observations were infrequent (with 20 years between wave 1 and wave 3). Nonetheless the findings are suggestive. A stronger effect of poor health at a younger age might be attributed to the scarring effect of non-employment previously discussed. Early poor health might then have a cumulative effect on the likelihood of non-employment.

Van der Wel (2011) provides more recent evidence building on the earlier research by Korpi (2001). The findings in relation to health based selection into and out of unemployment were discussed earlier in the review in section 2.3 but Korpi also found strong evidence of accumulating labour market disadvantage with respect to ill health. An important conclusion is that an initial disadvantage in health generates additional disadvantage in the labour market. Korpi does focus on physical health but the paper is an early example of longitudinal analysis of accumulating disadvantage resulting from poor health in an area in which limited research has been conducted.

Hum *et al.* (2008) and Smith (2009) provide economic analysis of the effects of health on labour supply over a longer timeframe than previous studies. Smith (2009) used the US Panel Study of Income Dynamics (PSID) to examine the impacts of childhood health for those aged 16 or less in 1968 or born by 1984 (children of the original PSID respondents) while Hum *et al.* (2008) used the Canadian panel data Survey of Labour and Income Dynamics for 21 to 65 year old men. The magnitude of this estimated effect differs with Smith (2009) finding a large effect of childhood health on labour supply in the U.S. while Hum *et al.* (2008) find a smaller effect of health, noting that cross sectional estimates overstate the impact of health on labour supply and that unobserved effects and endogenous health status are likely to have biased previous estimates (many of which focused mostly on older men), resulting in larger estimated effects than is actually the case.

The difference in the magnitude of the findings of these two studies might be attributed to their different focuses. Smith (2009) analyses the effect of childhood health on weeks worked while Hum *et al.* (2008) focuses on health measured for men of the ages 21 to 65 in a life cycle model of labour supply. The health measures used, however also differed in other respects. Smith (2009) used a single index of health, a retrospective self-evaluation using the standard 5-point scale of ‘excellent’, ‘very good’, ‘good’, ‘fair’ and ‘poor’. Accuracy of such a retrospective measure might be debatable though the evidence presented suggests that people remember childhood health well. The measure is still prone however to the criticisms related to self reports outlined earlier in this chapter and set out in more detail in chapter 4. Hum *et al.* (2008) accounted for endogeneity of health by using a constructed health index as an instrument for self-reported health.

Smith (2009) also limited their sample to persons in early and mid-adulthood in order to include the most comprehensive family background measures available in the PSID as control variables. The advantages of their study are the examination of family effects which they find to be important and the PSID also contains the best American panel data for income and wealth, two other outcomes used in their study.

Hum *et al.* (2008) uses a less restrictive age range in their study and also incorporate panel methods used to account not only for unobserved heterogeneity but also endogeneity. Both unobserved heterogeneity and endogeneity of health are found to be important. The authors note that their findings suggest that informal and cross sectional evidence which uses endogenous health outcomes and does not control for unobserved effects overstates the impact of health on labour supply. They also estimate the effects within a life cycle model of labour supply. The main limitation of the study is the sample being confined to men only.

Hum *et al.* (2008) also find that the health impact on labour supply is significant for younger and middle-aged men and increases only modestly with age. This highlights the importance of considering the whole of the working age population in analysing impacts of health on labour market outcomes and provides evidence of accumulating disadvantage. Even though the study finds a smaller effect of health on labour supply than previous studies, the health impact remains statistically significant and the estimated effects have implications for income and earnings later in life.

The impacts of health on earnings trajectories and levels are illustrated in studies by Lundborg *et al.* (2014) and Haas *et al.* (2011). Haas *et al.* (2011) used the U.S. Health and Retirement Study and found that poor childhood health is associated with substantially diminished labour market earnings over the work career. This effect of poor childhood health on career earnings is not surprising given the effect of childhood health on labour supply previously discussed. The effect of health on hours worked noted in the previous section cannot be ignored either in terms of the possible contribution of this to the impact of health on career earnings.

Haas *et al.* (2011) find that earnings differentials by childhood health differ by gender. Aside from women earning less on average over the life cycle compared with men who experience poor health, there are gender differences in the growth rates of earnings by health. For men, earnings differentials grow larger over early to mid-career before slowing while for women earnings differentials emerge later in their career and do not converge. This is most likely due to differences in patterns of labour market participation over the life cycle. From age 40, as employment becomes more common among women, the impact of health seems to be a more important predictor of earnings for women than men.

The study does suffer some serious limitations. Haas *et al.* do not control for selection. Those with zero earnings in a given year are omitted and this is particularly problematic for estimations of effects on earnings for women who (on average) spend a much larger proportion of their working lives out of the labour market compared with men. The study also only observes individuals until age 50 and the authors note that chronic disease has its greatest impact on labour supply after age 50. Despite these limitations, results are noted to be somewhat smaller than a comparable study by Johnson and Schoeni (2011) analysing the effect of poor health at birth on adult outcomes (including labour market earnings).

Haas *et al.* (2011) also use retrospective measures of poor childhood health. Although previous research has shown these retrospective reports to be of reasonable quality they do only provide a broad overview of early life health status. The authors note that they cannot make definitive causal claims about the relationship between health and career earnings. The observations of labour market outcomes are collected independently of childhood health and their data contain no source of exogenous variation in childhood health to allow use of an instrument to control for endogeneity. The study is, however, the first analysis of the impact of childhood health on life cycle labour market outcomes and the results are suggestive in a research area with little prior evidence.

Lundborg *et al.* (2014) conducted a more recent study of the relationship between early life health and adult earnings for Swedish males. They use data obtained from medical examinations during mandatory military enlistment tests at age 18 and link these data to register data on adult earnings. They find that poor early life health has an adverse effect on future earnings, with most major diagnoses of health conditions having long-run effects. They also examine results including sibling fixed effects and twin-pair fixed effects and find that while the magnitude of the estimates is reduced, the effects remain substantial. Their study is limited by the restriction of the sample to men. They use a range of health measures however they do not control for the endogeneity of these measures.

The cumulative effects of poor health on income suggested in these papers can be expected to affect wealth as earnings over the life course are a major determinant of wealth. Studies into the effect of health on wealth appear to be confined to analyses of wealth as a measure of SES rather than analysing cumulative disadvantage. They also study only a subset of the working age population.

Michaud and van Soest (2008) use the HRS to analyse competing explanations of the health-wealth gradient. They examine couples aged 51-61 in 1992 and find causal effects of health for both spouses on household wealth. The models incorporated panel data methods including controls for unobserved heterogeneity and used a constructed health index similar to the method described earlier. Smith (2009) examined the effect of childhood health on wealth for a broader age range. As described earlier, however, the sample only covered those in early and mid-adulthood. He finds that childhood health has a large effect on wealth although the limitations (set out above) must be considered.

The literature reviewed in this section provides some evidence of labour market related accumulating disadvantage resulting from poor health. There remains much more to be studied in this area in order to confirm this cumulative effect through further empirical evidence and examine more thoroughly the degree to which there is cumulative disadvantage. The limited evidence to date finds that poor health has adverse implications for income later in life. The literature reviewed indicates that it is those who are already disadvantaged (low socioeconomic position, experiencing unemployment or not in the labour force) who experience accumulating disadvantage. This indicates that health-related accumulating labour market disadvantage is likely to result in increased disadvantage later in life, given that those experiencing poor health are more likely to be already disadvantaged (with less education and in the lower end of the income distribution).

Section 2.4 reviewed empirical evidence on health and labour market outcomes, establishing that health not only affects the likelihood of employment but also affects labour market outcomes amongst those who are employed. Disadvantage and cumulative disadvantage can manifest not just through health effects on labour supply over the life course but also has the potential to manifest through health effects on characteristics of employment amongst persons who are employed.

Research has considered a number of labour market outcomes but as highlighted in section 2.4, it has concentrated on certain specific outcomes. In order to fully understand the ways in which poor health results in disadvantage, empirical research needs to consider the effect of health on all the labour market outcomes which might play a role in contributing to the disadvantage experienced later in life. While wages and hours worked do capture part of this for the employed, there are other characteristics of employment which might be of relevance.

There is a consensus in the literature that disadvantage in the labour market can accumulate over the life cycle. While literature has considered the effect of health early in life on later health, there appears to be limited analysis of the existence (or not) of accumulating labour market disadvantage associated with poor health and none of the current studies provide evidence for Australia. The focus in the literature on accumulating disadvantage is also limited in terms of most studies focusing on a subset of the population (men only or limited age brackets). There is also further research needed in order to provide evidence accounting for issues with methodology, particularly with respect to health measures.

This thesis aims to extend the analysis of the effects of health on labour market outcomes in Australia and cumulative effects arising from this. More specifically, it examines the effects of health on form of employment and occupation, two under-examined labour market outcomes with the potential to have lasting effects. It then analyses the effect of health on indicators of accumulating labour market disadvantage in order to better understand the degree to which poor health results in accumulating disadvantage over the life course.

2.5 Conclusion

This chapter has set out the current main theoretical framework used in research on the effects of health on labour market outcomes, the Grossman model, and discussed issues surrounding measurement of health and causal relationships before reviewing the recent empirical literature. The review began by presenting evidence on interactions between health and labour market outcomes and finished by reviewing the current state of research into labour market related accumulating disadvantage arising from poor health. It highlighted gaps within the literature as well as methodological strengths and limitations in current empirical work.

While the Grossman model is widely used, there have been a number of critiques as identified in section 2.1.3. Keeping this in mind, the thesis will be informed by this framework and the basic relationships set out in the model but in undertaking empirical work there are still theoretical contributions to be made. Findings from analyses will be compared to theoretical expectations to determine whether they are broadly in line with current theory or whether there are other relationships at work not captured within the current framework.

The literature reveals that poor health has a negative effect on labour market outcomes studied thus far though a great deal of the focus has been on the effects of physical health and on older , particularly male, workers. Poor health reduces the likelihood of labour force participation, reduces chances of gaining employment and retaining employment, lowers hours of work, wages and earnings and is linked with early retirement. The limited evidence on the effect of health on accumulating labour market disadvantage suggests that poor health results in less time spent in employment over the life cycle and lower career earnings.

The cumulative effect of labour market disadvantage arising from poor health is likely to result in further disadvantage later in life. Labour market disadvantage has the potential to affect wealth over the life cycle through its effects on earnings and therefore might affect resources available late in life. While empirical studies have greatly increased knowledge of the effects of health on labour market outcomes and begun to analyse cumulative disadvantage arising from this, we still do not reliably know the extent of the effect of health on the full range of labour market outcomes and disadvantage arising from this.

Longitudinal data are required in order to establish causal relationships over any period of time and good longitudinal datasets with representative samples are only a recent development, with most being collected in the last 10-15 years. As a result, much of the evidence on links between health and labour market outcomes is based on cross-sectional studies or short panels for specific labour market outcomes and the focus until recently was almost exclusively on older white men -far from a representative sample. It is only in the last few years that some studies have emerged which use a representative sample and longitudinal data and take account of methodological issues associated with choice of health measure as well as exploiting panel data as far as possible.

This thesis will be informed by the existing theoretical framework set out in the Grossman model and use recent Australian longitudinal data to analyse under-examined labour market outcomes associated with disadvantage and to provide empirical evidence on the existence and degree of cumulative disadvantage arising from poor health. Recent developments in addressing issues with regard to choice of health measure will be adopted so that the health measure used accounts for methodological concerns and better reflects the multidimensional nature of health. Panel data will be exploited in order to identify causal relationships and the representative nature of these data will enable identification of differences across groups (e.g. gender, age) and will enable a better understanding of the degree of cumulative health related labour market disadvantage.

3. Links between Health and Labour Market Outcomes: A Profile

3.1 Introduction

This chapter describes data used in this thesis to investigate relationships between health and labour market outcomes and evidence of cumulative disadvantage. These data are then used to provide a profile of associations between health and selected labour market outcomes and indicators of disadvantage. This includes those identified in the review of the previous chapter as well as some additional relationships identified from available data. Using cross-tabulations the profile illustrates gross relationships between health and labour market outcomes. While these cannot be relied on for causal inference they do give an initial feel for where relationships exist and which relationships should be explored using longitudinal data analysis in the following chapters.

There are almost countless tables which could have been included in discussing interactions between health and labour market outcomes and indicators of accumulating disadvantage however this thesis seeks to avoid repetition. Many of these are available from other sources and therefore those selected for inclusion in this chapter are tables which are not already readily available elsewhere, with choice being informed by the literature. The tables are also selected based on hypotheses which form the basis of the empirical chapters to come as well as making use of the available data sets.

The data used in the cross-tabulations are drawn from three data sources: confidentialised unit record files (CURF) data from the 2010 ABS General Social Survey, CURF data from the 2007-08 ABS National Health Survey and data from the Household, Income and Labour Dynamics in Australia (HILDA) survey. A description of these datasets is provided in section 3.2. Section 3.3 provides the profile of the links between health and selected labour market outcomes by presenting descriptive cross-tabulations drawn from these data. Section 3.4 presents cross-sectional indicators of accumulating disadvantage. A summary is presented at the end of the chapter (Section 3.5).

3.2 Data

3.2.1 The ABS General Social Survey

The General Social Survey (GSS) is conducted every four years by the Australian Bureau of Statistics (ABS). Details of the GSS are documented in the General Social Survey User Guide published by the ABS (ABS, 2011b). The 2010 GSS is the third in the series, with the first conducted in 2002 and the second in 2006. The 2010 GSS successfully surveyed a sample comprising 15,028 private dwellings. The initial sample selected was approximately 17,158 dwellings giving a response rate of 87.6 percent (this is comparable with response rates of 86.5 percent in 2006 and 91 per cent in 2002 and is a very high response typical of surveys conducted by the ABS)[6]. Face-to-face Interviews were conducted between August and November in 2010. Information was obtained from one person aged 18 years or older in each selected household. If there was more than one person of this age in the household then the person interviewed was randomly selected. The random selection of the GSS sample was specifically designed to provide national and state estimates. Weights are provided to ensure these data provide cross-sectional statistics representative of the Australian population.

The GSS survey collects information on people's health, family relationships, social and community involvement, employment, income and financial stress, assets and liabilities, housing and mobility, crime and safety, information technology, transport, experiences of homelessness, attendance at cultural and leisure venues and sports attendance and participation, as well as demographic information (ABS, 2011b). The health measures included in the GSS were self-assessed health status, disability status, disability type, whether the individual had a health related education restriction and whether the individual had a health related employment restriction. Information collected on labour market activity includes labour force status; Full-time/part-time status; Hours usually worked in all jobs; Occupation in main job;

[6] The initial sample was reduced from approximately19,576 private dwellings to approximately 17,158 dwellings after excluding vacant, under construction or derelict dwellings and those with no residents in scope for the survey

Expected future duration in current job; Leave entitlements in main job; Retirement status, duration of unemployment and employment type.

The labour market information collected in the GSS is not as comprehensive as that collected in the Household, Income and Labour Dynamics in Australia survey and the cross-sectional nature of the GSS is another limitation when conducting statistical analyses as it precludes sophisticated analysis of causal relationships over time. For this reason, the GSS is preferred in this thesis for cross-tabulations considering descriptions of gross relationships between health and labour market outcomes rather than econometric work. The sampling design used by the ABS makes the GSS ideal for this purpose.

3.2.2 The ABS National Health Survey (NHS)

The NHS is also conducted by the Australian Bureau of Statistics (ABS). Details of the NHS survey are documented in the National Health Survey User Guide published by the ABS (ABS, 2009c). The survey has been conducted every 3 years since 2001 and was conducted every 5 years prior to that. At the time of the analysis the most recent NHS was that conducted in 2007-08. Previous surveys were conducted in 1989-90, 1995, 2001 and 2004-5. This thesis uses the 2007-08 NHS dataset for easiest comparison with the cross-tabulations from the GSS and HILDA datasets which use data from the year 2010. The 2007-08 NHS selected an active sample of 17,426 private dwellings of which 15,792 dwellings responded throughout Australia. This gave a response rate of 90.6 per cent[7]. This is comparable with the response rates for the 2001 and 2004-05 NHS surveys which were 92 percent and 89.4 per cent respectively (ABS, 2002b; ABS, 2006c). Face-to-face interviews were conducted between August 2007 and July 2008. Information was obtained about one adult and one child aged 0 to 17 years in each selected household. A personal interview was conducted with a selected adult in each selected household and this adult was asked to respond on behalf of selected children under 15 years of age.

[7] 19,979 private dwellings were initially selected for the NHS sample. This initial sample was reduced to the active sample of 17,426 dwellings after excluding vacant and derelict dwellings and those where all persons were not in scope of survey

Children aged 15 to 17 years were interviewed in person unless there was a request for an adult to be interviewed on their behalf. In total, 20,788 people participated in the survey with 15,779 of these aged 18 and over. NHS data was collected from a stratified area based random sample designed to provide detailed and reliable estimates of State and Territory, capital city/rest of state, region and Australia wide characteristics.

The NHS is primarily a health survey and as such collected information about respondents' health status, presence of and type of long term conditions, health related behaviours (e.g. smoking, alcohol consumption and exercise), recent injury events, health-related aspects of their lifestyle and actions recently taken in regard to their health. The survey also collected information on a range of demographic and socioeconomic characteristics including some limited information on labour market activity. The main labour market information collected was employment status, hours worked, industry, occupation and income measures.

As with the GSS, labour market information collected in the NHS is not as comprehensive as that collected in the Household, Income and Labour Dynamics in Australia survey and is also more limited than that included in the GSS. The NHS does contain more detailed health measures than the GSS but similarly to the GSS, its cross-sectional nature limits identification of causal relationships over time. For this reason, the NHS is also used solely in this thesis for cross-tabulations considering descriptions of gross relationships between health and labour market outcomes rather than econometric work. The sampling design of the NHS, as with the design of the GSS, makes it well suited for this purpose.

3.2.3 The Household, Income and Labour Dynamics in Australia Survey

The Household, Income and Labour Dynamics in Australia (HILDA) survey is described in detail in chapter 4. The survey is conducted by the Melbourne Institute of Applied Economic and Social Research at the University of Melbourne. It is a household based panel survey collecting information about economic and subjective well-being, labour market dynamics and family dynamics.

The HILDA survey has very detailed coverage of individual labour market activities and also contains information on labour market history. Both the personal interviews and self-completion questionnaires contain information on individual health. Individuals were asked if they had a long term condition restricting everyday activities lasting (or likely to last) six months or more. They were also asked if they had a work-limiting condition. In the self-completion questionnaire, individuals were asked the Short-Form 36 health status questions (SF-36). The SF-36 measures general health and wellbeing and produces scores for eight dimensions of health (Ware *et al.* 2000). The first question in the SF-36 is the standard self reported health measure, scaled from poor to excellent health. The HILDA survey also contains a wide range of demographic information.

The inclusion of detailed information on labour market activities combined with the information collected on health makes HILDA very suitable for studying interactions between health and labour market outcomes. HILDA has a large sample which was designed from the first wave of data collection to be representative of the Australian population. The longitudinal nature of the data means that attrition causes the sample to become less representative over time but HILDA has adopted strategies including generating population weights to combat this[8]. While the ABS surveys have superior response rates making them the most accurate in providing estimates of Australian characteristics, HILDA data are used in the profile of links between health and labour market outcomes because these data also perform well in providing representative estimates of Australian characteristics and the HILDA surveys contain information on many different dimensions of labour market outcomes not included in the GSS and NHS.

Data from 2001-2010 are available with release 10 of the HILDA survey used in this thesis. Wave 10 of HILDA (data collected in 2010) is predominantly used in this chapter to ensure comparability between tables generated using HILDA and those estimates using ABS survey data. By using wave 10 of HILDA, data used in tables

[8] Sample size, data representativeness and the issues surrounding attrition in HILDA are discussed in detail in chapter 4

presented in this chapter were collected in the same year as that collected by the GSS.

3.2.4 Summary Statistics from HILDA

Summary statistics for the HILDA variables used in both cross-sectional analyses contained in this chapter and longitudinal analyses in the following chapters are given in Table 2. These include demographic variables, measures of health and labour market outcomes. HILDA was chosen as the data source for this table because these data are used for the econometric analyses presented in this thesis. The data are limited to those of standard working age—15-64.

The means and proportions in Table 2 are an average of the pooled sample of ten waves of HILDA data. The reason for inclusion of these variables is fairly self-explanatory with most being variables measuring health or labour market outcomes (or affecting the decision to participate in the labour market) and the demographic and other variables being factors established in the literature as affecting health and/or labour market outcomes and therefore of interest in this thesis.

Table 2: Means and Proportions of HILDA Covariates by Sex, 15-64 year olds

Variable Name	Definition	Male	Female
Demographics			
Age	Mean, in years	40.36	40.56
Marital Status	Married/Partnered	0.68	0.69
	Separated/Divorced/Widowed	0.08	0.14
	Never Married	0.24	0.18
Time lived in Australia	0-4 years	0.01	0.01
	5-9 years	0.02	0.02
	10-19 years	0.05	0.05
	20+ years	0.13	0.13
Country of Origin	Australian born	0.79	0.79
	Migrant	0.21	0.21
Educational Attainment	Degree or above	0.22	0.25

Variable Name	**Definition**	**Male**	**Female**
	Advanced diploma/Diploma	0.09	0.10
	Certificate III/IV	0.29	0.15
	Certificate I/II	0.01	0.02
	Year 12	0.14	0.16
	Year 11 or below	0.25	0.32
Child 0-4	Has child(ren) aged 0 to 4	0.15	0.17
Child 5-14	Has child(ren) aged 5 to 14	0.22	0.28
Household size	One person	0.15	0.11
	Two persons	0.29	0.33
	Three persons	0.18	0.19
	Four persons	0.22	0.22
	Five persons	0.10	0.10
	Six or more persons	0.05	0.05
Owns home	1 if owns home, 0 otherwise	0.68	0.69
Labour Force Status	0 not employed, 1 employed	0.84	0.69
Non-labour income	Real weekly non labour income	258.48	216.69
Capital income	Real annual capital income	2628.25	1861.45
Superannuation	Real mean superannuation	84792.52	43112.08
Net worth	Real mean household net worth	660211.90	663990.90
Spouse labour force status	1 if has spouse in employment, 0 otherwise	0.47	0.56
Spouse wage	Real hourly wage of partner	11.67	15.02
Employment history	Mean years in employment since first leaving full-time education	21.53	16.75
Unemployment history	Mean years in unemployment since first leaving full time education	0.74	0.53
Not in labour force history	Mean years not in the labour force since first leaving full time education	1.45	6.32
Unemployment rate	Mean, percent	5.05	4.82
Rural	Lives in rural area	0.14	0.13
State	NSW	0.29	0.30

Variable Name	Definition	Male	Female
	VIC	0.24	0.24
	QLD	0.21	0.21
	SA	0.09	0.09
	WA	0.10	0.09
	TAS	0.03	0.03
	NT	0.01	0.01
	ACT	0.02	0.02
Health and Health Related			
Self assessed health	Mean self reported health status, 1=poor, 2=fair, 3=good, 4=very good, 5=excellent	3.44	3.44
Small health shock	1 if health somewhat worse than last year, 0 otherwise	0.10	0.12
Large health shock	1 if health much worse than last year, 0 otherwise	0.01	0.01
Smoker	Currently smoking or ever smoked	0.57	0.49
Lack physical activity	No physical activity at all or less than once per week	0.23	0.29
Heavy drinker	Defined as drinking more than 6 standard drinks a day when drinking	0.15	0.05
Social support	Scale 1-7, more support	5.28	5.51
Physical functioning	SF-36 Index of physical functioning, ranging from 0 to 100	87.73	85.79
Mental health	SF-36 Index of mental health, ranging from 0 to 100	75.17	72.97
General health	Index of general health, ranging from 0 to 100	69.61	70.20
Work Limiting Long term Health Condition	Has long term health condition which limits type or amount of work	0.15	0.15
Has Long Term Health Condition not Limiting Work	Has long term health condition which has no impact on work	0.08	0.06
Has no Long Term Health Condition	Does not have a long term health condition	0.78	0.78

Variable Name	Definition	Male	Female
Long term condition such as Arthritis, Asthma, Heart Disease, Alzheimers, Dementia	Has long term condition such as Arthritis, Asthma, Heart Disease, Alzheimer's, Dementia	0.07	0.09
Sight problems not corrected by glasses	Has sight problems not corrected by glasses	0.02	0.01
Condition restricting physical activity or physical work (e.g. back problem, migraines)	Has condition restricting physical activity or physical work (e.g. back problem, migraines)	0.08	0.08
Shortness of breath or difficulty breathing	Has shortness of breath or difficulty breathing	0.02	0.02
Effects as a result of stroke, head injury or other brain damage	Has effects as a result of stroke, head injury or other brain damage	0.01	0.01
Injury or illness	1 if suffered serious injury or illness in past year, 0 otherwise	0.08	0.07
Health index	Index with values 0-100	69.30	72.44
Employment related (only observed for the respondents in employment)			
Duration with current employer	Mean, in years	7.52	6.19
Occupation	Managers	0.17	0.10
	Professionals	0.20	0.28
	Technicians and Trades Workers	0.23	0.04
	Community and Personal Service Work	0.06	0.14

Variable Name	Definition	Male	Female
	Clerical and Administrative Workers	0.07	0.25
	Sales Workers	0.05	0.10
	Machinery Operators and Drivers	0.11	0.01
	Labourers	0.11	0.08
Self Employed	Self employed	0.12	0.07
Form of employment	Fixed term	0.08	0.09
	Casual	0.12	0.21
	Permanent	0.66	0.61
Part time	1 if usually works less than 35 hours per week, 0 otherwise	0.11	0.44
Hours worked	Mean, hours	44.04	32.94
Own wage	Real wage	25.68	24.13
Union	Union member	0.25	0.26
Private sector	Employed in private sector	0.81	0.70
Training	Took part in work related training in past 12 months	0.37	0.39
Industry	Agriculture, forestry and fishing	0.05	0.02
	Mining	0.03	0.00
	Manufacturing	0.14	0.05
	Electricity, gas, water and waste services	0.02	0.00
	Construction	0.13	0.02
	Wholesale trade	0.04	0.02
	Retail trade	0.07	0.11
	Accommodation and food services	0.04	0.06
	Transport, postal and warehousing	0.07	0.02
	Information media and telecommunications	0.03	0.02
	Financial and insurance services	0.03	0.05
	Rental, hiring and real estate services	0.01	0.02
	Professional, scientific and technical services	0.08	0.08
	Administrative and support services	0.02	0.03
	Public administration and safety	0.08	0.06

Variable Name	**Definition**	**Male**	**Female**
	Education and training	0.05	0.15
	Health care and social assistance	0.04	0.22
	Arts and recreation services	0.02	0.02
	Other services	0.04	0.04
N	(ten waves pooled)	52,012	53,967

Notes: (1) Means are for the pooled data (i.e. ten waves 2001-2010). (2) Excludes full time students. (3)Some groups of variables do not sum to 100 due to level not determined for some respondents. (4) Hourly wage rate, partner wage rate, non-labour income, superannuation and household net worth are all inflated to the value in the year 2010 by the RBA annual inflation rate over the period (2001-2010) derived from the ABS Consumer Price Index. (5) Details on the construction of the health index are set out in Chapter 4. (6) Occupation classifications are defined by the ABS Australian and N. Z. Standard Classification of Occupations (ANZSCO) 2006 1-digit code, Cat. No. 1220.0. (7) Industry classifications are defined by the ABS Australian and N. Z. Standard Industrial Classification (ANZSIC), 2006 (Revision 1.0) 1-digit code, Cat. No. 1292.0

There are 52,012 observations for men and 53,967 observations for women over the 10 wave unbalanced panel used to generate the summary statistics in Table 2[9]. More than three quarters of respondents are Australian born and the mean age of the sample is just over 40 years of age for both men and women. Just over two-thirds of both men and women are married or living with a partner. A higher proportion of men are employed (84 per cent) compared with women (69 per cent).

Twenty-two percent of men and women have some kind of long term health condition. More than two thirds of these health conditions impact upon work with 15 percent of men and women reporting having a work limiting health condition. Mean self-reported health status is 3.4 for both men and women reflecting the high proportion of people reporting good or very good health. Eleven percent of men and 13 percent of women experienced a health shock but the majority of health shocks were of somewhat worse health than in the previous year, with only 1 percent reporting much worse health than in the previous year. Eight percent of men and 7 percent of women experienced serious injury or illness in the past year.

[9] These observation numbers do not take into account missing values for individual survey questions. Once missing values are taken into account observation numbers are lower for most variables, particularly income variables, those observed only for employed persons and those variables included in the self-completion questionnaire (i.e. health variables). Data are also unweighted.

Men have much higher levels of superannuation on average compared with women. This can be attributed to their longer total employment history and higher wages, with men in the HILDA sample having spent an average of just over 21 years employed since leaving full-time education compared with just under 17 years spent employed for women. Women on average spend more time not in the labour force than men, and work fewer hours when they are employed.

Among those HILDA respondents who are employed, 21 per cent of women are employed on a casual basis compared with 12 per cent of men. A higher proportion of men are self employed (12 per cent compared with 7 per cent for women). Men are primarily employed full time with only 11 per cent of men working part time compared with 44 per cent of women. Men have also worked slightly longer on average with their current employer.

The HILDA survey and the variables included in the table are discussed in further detail in chapter 4 and in the chapters presenting empirical findings in the second part of the thesis. The next section uses descriptive cross-tabulations to identify gross relationships between health and selected labour market outcomes using the three data sources described in section 3.2.

3.3 Profile of Links between Health and Labour Market Outcomes

This section presents the profile of links between health and selected labour market outcomes. The following subsections use cross-tabulations drawn from GSS, NHS and HILDA data to illustrate the gross-relationships and trends in Australia. These cross-tabulations serve as prima facie evidence of relationships between health and employment on the dimensions of interest in this thesis.

The most suitable way to look at these trends is with the two ABS data sets. Data collected by the ABS have large samples, very high response rates and are designed to provide reliable estimates of characteristics of the Australian population even at a disaggregated level[10]. Having said this, there are other dimensions of interest in examining associations between health and labour market characteristics which are not captured in ABS data. These can be found in HILDA hence tables from HILDA are included in this chapter to examine additional trends of interest.

The following subsections present and discuss statistics covering three themes: 1) background statistics and background relationships between health and labour market outcomes; 2) associations between health and form of employment and 3) associations between health and occupation.

3.3.1 Background on Links between Health and Labour Market Outcomes

The prevalence of fair to poor self reported health increases with age, with 6.8 per cent of 15-24 years olds in the NHS reporting fair or poor health compared with 20.7 per cent of 55-64 year olds[11]. While poor health is much more prevalent amongst the aged, 12 per cent of working aged persons report fair or poor health (ABS, 2008b), and this has implications for labour market outcomes.

Within the datasets, a number of different measures of health are available including a single-item indicator of self assessed health status (with five response options), SF-36 health measures, measures of presence and type of long term condition and measures of disability status. There are associations between these different health measures. However differing proportions of the population are deemed to be in poor health depending on which health measure is chosen, and different health measures can be thought to be measuring different dimensions of poor health.

The intersection between disability, general health and serious medical condition was considered by Wilkins *et al.* (2010) using HILDA data for the entire population over age 14. In this case, a person is defined as having a disability if that individual has ‘any long-term health condition, impairment or disability that restricts the individual

[10] Due to the NHS having a larger sample size than the GSS, NHS data have been used where possible. GSS data have been used where NHS data did not contain the required information.
[11] calculations using the 2007-08 NHS CURF

in everyday activities and which has lasted, or is likely to last, for six months or more'. Poor general health is defined as a transformed score of less than 50 on the 0-100 scale of the SF-36 measure of general health. Serious medical conditions were respondents self reports of whether they had ever been told by a doctor or nurse that they had any of arthritis, asthma, cancer, chronic bronchitis or emphysema, diabetes, coronary disease, hypertension and any other serious circulatory condition.

Nearly half of the population aged 15 or over had one or more of the serious medical conditions while 28 per cent reported having a disability and 19 per cent had poor general health (Wilkins *et al.* 2010). Taking into account overlap between these measures, 11.3 per cent reported having poor general health, disability and at least one serious medical condition while 43.2 per cent were in good general health and had no disability or serious medical condition.

Disability is more strongly linked with having a serious medical condition than with poor general health. Large proportions of those reporting disabilities or serious medical conditions view themselves as being in good health. Wilkins *et al.* (2010) suggest that it may be the case that certain conditions may not translate to poor health if they are well managed.

It is important however to distinguish between conditions which limit type or amount of work and those which do not. Table 3 uses HILDA data to consider intersections between types of long term conditions (those which do/do not limit work) and poor general health, mental health and physical functioning. Poor mental health and poor physical functioning are defined as those with a transformed score of less than 50 for the relevant SF 36 measure.

Table 3 highlights the importance of distinguishing between long term conditions which do limit work and those which do not. Just over half of those with a work limiting condition are in poor general health compared with 20 per cent of people who have a long term condition which does not limit work. A similar pattern emerges for physical functioning and mental health-those with a work limiting condition comprise the majority who have poor physical functioning or poor mental health.

Table 3: Intersection between General Health, Physical Functioning, Mental health and Type of Long Term Condition, 25 to 64 year olds, 2010, Per cent

	Long term health condition limits type or amount of work	**Long term health condition has no impact**	**No long term health condition**	**Total**
	%	%	%	%
General Health				
Good general health	49.6	79.6	92.4	82.0
Poor general health	50.4	20.4	7.6	18.0
Total	100.0	100.0	100.0	100.0
Physical functioning				
Good physical functioning	66.5	91.7	96.5	89.6
Poor physical functioning	33.5	8.3	3.5	10.4
Total	100.0	100.0	100.0	100.0
Mental health				
Good mental health	82.1	90.8	94.5	91.5
Poor mental health	17.9	9.2	5.5	8.5
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Note: Population weighted results. Percentages may not add up to 100 due to rounding

Table 4 uses HILDA data to show intersections between self assessed health and poor general health, physical functioning and mental health[12]. Poor self assessed health is most closely linked with poor general health. There is a very strong overlap

[12] Self assessed health is collapsed into three categories for cross-tabulations as is the common practice by the ABS.

between very good/excellent health and good general health, physical functioning and mental health. Almost all respondents who report very good/excellent health are in good general health, have good physical functioning and good mental health.

Table 4: Intersection between General Health, Physical Functioning, Mental health and Self Assessed Health Status, 25 to 64 year olds, 2010, Per cent

	Very good/Excellent	**Good**	**Fair/Poor**	**Total**
	%	%	%	%
General health				
Good general health	99.6	86.8	25.0	79.6
Poor general health	0.4	13.2	75.0	20.4
Total	100.0	100.0	100.0	100.0
Physical functioning				
Good physical functioning	97.1	92.9	60.9	88.1
Poor physical functioning	2.9	7.1	39.1	11.9
Total	100.0	100.0	100.0	100.0
Mental health				
Good mental health	96.5	91.5	75.6	90.4
Poor mental health	3.5	8.5	24.4	9.6
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Note: Population weighted results. Percentages may not add up to 100 due to rounding

The self assessed health status measure is used in the remainder of this chapter. This is the measure most commonly used by the ABS when discussing health. It is considered a valid measure of health status as it has been shown in many studies to be a strong predictor of mortality and morbidity (Cai, 2010) and it is more likely to measure work capacity than more objective health measures such as measures of disability or medical conditions (Bound, 1991).

Calculations using NHS CURF data show that those in excellent or very good health are much more likely to be employed (and conversely, those in fair or poor health less likely to be employed). Three quarters of those under the age of 65 who report very good or excellent health are employed compared with only 36 per cent of persons in fair or poor health. This relationship aligns with the findings from the literature discussed in chapter 2. This pattern holds for both men and women although the difference by health status is less pronounced for women. It is also evident for all age groups but becomes more pronounced with age as prevalence of fair or poor health increases.

Although these data do not provide evidence of a causal relationship, this supports the finding in the review in the previous chapter of health based selection into employment. Persons in poor health are less likely to obtain employment. This has implications for incomes and experience of health related disadvantage. Beyond this, the figures on labour force status by health illustrate that health matters not just through affecting those who do not work. The proportion of persons in fair or poor health who are employed, 36 per cent, is no small number and this emphasizes the importance of determining more fully the impact poor health has on employment outcomes beyond the effect on labour force participation.

Table 5 reports transitions in self assessed health status between 2009 and 2010. This gives some indication of persistence of health status. Respondents who reported very good or excellent health showed the most persistence in health status. Just under two thirds of persons reporting fair or poor health in 2009 also reported fair or poor health in 2010. Wilkins *et al.* (2011) considered persistence of poor general health and mental health over a longer time period (2001-2008) using the SF 36 health measures in HILDA. They found that around 62 per cent of people had good general health over the whole eight year time frame while 5 per cent of respondents had poor general health over the duration of the same period. Persistent health problems were found to be much more common for older people and physical health problems are much more persistent than mental health problems.

Table 5: Self Assessed Health in 2009 compared with Self Assessed Health in 2010, 25 to 64 year olds, Per cent

	Self Assessed Health in 2010			
Self Assessed Health in 2009	Very good/Excellent	Good	Fair/Poor	Total
	%	%	%	%
Very good/Excellent	82.7	29.0	6.1	47.1
Good	16.0	60.3	30.4	35.5
Fair/Poor	1.3	10.7	63.5	17.4
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

While Table 5 suggests that many episodes of poor health are transitory, it is important to acknowledge that fluctuations in severity of conditions and changes in ability to manage health conditions can influence reports of health status (Wilkins *et al.* 2010). Many episodes of poor health are temporary but these fluctuations in relation to managing health conditions can result in some individuals reporting an improvement in health which is also temporary.

Calculations using HILDA (see Table A-1 and Table A-2 in the Appendix) show that those who reported fair or poor health in 2009 were a little less likely than those in better health to remain employed and more likely to remain out of the labour force. This increased likelihood of those in poor health remaining out of the labour force was noted by Headey and Warren (2008) who found that the most common reason men gave for not looking for work was own health or disability.

This section has discussed some background issues and statistics surrounding analysis of relationships between health and labour market outcomes. Firstly, poor health is a substantial issue among working age Australians. Fifteen per cent of both men and women report having a long term health condition that reduces their capacity to work. Second, there are different measures of health available and it is necessary to understand the relationships between them. Finally, transitions between health statuses and transitions between labour force statuses were considered and indicate that health is associated with employment status but also with changes in employment status.

As discussed in chapter 2, aside from playing a role in labour force participation, health also affects a number of labour market outcomes for those who are employed. It is important to establish the ways in which health related disadvantage may manifest amongst the employed, given the proportion of people in poor health who are employed. The next two sections examine the relationship between health and two specific labour market outcomes: form of employment and occupation.

3.3.2 Health and Form of Employment

The literature review in chapter 2 indicated that health influences labour force participation, likelihood of gaining employment, hours of work, earnings and retirement age. It may also be possible that health may affect form of employment. There is a collection of literature on the effect of form of employment on health (see for example Ferrie, 1999; De Witte, 1999; Benavides *et al.* 2000; Virtanen *et al.* 2005; Artazcoz *et al.* 2005, Richardson *et al.* 2012) but the reverse effect is also pertinent. A number of papers suggest there is a causal relationship between health and job characteristics such as job control and job demands (De Lange *et al.* 2004, 2005; Dalgard *et al.* 2009).

The relationship between health and form of employment is already partially identified through research into effects of health on hours worked but could have further implications not yet investigated in the current literature. Health may influence contract of employment and whether an individual works full time or part time (as distinct from simply fewer hours).

Calculations using NHS data support the findings in the literature that poorer health is associated with fewer hours of work. This is illustrated in Table 6 where hours worked have been categorized as part time or full time according to the ABS definition (see Table A-3 in the Appendix for definitions of forms of employment). The relationship appears more pronounced for men in terms of a linear relationship by health status however a higher proportion of both men and women who work part time report fair or poor health when compared with those in better health.

Significance tests were performed in order to further understand whether these differences are important. A spearman test strongly rejected the hypothesis that health and full time/part time work were independent. In addition to this, a Bonferroni correction provided further evidence that difference in health between those in part time and full time employment were significant, with the p-value from this test being very low for both men (p=0.000) and women (p=0.009).

Table 6: Full Time/Part Time Hours Worked by Health, 25 to 64 year olds, by Sex, 2007-08, Per cent

	Men			**Women**		
	Excellent or Very good	Good	Fair or Poor	Excellent or Very good	Good	Fair or Poor
	%	%	%	%	%	%
Part time	10.4	12.1	17.0	45.1	42.9	51.8
Full time	89.6	87.9	83.0	54.9	57.1	48.2
Total	100.0	100.0	100.0	100.0	100.0	100.0

Source: 2007-08 National Health Survey CURF data

Note: Population weighted results. Percentages may not add up to 100 due to rounding

The GSS contains information on whether respondents had leave entitlements. It is possible to use this information as a proxy for contract of employment, however this does not distinguish between fixed term and permanent employees nor does it accurately identify casual employees. The HILDA survey contains more detailed information on contract of employment, specifically identifying those in casual employment and those in permanent, ongoing employment. For this reason Table 7 uses HILDA data to determine the relationship between health and form of employment (contract of employment)[13].

[13] The HILDA survey contains two measures, one using the ABS definition of casual employment and the other self reported. The ABS defined measure does not distinguish those who are in fixed term employment and therefore the self reported measure is used in this thesis.

Table 7: Health by Form of Employment, 25 to 64 year olds, by Sex, 2010, Per cent

	Excellent or Very good	Good	Fair or Poor	Total
	%	%	%	%
Men				
Permanent/Ongoing	80.6	78.8	77.6	79.5
Fixed term	10.9	7.8	8.0	9.4
Casual	8.5	13.4	14.4	11.1
Total	100.0	100.0	100.0	100.0
Women				
Permanent/Ongoing	72.7	71.5	66.3	71.5
Fixed term	10.6	10.5	13.0	10.8
Casual	16.7	18.0	20.8	17.6
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Note: Population weighted results. Percentages may not add up to 100 due to rounding

Table 7 shows that a higher proportion of men and women who report fair or poor health are casually employed compared with those in better health. The differences by health do not appear large, especially between those in fair or poor health and those in good health. Significance tests were again performed to provide further evidence beyond a visual observation of the size of differences by health.

A spearman test strongly rejected the hypothesis that health and form of employment are independent. In addition to this, tests within forms of employment were conducted jointly with a Bonferroni correction. The results of this are presented in Table 8. The results show a significant difference in health between fixed term employees and those in permanent employment for both men and women. The difference in health between casual employees and permanent employees is also significant for both genders while that between fixed term and casuals is only significant for men[14].

[14] The self employed are not included in these tables however testing showed that the mean health of the self employed does not differ significantly from that of those in other forms of employment.

Table 8: Differences in Mean Health by Form of Employment, 25-64 year olds

	Men		Women	
	Permanent	Fixed Term	Permanent	Fixed Term
Fixed Term	-0.065		0.041	
	(0.448)		(1.000)	
Casual	0.176***	0.241***	0.103***	0.063
	(0.000)	(0.000)	(0.010)	(0.667)

Source: HILDA Release 10

Note: 1) Population weighted results. 2) P-values are reported in brackets. 3) ***Statistically significant at 1% level. 4) Health is ordinal and coded from 1 (fair or poor health) to 3 (very good or excellent health).

Table 9: Health by Detailed Form of Employment, 25 to 64 year olds, Per cent, 2010

	Excellent or Very good	**Good**	**Fair or Poor**	**Total**
	%	%	%	%
Full Time Permanent	68.0	69.9	63.7	68.3
Part Time Permanent	15.6	15.5	15.6	15.5
Full Time Casual	6.1	4.3	7.0	5.6
Part Time Casual	10.3	10.3	13.7	10.6
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Note: Population weighted results. Percentages may not add up to 100 due to rounding

The previous discussion did not take into account overlap between forms of employment. Casual employees can be employed on a full time or part time basis as can workers in the other form of employment categories. Table 9 uses HILDA data to display health by a more detailed breakdown of form of employment. It shows a

Observations on the self employed are low after disaggregating and this may affect reliability of results.

rather less clear pattern of health by form of employment for part time permanent and full time casual employees. It must be noted however that observations for these categories are lower with disaggregation, particularly for men and this does pose problems for further analysis at this level of disaggregation[15].

Calculations using HILDA data show that a smaller proportion of those who are in fair or poor health take part in work related training compared with those reporting better health (see Table 10). This can be attributed in part to the association between training and form of employment found in the literature (Arumpalam and Booth, 1998; Forrier and Sels, 2003; Draca and Green, 2004; Richardson and Law, 2009).

Table 10: Whether Took Part in any Work Related Training in the Last 12 Months by Health, 25 to 64 Year Olds, Per cent

	Very good/Excellent	**Good**	**Fair/Poor**	**Total**
	%	%	%	%
Yes	33.2	29.8	26.5	31.1
No	66.8	70.2	73.5	68.9
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Note: Population weighted results

De Lange *et al.* (2005) suggest there is good reason to pursue research on the causal relationship between health and form of employment. The statistics presented in this section support this, finding a significant cross sectional relationship between health and form of employment. Identifying causality in this relationship requires longitudinal data. The causal effect of health on form of employment is the subject of chapter 5.

3.3.3 Health and Occupation

[15] Significance testing using the Bonferroni correction also found that mean differences in health are not significant when comparing many of these forms of employment, particularly after disaggregating by gender. Differences in mean health between part time casuals and full time permanent workers are significant for both men and women highlighting the need to be aware of overlap in forms of employment.

The previous section discussed the relationship between health and form of employment. Another key labour market outcome is occupation-what occupation an individual is employed in, how health affects occupation and how changes in health may affect occupation. It is expected that health would affect the occupation a person is employed in and that changes in health, particularly a worsening in health, may change occupation.

Table 11: 1-Digit ANZSCO Occupation by Self Assessed Health, 25 to 64 year olds, 2007-08 Per cent

Occupation (main job)	**Excellent or Very good**	**Good**	**Fair or Poor**	**Total**
	%	%	%	%
Managers	63.4	27.9	8.7	100.0
Professionals	68.6	24.3	7.2	100.0
Technicians and Trades Workers	58.2	31.4	10.4	100.0
Community and Personal Service Workers	64.2	26.6	9.2	100.0
Clerical and Administrative Workers	66.9	24.5	8.6	100.0
Sales Workers	61.3	26.7	11.9	100.0
Machinery Operators and Drivers	46.9	40.5	12.6	100.0
Labourers	52.7	37.2	10.1	100.0
Total	62.2	28.6	9.2	100.0

Source: 2007-08 National Health Survey CURF data

Note: Population weighted results. Percentages may not add up to 100 due to rounding

Table 11 reports health by occupation using the broadest level of the ANZSCO. This shows that a very low proportion of machinery operators and drivers report excellent health. The same is true to a lesser extent for labourers. A higher proportion of machinery operators and drivers report fair or poor health in comparison with other occupations, with sales workers, technicians and trades workers and labourers also having a higher proportion reporting fair or poor health in comparison with the total proportion reporting poor health.

There are some sex differences in health by occupation (see Table A-5 and Table A-6 in the Appendix). The very low proportion of machinery operators and drivers reporting excellent health is evident for both genders as was the case in Table 11. A low proportion of female labourers report excellent health but this is less marked (though still evident) for men in comparison with other occupations. A higher proportion of male sales workers reports fair or poor health in comparison with other occupations. For women it is machinery operators and drivers and labourers with the highest proportions in fair or poor health.

Table 12: Non-manual/Manual Occupation by Self Assessed Health, 25 to 64 year olds, 2007-08, Per cent

	Excellent or Very good	**Good**	**Fair or Poor**	**Total**
	%	%	%	%
Non-manual	65.8	25.7	8.5	100.0
Manual	53.9	35.2	10.9	100.0
Total	62.2	28.6	9.2	100.0

Source: 2007-08 National Health Survey CURF data

Note: Population weighted results. Percentages may not add up to 100 due to rounding

The findings from Table 11 suggest that it is primarily those in manual occupations requiring physical labour who report poorer health (or are less likely to report excellent health). Table 12 categorises the 1-digit ANZSCO occupations roughly into manual versus non-manual occupations. The proportion in manual occupations who report excellent health is markedly lower than for those in non-manual occupations, reflecting the low proportion of machinery operators and drivers and labourers reporting excellent health.

Table A-7 and Table A-8 in the Appendix report the dichotomous classification of occupation by gender. The calculations show that the differences in Table 12 in health by occupation are observed for both men and women however they are larger for women than for men. The relationship was also examined by age (table unreported) and found to be strongest amongst older age groups.

The differences in health by occupation appear larger than those observed for form of employment in the previous discussion. Statistical tests confirm that the differences in mean health between persons in manual and non-manual employment are highly statistically significant and this is true for men (p=0.000) and women (p=0.000).

Table 13 and Table 14 use HILDA data to consider both transitions between occupations and in and out of employment by health. While observation numbers are not very high for those in fair or poor health after disaggregation, Table 13 can be considered suggestive. The levels of persistence in non-manual employment are similar regardless of health status, 90 per cent of those who were in a non-manual occupation in 2009 remained in a non-manual occupation in 2010. There was greater persistence in remaining out of work for those in poorer health and a higher degree of transition from manual employment to non-employment for those in poorer health between 2009 and 2010 compared with those who reported good health or better.

Table 13: Occupation/Labour force status in 2009 by Occupation/Labour force status in 2010, Persons reporting fair/poor health in 2009, 25 to 64 year olds, Per cent

	Occupation/Labour force Status in 2010			
Occupation/Labour force status in 2009	**Non-manual**	**Manual**	**Unemployed/Not in Labour Force**	**Total**
	%	%	%	%
Non-manual	90.3	4.2	5.5	100.0
Manual	13.8	70.7	15.5	100.0
Unemployed/Not in Labour Force	3.2	2.0	94.8	100.0
Total	25.9	10.4	63.7	100.0

Source: HILDA Release 10

Table 14: Occupation/Labour force status in 2009 by Occupation/Labour force status in 2010, Persons reporting good health or better in 2009, 25 to 64 year olds, Per cent

	Occupation/Labour force status in 2010			
Occupation/Labour force status in 2009	**Non-manual**	**Manual**	**Unemployed/Not in Labour Force**	**Total**
	%	%	%	%
Non-manual	89.6	3.8	6.6	100.0
Manual	12.7	80.1	7.1	100.0
Unemployed/Not in Labour Force	8.6	3.1	88.2	100.0
Total	51.4	17.7	30.9	100.0

Source: HILDA Release 10

Any study of the relationship between health and job change must pose the question of whether it is health changes which prompt job changes or vice versa. Given that poor health precedes job change in Table 13 there is some reason to believe that poorer health may prompt transitions out of manual jobs in particular but further research is required to conclusively answer this question.

The manual vs. non-manual distinction is not the only one that matters. Table 11, as previously discussed, presents 1-digit ANZSCO occupations by health and these occupations are hierarchical in terms of skills (see Table A-11 in the Appendix). Aside from the distinction between manual work requiring physical labour and non-manual work which might be less physical there is also level of occupation to consider, a measure of status. This is associated with income and has implications for health with literature previously finding that low status is associated with poorer health (see for example Marmot, 2004; Singh-Manoux *et al.* 2007). The pattern of occupation by health in Table 11 supports the finding from the literature. Occupations in which those in excellent health represent a much lower proportion are primarily lower skilled and therefore lower status (particularly machinery operators and drivers and labourers). Occupational status has implications in terms of income and also the damaging effects it can have on health therefore causality of this relationship is important.

The statistics presented in this section provide some evidence of relationships between health and occupation. The observed association between occupation and health is statistically significant but the statistics in this section do not establish causality. Employment which involves physically demanding work might logically have an adverse effect on health however health itself may also affect the occupation a person is employed in if they choose a job with lower physical demands to manage their health. Another aspect of occupation associated with health, related but with its own implications, is status or level of occupation and whether poor health has a causal effect on occupational status. An effect of health on occupation has been suggested in the literature (see Pelkowski and Berger, 2003; Cohiden *et al.* 2009; De Raeve *et al.* 2009; Halleröd and Gustaffson, 2011). These papers provide a starting point to inform further econometric analysis using longitudinal data and suitable econometric methods.

Longitudinal data analysis is required to disentangle causal effects and the causal effects of health on occupation (and effect of changes in health on occupation) is the subject of chapter 6.

3.4 Indicators of Accumulating Disadvantage

The discussion in section 3.3 focused on relationships between health and labour market outcomes. This thesis has a particular focus on the extent to which the relationships between health and labour market outcomes result in accumulating disadvantage. This section examines cross sectional indicators of labour market accumulating disadvantage associated with health status. Further longitudinal analysis on indicators of accumulating disadvantage is undertaken in chapter 7.

Labour Force History by Health and Age

The discussion in section 3.3.1 and in chapter 2 found that health and employment status are related. A smaller proportion of those in poorer health are employed compared with those in good health or better. Those in poor health are less likely to be employed and less likely to remain employed. This indicates that one source of cumulative health related labour market disadvantage could be in fewer years of employment over the life cycle.

Table 15 uses HILDA data to consider how time spent employed since first leaving full time education differs by self assessed health status. Table 15 measures labour force experience using wave 10 of HILDA and health is measured using wave 1 to capture some of the impact of health over time. It must be kept in mind that the measure of health status is current health status at time of interview in 2001 and is an imperfect indicator of the effect of health on the whole of labour force history. Nevertheless given that there is a certain amount of persistence in health status, analysis of association between reported health and labour force history is still informative.

Table 15: Mean Years Spent in Employment in 2010 by Age and Self Assessed Health in 2001

	25 to 34 years	**35 to 44 years**	**45 to 54 years**	**55 to 64 years**	**Total**
	Mean	Mean	Mean	Mean	Mean
Men					
Self assessed health status					
Very good/Excellent	9.7	19.8	29.9	38.7	24.7
Good	10.3	20.4	28.9	38.9	26.8
Fair/Poor	9.1	19.5	25.7	33.3	25.8
Total	9.7	19.5	29.1	37.7	25.5
Women					
Self assessed health status					
Very good/Excellent	9.2	17.2	24.0	31.0	20.6
Good	8.2	16.0	22.7	30.0	20.6
Fair/Poor	7.1	13.5	19.6	24.3	17.7
Total	8.3	16.1	22.9	29.4	20.2

Source: HILDA Release 10

Notes: Time spent in employment is measured as mean years spent in paid work since first leaving full time education.

At first glance, the relationship for time spent employed by health status (without disaggregating by age) appears puzzling (see last column of Table 15). Men in poorer health have spent more time employed on average than many of those in better health. In interpreting this we must keep in mind age profiles for these health categories. Health declines with age so that most of those reporting worse health are people in the older age groups. After disaggregating by age group, the trend reverses for men with those in poor health having spent less time employed (on average) than people who report good health or better.

Table 16: Mean Years Spent Unemployed or Not in the Labour Force in 2010 by Age and Self Assessed Health in 2001

	25 to 34 years	**35 to 44 years**	**45 to 54 years**	**55 to 64 years**	**Total**
	Mean	Mean	Mean	Mean	Mean
Men					
Self assessed health status					
Very good/Excellent	1.4	2.0	2.0	3.1	2.1
Good	2.3	2.4	3.9	3.3	3.1
Fair/Poor	2.3	3.9	6.8	10.0	7.0
Total	1.6	2.3	3.2	4.2	3.0
Women					
Self assessed health status					
Very good/Excellent	2.8	4.7	8.2	11.2	6.8
Good	3.6	7.0	9.5	12.6	8.7
Fair/Poor	5.5	9.3	14.1	19.9	13.5
Total	2.8	5.8	9.1	12.9	8.2

Source: HILDA Release 10

Notes: Time spent unemployed or not in the labour force is measured as mean years spent either unemployed or not in the labour force since first leaving full time education.

Table 16 presents the converse picture to Table 15 by considering time spent out of work (unemployed or not in the labour force) by self assessed health status. Average time spent out of work differs by health status for both men and women with the disparity by health status becoming larger for older age groups. Persons in poorer health spend more time on average out of work.

The findings from Table 15 and Table 16 suggest that poorer health is associated with fewer years of employment (and more time spent out of work) over the life cycle. Joblessness has effects on income, health and wealth. This is a clear indicator of likely accumulating disadvantage. Those with poorer health will experience adverse effects on income and wealth through the effects of being out of work for longer periods than those in better health over the life cycle. This will also be exacerbated by the relationship between health and retirement found in chapter 2. Those in poorer health also retire earlier on average which would increase the degree of income and wealth disadvantage (in particular) associated with fewer years spent employed.

Health and Income

The adverse effects of poor health on current income are illustrated in Table 17. This shows that a low proportion of people in the lowest quintile of household disposable income (the 1st quintile) report excellent health compared with those in higher quintiles of income. Likewise, those in the lower quintiles of household disposable income contain the highest proportion reporting fair or poor health. Persons in fair or poor health represent more than a third of those in the lowest quintile of household disposable income and only represent 12 per cent of the top quintile. This reflects, among other things, their higher likelihood of being out of work and dependent on welfare for their main source of income (GSS, table unreported).

Table 17: Quintile of Household Disposable Income by Self Assessed Health, 25 to 64 year olds, 2010, Per cent

	Very good/Excellent	**Good**	**Fair/Poor**	**Total**

	%	%	%	%
1st Quintile	24.8	39.8	35.4	100.0
2	39.8	38.6	21.5	100.0
3	44.0	36.6	19.4	100.0
4	51.5	35.3	13.3	100.0
5th (top) Quintile	53.6	34.2	12.1	100.0
Total	42.6	36.9	20.5	100.0

Source: HILDA Release 10

Note: Population weighted results. Percentages may not add up to 100 due to rounding

Table 18: Household Income Quintile in 2009 by Household Income Quintile in 2010, Persons Reporting Fair/Poor Health in 2009, Per cent

	2010					
	1	**2**	**3**	**4**	**5**	**Total**
2009	%	%	%	%	%	%
1	82.5	29.0	5.5	2.5	0.7	43.3
2	11.7	48.5	22.5	6.9	4.0	20.4
3	3.9	15.5	48.6	22.0	8.0	15.1
4	1.2	4.5	17.4	46.5	13.3	10.1
5	0.7	2.5	6.0	22.0	74.0	11.2
Total	100.0	100.0	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Table 19: Household Income Quintile in 2009 by Household Income Quintile in 2010, Persons Reporting Good Health or Better in 2009, Per cent

	2010					
	1	**2**	**3**	**4**	**5**	**Total**
2009	%	%	%	%	%	%
1	72.1	16.7	3.9	2.2	1.2	19.2
2	18.5	55.9	19.8	5.5	2.1	19.9
3	5.6	17.6	51.0	20.6	5.2	19.7
4	2.8	6.9	20.1	53.5	19.1	20.6
5	1.0	3.0	5.2	18.2	72.4	20.7
Total	100.0	100.0	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Table 18 and Table 19 suggest that persons experiencing poorer health are also less likely to transition into higher quintiles compared with those reporting good health or better[16]. A larger proportion of individuals in poorer health remain in lower quintiles in the following year compared with individuals who reported good, very good or excellent health.

The previous discussion suggests that there is a long term relationship between health and income. Taking the evidence on associations between health and labour force experience at the beginning of this section and combining that with the evidence on relationships between health and income presented it is not hard to imagine that over time, there would be a growing disparity in income received between those in poorer health and those who experience good health.

Health and Wealth

While the discussion of the relationship between health and income was not able to expressly identify a cumulative aspect, an analysis of the relationship between health and wealth can be more illuminating, particularly when examined by age group.

In the subsequent analysis, all monetary values are expressed at 2010 prices (based on the ABS Consumer Price Index) to remove the effects of inflation. HILDA contains a number of measures of wealth and two key measures are used in this analysis: household net worth and individual superannuation. Table 20 considers the relationship between self assessed health in 2002 and change in household net worth between 2002 and 2010. There is a rather large disparity in growth in household net worth between those in very good or excellent health and persons in fair or poor health and this is the case for both men and women. The gap does not differ greatly with age however the measure is at the household level which may mask individual effects arising from an individual experiencing poor health.

[16] Observation numbers for those in fair or poor health are low at this level of disaggregation however these results can be considered suggestive.

Table 20: Mean Change in Household Net Worth between 2002 and 2010 by Self Assessed Health in 2002 and by Age

	25 to 34 years	**35 to 44 years**	**45 to 54 years**	**55 to 64 years**	**Total**
	Mean change $	Mean change $	Mean change $	Mean change $	Mean change $
Men					
Self Assessed Health					
Very good/Excellent	355,988.1	389,180.2	477,316.6	350,909.0	395,534.0
Good	251,547.3	288,233.9	424,916.8	220,547.4	304,749.8
Fair/Poor	199,866.6	213,594.0	257,975.4	198,217.7	220,163.0
Total	308,941.3	329,538.6	420,239.8	267,089.6	336,616.3
Women					
Self Assessed Health					
Very good/Excellent	355,467.7	393,581.7	465,319.2	260,848.9	378,219.8
Good	235,487.7	298,008.4	418,619.5	108,500.3	276,699.7
Fair/Poor	155,099.5	346,817.0	267,908.9	101,254.6	226,350.7
Total	301,102.1	354,389.4	410,852.3	169,390.5	321,060.5

Source: HILDA Release 10

Table 21: Mean Change in Superannuation in Total Dollars (Not Retired) between 2002 and 2010 by Self Assessed Health in 2002 and by Age

	25 to 34 years	35 to 44 years	45 to 54 years	55 to 64 years	Total
	Mean change $	Mean change $	Mean change $	Mean change $	Mean change $
Men					
Self Assessed Health					
Very good/Excellent	58,535.8	69,698.4	77,789.3	-39,032.4	51,885.4
Good	37,265.5	53,677.2	72,011.8	-50,050.4	36,087.0
Fair/Poor	40,656.5	33,728.2	7,185.8	-13,702.8	11,691.3
Total	50,040.2	59,178.4	63,478.2	-36,282.9	40,152.2
Women					
Self Assessed Health					
Very good/Excellent	26,474.4	36,715.4	44,867.1	2,640.6	30,348.7

Good	20,813.1	22,683.3	22,605.9	-12,583.3	14,947.0
Fair/Poor	22,817.6	18,300.1	17,369.7	-3,414.8	13,168.2
Total	24,427.0	29,682.8	31,527.5	-4,570.7	22,501.8

Source: HILDA Release 10

Table 21 examines the relationship between self assessed health in 2002 and change in superannuation between 2002 and 2010 for individuals who were not retired. This is an individual measure and will therefore more closely capture the effect of poor health on individual wealth. Growth in superannuation differed by health status with persons in very good or excellent health experiencing the highest growth in superannuation. The exception is those aged 55 to 64. People aged 55 to 64 experienced a decline in superannuation over this time and this is likely to be attributed to the effects of the global financial crisis and some within this age group beginning to draw down on their superannuation. Unlike the case for household net worth, the disparity in growth in superannuation by health does differ with age, becoming largest for those aged 35 to 54.

The findings from Table 20 and Table 21 indicate that poor health is associated with a reduction in wealth accumulation. Superannuation contributions are closely linked with labour market outcomes (years and hours worked and wages) which strongly suggests that disparities in superannuation by health can be attributed to the relationships between health and labour market outcomes.

The discussion in this section has identified three indicators of accumulating disadvantage: firstly, health is linked with years spent in employment (or time out of paid work); second, that health and income are linked and there is persistence in this relationship and finally that those in poorer health experience a lower rate of wealth accumulation. Causal links between health and indicators of accumulating disadvantage will be explored in chapter 7.

3.5 Summary

This chapter has described data used in this thesis and profiled some of the cross sectional relationships between health and labour market outcomes using data from the ABS General Social Survey, National Health Survey and the HILDA survey. The profile set out relationships between different measures of health, noting that there are intersections between these and found that health is associated with employment status but also with changes in employment status. It then considered two key labour market outcomes: form of employment and occupation. Cross sectional relationships were identified between health and form of employment as well as health and occupation.

These cross sectional relationships were found to be highly significant. Form of employment has a statistically significant relationship with health status, as does occupation. Men and women in part time employment report poorer health compared with those in full time employment. Men and women in casual employment also report poorer health compared with those in permanent employment. In the case of occupation, a higher proportion of men and women in manual occupations report poorer health (and conversely a lower proportion report excellent health).

These findings reinforce the idea that health matters not just for those who are unable to work, health also matters amongst those who are working. The statistics presented support the need to further investigate the relationships to establish whether health has a causal effect on these labour market outcomes once suitable econometric methods are applied to longitudinal data. A causal effect of health on these labour market outcomes has implications for earnings via training but also lower income as suggested previously.

The final section of this chapter examined three indicators of accumulating disadvantage. An analysis of relationships between health and labour force history, income, and wealth provided some cross sectional evidence linking the relationships between health and labour market outcomes to accumulating disadvantage for those in poorer health. Poorer health is associated with fewer years in employment, lower income and a lower rate of wealth accumulation. There is clear cross sectional evidence of health related accumulating disadvantage which requires further testing to establish whether health causes this disadvantage.

The next chapter identifies issues in modelling the effects of health on the outcomes of interest, laying the groundwork for chapters 5 through 7 to build on the cross sectional evidence provided in this chapter to conduct econometric investigations aimed at disentangling the causal effects behind these relationships.

4. Modelling Issues

4.1 Introduction

Chapters 5, 6 and 7 conduct econometric analyses based on the relationships identified in the previous chapter however there are a number of methodological issues involved in analysing relationships between health and labour market outcomes. This chapter focuses on the particular issues which must be considered before undertaking analysis of these relationships beginning with concerns surrounding measure of health (an issue specific to analysing health) then moving on to more broad issues encountered in econometric analysis and ways in which these can be addressed.

The chapter begins in section 4.2 by discussing the concerns surrounding choice of health measure. Section 4.3 outlines the method used in this thesis to address these concerns. Section 4.4 sets out methodological issues involved in econometric modelling of relationships between health and labour market outcomes using the example of employment participation. Section 4.5 presents results from different model specifications which illustrate the preferred modelling approach and section 4.6 concludes.

4.2 Issues Surrounding Choice of Health Measure

Section 2.2.1 of chapter 2 set out what is meant by health in this thesis and discussed the different ways health can be measured. It was noted there that the measures contained in survey data have advantages and disadvantages and that there have been criticisms of health measures, particularly with regard to subjective self reported measures. This section expands on the brief discussion in chapter 2.

There is a growing literature on the concerns with using subjective measures of health to estimate causal effects of health on labour market outcomes (see for example, Anderson and Burkhauser 1985; Stern, 1989; Bound 1991; Kerkhofs and Lindeboom 1995, Bound *et al.* 1999; Disney *et al.* 2006; Bound *et al.* 2010). A number of potential problems have been identified. Firstly, self reported measures are subjective and are not likely to be comparable across different groups. This lack of comparability has been found in a number of recent papers including Beam Dowd and Zajacova (2007), Singh-Manoux *et al.* (2007) and Kapteyn *et al.* (2009). Secondly, they are likely to be endogenous to labour market status with those not in the labour force in particular being more likely to report poor health to justify non-participation (Stern 1989; Dwyer and Mitchell 1999; Cai and Kalb 2006). Third, subjective measures are usually categorical whereas most researchers are interested in measuring a continuous construct of health (Bound *et al.* 2010). Finally, while health is known to affect the likelihood of employment (and is hypothesised to affect other labour market outcomes), employment (particularly certain forms of employment or occupation) can also affect health.

One strategy to address these problems is to use more objective measures of health status as an alternative to self-reported measures, for example using measures of disability or medical conditions. The problem with this approach is that these more objective measures of health are designed to measure ill-health rather than work capacity (Bound, 1991). These measures are not highly correlated with the aspect of health affecting work capacity and therefore lead to a downward biased estimate of the effect of health on labour market outcomes (Bound, 1991). They can also, if obtained from self reports, still be prone to the same justification bias as the more subjective rating of self assessed health status.

The central issues with regards to endogeneity of measures of health can be laid out as follows. It is assumed that the probability of employment (E_{it}) is a linear function of unobserved true health H_{it} and of other variables Z_{it} which capture the other factors affecting the probability of employment[17].

$$E_{it} = Z_{it}\beta + H_{it}\alpha + e_{it} \qquad (1)$$

Likewise, the specific labour market outcome of interest (e.g. form of employment obtained) is assumed to be a linear function of unobserved true health H_{it} and of

[17] The linearization of employment in this discussion is merely to simplify the example. Employment is not treated as linear in the analysis later in this chapter.

other variables V_{it} which capture other factors affecting form of employment obtained[18].

$$FOE_{it} = V_{it}\beta + H_{it}\delta + u_{it} \qquad (2)$$

Self assessed health measures true health with error:

$$SAH_{it} = H_{it} + v_{it} \qquad (3)$$

The measurement error v_{it} may be random or it may be correlated with E_{it} (and FOE_{it}). If there is correlation this represents the endogeneity referred to above. By substitution:

$$E_{it} = Z_{it}\beta + SAH_{it}\alpha + (e_{it} - \alpha v_{it}) \qquad (4)$$

And

$$FOE_{it} = V_{it}\beta + SAH_{it}\delta + (u_{it} - \delta v_{it}) \qquad (5)$$

If either of these equations is estimated, there will be bias in the estimates of α and δ.

This chapter follows the approach suggested by Bound (1991) and Bound *et al.* (1999) and implemented by Au *et al.* (2005), Disney *et al.* (2006), Zucchelli *et al.* (2007), Hagan *et al.* (2009), Jones *et al.* (2010), García-Gómez *et al.* (2010) and Bound *et al.* (2010). This involves using a latent variable model to construct an index of health (or measure of health stock). The process for constructing this index of health is discussed in the next section.

4.3 Constructing the Health Index

In order to construct the index of health, the self assessed health measure is modelled as a function of demographic characteristics and more objective measures of health. The idea behind this is to use the more objective measures of health as health indicators which act as instrumental variables to "purge" the self assessed health measure of measurement error and justification bias. The latent measure of the health

[18] The linearization of form of employment here is for purpose of simplification. As with employment, form of employment is not treated as linear in the econometric analyses.

stock is created using the predicted values from estimated models of self assessed health.

While the proposed health index HI_{it} is still likely to measure true health with error:

$$HI_{it} = H_{it} + z_{it} \qquad (6)$$

the advantages of the index rest on two propositions, 1) because of the nature of the questions underlying the index (e.g. presence of particular medical conditions), the components of the index and the index itself do not suffer from justification bias. 2) because the index is comprehensive (ranging from 0 to 100 and considering health indicators and socioeconomic characteristics as predictors), the degree of measurement error is minimised and may be less than the measurement error in self assessed health (Au *et al.* 2005).

The health index is created by estimating a model of self assessed health as described above. The method used to create the health index is similar to that used by Au *et al.* (2005), Disney *et al.* (2006), Zucchelli *et al.* (2007), Hagan *et al.* (2009), García-Gómez *et al.* (2010) and Jones *et al.* (2010). The dependent variable is the 5-item self assessed health measure. Categorical self assessed health is assumed continuous for the purposes of this first stage regression[19]. Linear regression is used to estimate the model of self assessed health. The idea of the technique is that there is a latent and continuously distributed variable representing propensity of reporting a specific health status and this is underlying the responses in the original dependent variable. This is argued to be a more accurate measure of health than the 5 class self assessed health variable.

The variables included in this equation are demographic characteristics and more objective measures of health and these variables are defined in more detail in Table 2 in Chapter 3. In constructing the health index, Au *et al.* (2005), Disney *et al.* (2006) and Bound *et al.* (2010) included sociodemographic variables as well as health

[19] This allows the model to be estimated by linear regression and to produce residuals which are not correlated with fitted values and covariates. The resulting fitted values were compared to those obtained by ordered probit (the usual approach) and were found to be extremely similar. This suggests that the assumption of health being continuous is not unreasonable for the purposes of constructing the health index.

indicators in their model of health. Jones *et al.* (2010) and García-Gómez *et al.* (2010) include only health indicators and reserve the use of socioeconomic characteristics as indicators of reporting bias. Including only health indicators makes the assumption that, conditional on the health indicators, any association between self-reported health and socioeconomic characteristics does not reflect genuine variation in health. While this is possible, both approaches have merit. This thesis includes sociodemographic characteristics in the model of self-reported health to remove the need for this strict assumption.

The fitted values from estimating the model of self assessed health are used to create a measure of the health stock. These values are then transformed into a linear health index ranging in value from 0 to 100 which is used to measure health in the econometric analyses in this thesis. The health index is constructed separately for each wave of HILDA and separately by gender. The estimates of the model of self assessed health for wave 1 are reported in Table 22[20]. Estimates for the other waves are very similar.[21]

The coefficients obtained from the regression in Table 22 do not have a simple interpretation in terms of magnitude given the nature of the dependent variable but can be interpreted as qualitative information from sign and significance as to whether each is associated with better or poorer health. Most of the health variables are statistically significant, as are some demographics, particularly tertiary education, being a recently arrived immigrant (0-4 years living in Australia) and age (for men). Social support is also highly significant (at the 1% level).

Table 22: Estimates (and Standard Errors) in the 2001 HILDA Linear Regression for Self-Assessed Health (SAH) on Demographics and Health Measures (Age 15-64)

	Men	Women
Age	-0.0197*** (0.0059)	0.0025 (0.0055)

[20] Note that health measures are taken from the self-completion questionnaire in HILDA and are therefore responsible for a reduction in sample size. Observations lost are assumed missing at random.
[21] Estimates from other waves are available upon request

	Men	Women
Age Squared	0.0002** (0.0001)	-0.0001 (0.0001)
Married/De Facto	-0.0323 (0.0322)	-0.0315 (0.0270)
Household Size	-0.0048 (0.0095)	0.0161* (0.009)
Owns home	0.0291 (0.0287)	0.0631** (0.0264)
Degree or above	0.199*** (0.0349)	0.100*** (0.0300)
Advanced Diploma/Diploma	0.137*** (0.0445)	0.0338 (0.0403)
Cert III/IV	0.0495 (0.0315)	0.0519 (0.0364)
Cert I/II	0.0692 (0.112)	0.0953 (0.0893)
Year 12	0.0643* (0.0378)	0.0697** (0.0320)
SF-36 Mental Health	0.0113*** (0.0009)	0.0121*** (0.0008)
SF-36 Physical Functioning	0.0094*** (0.0008)	0.0010*** (0.0008)
Has Work Limiting Long term Health Condition	-0.579*** (0.0468)	-0.642*** (0.0454)
Has Long Term Health Condition not Limiting Work	-0.284*** (0.0492)	-0.207*** (0.0603)
Long term condition such as Arthritis, Asthma, Heart Disease, Alzheimer’s, Dementia	-0.218*** (0.0469)	-0.220*** (0.0438)
Condition restricting physical activity or physical work (e.g. back problem, migraines)	-0.166*** (0.0491)	-0.0662 (0.0478)
Shortness of breath or	-0.460***	-0.105

	Men	Women
difficulty breathing	(0.0923)	(0.0976)
Effects as a result of stroke, head injury or other brain damage	-0.255** (0.127)	0.158 (0.182)
Sight problems not corrected by glasses	0.0423 (0.0796)	-0.0762 (0.110)
Social Support	0.0639*** (0.0138)	0.0469*** (0.0125)
Smoker	-0.147*** (0.0241)	-0.115*** (0.0222)
Heavy Drinker	-0.0706*** (0.0274)	-0.0592 (0.0363)
Lack of Physical Activity	-0.206*** (0.0292)	-0.244*** (0.0249)
Has lived in Australia 0-4 years	0.307*** (0.0825)	0.179*** (0.0656)
Has lived in Australia 5-9 years	0.117 (0.0747)	-0.108 (0.0790)
Has lived in Australia 10-19 years	0.119** (0.0493)	-0.0321 (0.0447)
Has lived in Australia 20+ years	0.0317 (0.0363)	0.0180 (0.0354)
Capital Income ($1000's)	0.000001 (0.000001)	0.000002 (0.000002)
Weekly Non Labour Income ($100's)	0.000003 (0.00003)	-0.00004 (0.00004)
NSW	0.0832 (0.0809)	0.148* (0.0816)
VIC	0.0550 (0.0813)	0.121 (0.0817)
QLD	0.0307 (0.0827)	0.0323 (0.0829)
SA	0.0347 (0.0871)	0.0714 (0.0866)
WA	0.102	0.0797

	Men	Women
	(0.0859)	(0.0857)
TAS	0.112 (0.106)	0.152 (0.102)
NT	0.0397 (0.174)	0.0341 (0.164)
Constant	2.193*** (0.173)	1.709*** (0.157)
R^2	0.378	0.362

Notes: 1) Dependent variable is 5-item self assessed health. 2) Sample sizes: 4645 Men and 5193 Women. 3) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 4) Standard errors reported are Huber-White robust standard errors

In order to illustrate the relationship between the health index and self assessed health status, Figure 1 and Figure 2 display histograms showing the distribution of self assessed health and the health index, respectively. Table 23 displays mean scores of the health index by self assessed health status, long term condition and age as well as the correlation between self assessed health and the health index.

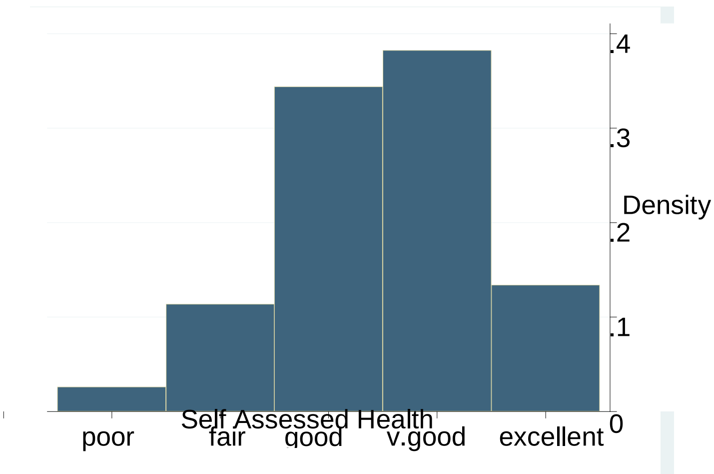

Figure 1: Histogram of Self Assessed Health

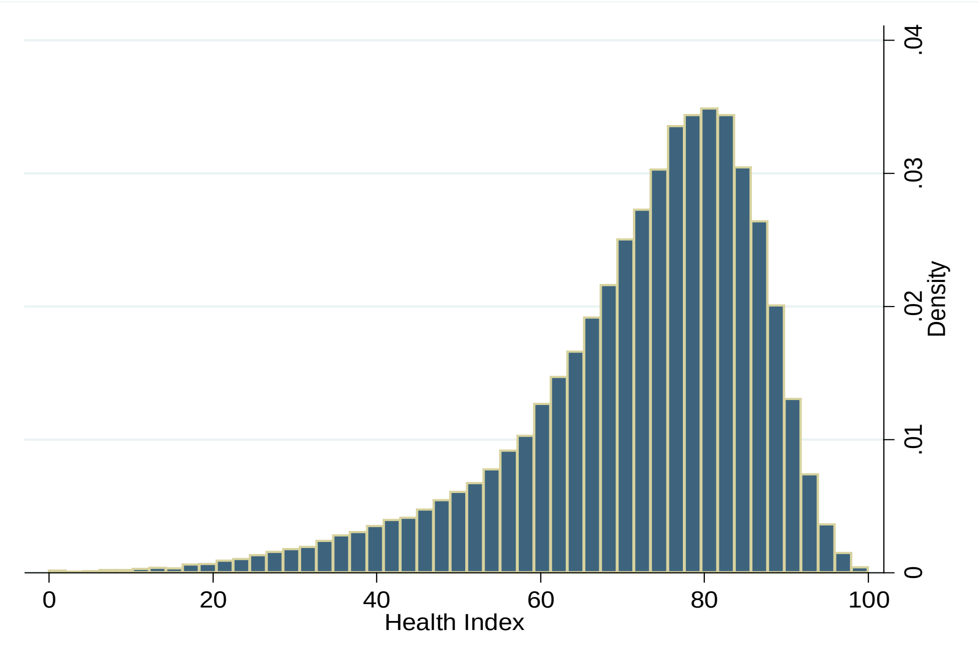

Figure 2: Histogram of Health Index

Table 23: Mean Scores of Health Index, Men and Women (Aged 15-64)

	Men	**Women**
Total	70.5	73.2
Self Assessed Health		
Excellent	80.7	83.8
Very good	75.7	79.2
Good	68.3	70.8
Fair	54.2	54.8
Poor	34.5	37.4
Long term condition		
Has Work Limiting Long Term Condition	46.4	47.1
Has Long Term Condition not Limiting Work	64.3	65.2
No Long Term Condition	75.0	78.3
Age Group		

15-24	78.9	78.1
25-34	74.1	76.9
35-44	69.4	74.0
45-54	66.2	69.6
55-64	62.3	65.4
Correlation between HI and SAH	0.561	0.579

A comparison of Figure 1 and Figure 2 shows the continuous distribution of the health index in comparison with self assessed health. Combining the information from the histograms and information from Table 23 it can be seen that the distribution of the health index is skewed to the right. Those reporting good or very good self assessed health comprise the majority of respondents and these respondents have a fairly high mean score on the health index.

Unlike the categorical measures, the continuous nature of the health index reflects a less constrained measure which can be compared across groups (due to socioeconomic factors and more objective variables included in its construction). This is apparent in Table 23 with mean score of the health index declining with age. The measure also incorporates different dimensions of good health by including health indicators reflecting physical functioning, mental health, work limiting disability and other conditions in constructing the index. The intersection between the health index and the other health measures in Table 23 is consistent with that observed between the different health measures in Chapter 3. The health index is related to the other health measures via the method used in its construction but by incorporating different dimensions of health it more accurately represents true health.

4.4 Methodological issues involved in modelling links between health and labour market outcomes

This thesis is interested in the effect that health has on different labour market outcomes and the degree to which any health related labour market disadvantage has a cumulative effect. Before analysing the effect of health on labour market outcomes, it is useful to consider factors affecting employment participation particularly because many labour market outcomes are not observed unless an individual is employed. The relationship between health and employment participation have been the subject of other research (see for example Bound *et al.* 1999; Au *et al.* 2005; Disney *et al.* 2006; Cai, 2010; Oguzoglu, 2010; García-Gómez *et al.* 2010). There are a number of methodological issues involved in modelling the effect of health on labour market outcomes. Many of these were discussed in brief in the review of the literature in Chapter 2. This section sets out these issues in more detail and illustrates some of the modelling approaches which can be used to estimate a dynamic model of employment participation

4.4.1 Data

This analysis uses 10 waves of the Household, Income and Labour Dynamics in Australia (HILDA) data. These data cover the time period from 2001-2010.

The Household, Income and Labour Dynamics in Australia (HILDA) survey began in 2001. It is funded by the Australian Commonwealth Department of Social Services and conducted by the Melbourne Institute of Applied Economic and Social Research. As stated in chapter 3, it is a household based panel survey collecting information about economic and subjective well-being, labour market dynamics and family dynamics. Details of the survey are documented in Watson and Wooden (2002a).

Data in HILDA were collected using four different survey instruments: a household form, household questionnaire, person questionnaire and a self-completion questionnaire. The household form collected information about the dwelling and household members of participating households. The household questionnaire collected information about the household, including use of childcare and housing while the person questionnaire collected detailed information on employment, income, family and background from each person in the household aged 15 years and over. The self-completion questionnaire collected primarily attitudinal data from each person in the household aged 15 years and over.

In the first wave, 11,693 households were identified as in scope. From these, 7682 households were interviewed giving a household response rate of 66 per cent. Within the 7692 households, 15,127 people were eligible for an interview. Of these, 13,969 people were successfully interviewed. Interviews for wave 2 onwards have been conducted annually with all adult members of each household.

While the wave 1 sample of HILDA was intended to be representative of the Australian population, and was fairly representative, non-response was not random. Sydney residents are underrepresented as are unmarried persons and immigrants from a non-English-speaking background. Women are overrepresented and men are underrepresented. Despite these biases, the size of the discrepancies is not considered large and do not discredit the data (Watson and Wooden, 2002b).

Attrition is often a problem with longitudinal survey data. Attrition reduces the precision of survey estimates and since it tends not to be random, it may bias population estimates. Watson and Wooden (2006) studied longitudinal survey response in HILDA. They found that of those persons interviewed in wave 1, 74 per cent were re-interviewed in wave 5. The retention rate over the five waves rises to 78 per cent if deaths and movements out of scope are excluded. Wave-on-wave attritions rates for have fallen with each wave, with attrition rates of 13.2 for wave 2, 9.6 for wave 3, 8.4 for wave 4 and 5.6 for wave 5. These compare favourably with other international leading household panel studies (Watson and Wooden, 2006). HILDA provides cross section as well as longitudinal weights so that differences between responding sample and selected samples can be corrected. Longitudinal data also becomes less representative due to changes in the population over time. One particular source of this is migration, both immigration and emigration. Weights don't account for these population changes.

As described in chapter 3, the inclusion of detailed information on labour market activities combined with the information collected on health makes HILDA very suitable for studying interactions between health and labour market outcomes. No other longitudinal Australian dataset combines the same level of detailed information on labour market activities and information on health. HILDA's strengths with regard to its longitudinal nature enabling identification of causal effects, as well as the inclusion of information vital to answering the research questions of interest make it the clear choice for the longitudinal analyses in this thesis.

4.4.2 Modelling approaches

The employment participation model is a model with a binary dependent variable. The dependent variable takes on the value 1 if employed and 0 otherwise. Three types of models were used to examine dynamics

1) A basic pooled model with a lagged dependent variable and no allowance for unobserved heterogeneity
2) A dynamic random effects probit model with a lagged dependent variable and unobserved heterogeneity but assuming initial conditions are exogenous
3) A dynamic random effects probit model with a lagged dependent variable, unobserved heterogeneity and endogenous initial conditions

The starting model (in the case of dynamic random effects models) is specified as:

$$y_{it} = \beta' X_{it} + \gamma y_{i,t-1} + \alpha_i + \varepsilon_{it} \qquad (1)$$

where y is the binary Employed vs. not employed variable.

Methodological issues to be considered in estimating this type of model include state dependence, unobserved heterogeneity, the role of initial conditions and (given that health is central to this thesis) the choice of health measure included as an explanatory variable. Choice of health measure and the approach to be used in this thesis was discussed earlier in this chapter and issues surrounding this need not be repeated here.

All the effects of state dependence are characterised through the coefficient on the lagged dependent variable ($y_{i,t-1}$). The larger the value of this coefficient, the greater the degree of state dependence in the likelihood of being employed in the following period.

Unobserved individual heterogeneity is given by α_i and ε_{it} with the former being a time-invariant parameter and the latter representing the time variant component of individual specific effects. These are assumed independent across individuals and to have a normal distribution.

There is an issue concerning the initial condition-whether employment in the initial year is correlated with the time invariant individual specific effect. If there is such a correlation, there will be correlation between the error term (e_{it}) and the lagged dependent variable which leads to biased estimates. There are three main approaches used for handling endogenous initial conditions. These are methods developed by Heckman (1981), Orme (1997, 2001) and Wooldridge (2005). The Orme and Wooldridge methods are far less computationally intensive than Heckman's method and thus have been much more widely used in recent work. Given that each of these approaches have been found to yield similar results in dynamic random effects probit models (Arulampalam and Stewart, 2009; Jenkins and Cappellari, 2008), the Wooldridge method is used in the case as it is simple to incorporate.

The Wooldridge method involves modelling the distribution of employment indicators from $t_i = 2, \ldots, T_i$ and conditioning on the mean of the set of time variant explanatory variables and the binary employment indicator for the initial year. This is given as:

$$y_{it} = \beta' X_{it} + \gamma y_{i,t-1} + \zeta \hat{y}_{i,1} + \lambda \overline{x}_i + \alpha_i + \varepsilon_{it} \qquad (2)$$

and has the benefit of having built in the Mundlak (1978) and Chamberlain (1984) augmentation for random effects models to allow for any potential correlation between the individual specific effects and explanatory variables (i.e. inclusion of the average of the Xs).

The Wooldridge estimator was developed assuming a balanced panel. It can be applied to unbalanced panels if it can be assumed that the unobservable determinants of attrition are not correlated with unobservables determining probability of employment but even where this is not the case the impact of attrition has been found to be small (Cappellari and Jenkins, 2008). Given this robustness to deviation from the assumption the method is applied to these data which are unbalanced.

4.4.3 Sample and Explanatory variables

The sample used for the econometric analyses was restricted to those aged between 15 and 64 years excluding full time students. Summary statistics for many of the variables included in the analyses in this chapter can be found in Table 2 in Chapter 3. Table 24 sets out the variables used in the model in this chapter and the definitions of these variables.

After taking account of missing values, the estimation sample comprises 55,662 person-wave observations for 10,137 individuals[22]. Due to the inclusion of a lagged dependent variable (and lagged health featuring as an explanatory variable), the estimating sample comprises data from waves 2 to 10 of HILDA.

Table 24 : Variables Used in Employment Model

Variable	**Description of Variable**
Employed	1 if employed, 0 otherwise
Employed at t-1	1 if employed in previous year, 0 if not employed in previous year
Employed at t=1	1 if employed in initial wave of data, 0 otherwise
Post GFC	1 if observation is from 2008 or later, 0 otherwise
Female	1 if female, 0 otherwise
Lagged health index	Health index score from previous year
Initial health	Health index score from initial wave of data
Has children aged 0-4	1 if has children aged 0-4, 0 otherwise
Has children	1 if has children aged 5-14, 0 otherwise

[22] These missing observations are assumed to be missing at random.

Variable	Description of Variable
aged 5-14	
Married/De Facto	1 if married or has partner, 0 otherwise
Partner is employed	1 if has partner in employment, 0 otherwise
Weekly non labour income ($100's)	Real weekly non labour income divided by 100
Partner wage	Real hourly wage of partner, takes value 0 if has no partner
Rural	1 if lives in rural area, 0 otherwise
Migrant	1 if migrant, 0 if Australian born
Experience	Years in employment since leaving full time education
Experience squared	Years in employment since leaving full time education squared
Economic inactivity	Years not employed since leaving full time education
Economic inactivity squared	Years not employed since leaving full time education squared
Unemployment rate	Unemployment rate calculated by age, sex, state of residence and year
Education	Measured by dummy variables reflecting highest educational attainment
Degree or above	1 if has degree or above, 0 otherwise
Advanced diploma/diploma	1 if has advanced diploma or diploma, 0 otherwise
Certificate	1 if has certificate I/II/III or IV, 0 otherwise
Year 12	1 if has year 12, 0 otherwise
Year 11 or below	Reference category, 1 if has year 11 or below

Notes: Hourly wage rate, partner wage rate, non-labour income, superannuation and household net worth are all inflated to the value in the year 2010 by the RBA annual inflation rate over the period (2001-2010) derived from the ABS Consumer Price Index.

Many of the variables included in the analyses require little explanation, as they are commonly used in labour supply models in economics (e.g. level of education, marital status). There are some variables however which do require further explanation.

Total years of labour force experience are included to capture the effect of previous employment history. Economic inactivity (years spent out of employment) is included to represent de-skilling and strength of attachment to the labour force.

Lagged and initial health are included in order to reduce the possibility of simultaneity bias. By using lagged health, the change in health occurs before any change in labour market status. Inclusion of both initial period health and lagged health allows for the estimated coefficient on lagged health to be interpreted as a deviation from an underlying health stock represented by initial health (García-Gómez *et al.* 2010; Jones *et al.* 2010; Hagan *et al.* 2009).

Presence of children was represented by a set of dummy variables as the relationship between having children and the dependent variables was expected to differ by age of children. A state, gender and age group specific unemployment rate was included in the employed equation to account for the discouraged worker effect which results from a higher unemployment rate.

As discussed earlier, a lag of the employed variable is included to capture state dependence. A variable representing the initial period binary outcome (an initial period employment indicator) was derived for each individual and included in the model specification dealing with initial conditions.

The longitudinal time averaged variables were derived for each individual by calculating the averages over the number of waves each individual participated in for each time variant variable included. These capture relatively fixed underlying differences between individuals, the Mundlak adjustment described in the previous section.

The next section presents results from estimating the three types of models set out at the beginning of section 4.4.2.

4.5 Results from Estimating Models of Employment Participation

This section presents estimates which check the robustness of results to the choice of model specification. Three different estimators are used: a pooled probit model, a dynamic random effects probit model assuming initial conditions are exogenous and a dynamic random effects probit model assuming endogenous initial conditions (the Wooldridge estimator).

The significance (or not) of the lagged dependent variable will determine whether dynamics are relevant while comparison of the pooled results with the random effects probit models will determine to what extent unobserved heterogeneity is important and whether a panel data model is to be preferred over simply pooling the data. Finally, comparing models with and without the control for initial conditions will identify the extent to which initial conditions play a role.

Table 25 presents results using the three different estimators[23]. To enable interpretation, the estimates reported are the marginal effects. The effect of being employed at t-1 is highly significant in all three specifications providing strong evidence of state dependence. This indicates that dynamics are relevant. This effect is overstated when initial conditions are ignored and when data are pooled. Nevertheless, the size of the effect is substantial.

Table 25: Estimates (and Standard Errors) from dynamic marginal effects probit models of probability of employment at year *t*, Persons aged 15 to 64

	Pooled	**Initial conditions exogenous**	**Wooldridge**
Employed at t-1	0.533*** (0.0063)	0.382*** (0.0117)	0.291*** (0.0116)
Employed at t=1			0.134*** (0.0087)
Post GFC	0.00098	-0.0037	-0.0051

[23] Models were estimated both for all persons and separately by gender. The results by gender can be found in Table A-9 and Table A-10 in the Appendix.

	Pooled	Initial conditions exogenous	Wooldridge
	(0.0043)	(0.0048)	(0.0046)
Female	-0.0509*** (0.0039)	-0.0531*** (0.0044)	-0.0546*** (0.0044)
Lagged health index	0.0017*** (0.0002)	0.0014*** (0.0002)	0.0014*** (0.0002)
Initial health	0.0012*** (0.0002)	0.0016*** (0.0002)	0.0012*** (0.0002)
Has children aged 0-4	-0.140*** (0.0068)	-0.124*** (0.0103)	-0.134*** (0.0105)
Has children aged 5-14	0.0217*** (0.0039)	-0.0006 (0.0063)	-0.0006 (0.0060)
Married/De Facto	-0.0489*** (0.0047)	-0.0518*** (0.0075)	-0.0490*** (0.0071)
Partner is employed	0.0850*** (0.0054)	0.0680*** (0.0075)	0.0686*** (0.0072)
Weekly non labour income ($100's)	-0.0014*** (0.0002)	-0.0011*** (0.0002)	-0.0011*** (0.0002)
Partner wage	-0.0003*** (0.0001)	-0.0001* (0.0001)	-0.0001* (0.0001)
Rural	-0.0047 (0.0049)	-0.0060 (0.0054)	-0.0071 (0.0054)
Migrant	-0.0133*** (0.0043)	-0.0183*** (0.0051)	-0.0131*** (0.0051)
Experience	0.0095*** (0.0006)	0.0094*** (0.0012)	0.0083*** (0.0011)
Experience squared	-0.0003*** (0.00001)	-0.0003*** (0.00001)	-0.0002*** (0.00001)
Economic inactivity	-0.0183*** (0.0006)	-0.0132*** (0.0013)	-0.0120*** (0.0013)
Economic inactivity squared	0.0003*** (0.00002)	0.0004*** (0.00002)	0.0003*** (0.00002)

	Pooled	Initial conditions exogenous	Wooldridge
Unemployment rate	-0.0036*** (0.0009)	-0.0027*** (0.0010)	-0.0029*** (0.0010)
Degree or above	0.0276*** (0.0046)	0.0950*** (0.0172)	0.102*** (0.0153)
Advanced Diploma/Diploma	0.0073 (0.0059)	0.0724*** (0.0136)	0.0708*** (0.0116)
Certificate	0.0183*** (0.0045)	0.0643*** (0.0108)	0.0656*** (0.0097)
Year 12	-0.0019 (0.0056)	0.0291* (0.0171)	0.0366** (0.0147)
Time averaged characteristics			
Experience		0.0012 (0.0011)	0.0005 (0.0010)
Economic inactivity		-0.0087*** (0.0012)	-0.0063*** (0.0012)
Unemployment rate		-0.0052*** (0.0019)	-0.0019 (0.0018)
Has children aged 0-4		-0.0522*** (0.0108)	-0.0391*** (0.0106)
Has children aged 5-14		0.0390*** (0.0086)	0.0528*** (0.0085)
Married/De facto		0.0037 (0.0120)	0.0036 (0.0117)
Partner is employed		0.0447*** (0.0107)	0.0295*** (0.0106)
Weekly non labour income ($100's)		-0.0010** (0.0004)	-0.0009** (0.0004)
Partner wage		-0.0007*** (0.0002)	-0.0007*** (0.0002)
Degree or above		-0.0870***	-0.109***

	Pooled	Initial conditions exogenous	Wooldridge
		(0.0274)	(0.0263)
Advanced Diploma/Diploma		-0.0984*** (0.0306)	-0.103*** (0.0294)
Certificate		-0.0595*** (0.0163)	-0.0664*** (0.0156)
Year 12		-0.0305 (0.0221)	-0.0411* (0.0211)
Constant	-0.947*** (0.068)	-0.673*** (0.119)	-0.903*** (0.129)
Rho		0.259*** (0.015)	0.321*** (0.015)
Sample	55,662	55,662	55,662
Individuals	10,137	10,137	10,137
Pseudo R^2	0.519	0.528	0.535
Log Likelihood	-13919.20	-13656.03	-13458.54
BIC	28089.73	27716.36	27332.31

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students. 3) Data are marginal effects for probit model. 4) Rho is the proportion of the total variance contributed by the panel-level variance component.

If Rho is statistically significant then a significant proportion of total variance in the employed model is explained by panel level variance (there is unobserved heterogeneity). Rho is strongly significant in both columns 2 and 3 of Table 25 indicating that there is unobserved heterogeneity.

Employment in the initial period is also highly significant. This suggests that initial conditions do play a role and cannot be ignored. Post GFC is included to reflect the effects of the global financial crisis on the likelihood of employment. The Post GFC variable is not significant in Table 25 however the unemployment rate is also included as a control variable. The unemployment rate is significant, with a higher unemployment rate decreasing the likelihood of employment. This may capture some of the effects of the GFC.

The remaining variables have the expected effects. Better health increases the likelihood of employment as does employment experience. The extent of economic inactivity is also significant and has the expected negative effect. Higher levels of education increase the likelihood of employment. Non labour income has a negative effect although the magnitude is very small. Migrants are less likely to be employed.

Women are less likely to be employed than men as are those with young children aged 0-4. There are however gender differences (see Table A-9 and Table A-10 in the Appendix). The magnitudes of the effects of almost all the significant variables are larger for women. The presence of young children has a strong negative effect on the likelihood of employment for women but has no significant effect for men. Employment in the previous year has a larger effect for women, as does employment experience and higher levels of education.

The time averaged variables play an important role with many of these being highly significant. As discussed in the previous section these variables represent the Mundlak corrections and are included to control for relatively fixed underlying differences between individuals. The significance of these variables suggests these differences are significant determinants of employment.

The results of these estimates indicate that dynamics are relevant, unobserved heterogeneity is important and that initial conditions do play a role.

4.6 Summary

This chapter began by discussing the concerns surrounding choice of health measure when analysing relationships between health and labour market outcomes. To address these concerns, a health index was constructed which used predicted values from a model of self assessed health to create a health measure ‘purged’ of bias as has been proposed in recent literature. This health index is used as the health measure in the econometric analyses in this thesis.

The remainder of the chapter then set out methodological issues involved in econometric analysis of health and labour market outcomes and used longitudinal data to study the relationship between health and employment participation to illustrate the importance of considering these methodological issues.

The results presented in this chapter provide strong evidence that in modelling employment participation, a) dynamics should be included, b) a panel data model is to be preferred so that unobserved heterogeneity can be accounted for and c) that initial conditions cannot be ignored. These findings will inform the econometric analysis and methods for dealing with econometric issues in the second part of this thesis, in particular for the next two chapters where econometric analysis of the relationship between health and key labour market outcomes will be undertaken.

PART II: Empirical Findings

5. The Effects of Health on Form of Employment

5.1 Introduction

This chapter presents the econometric findings from estimating form of employment equations. The specific research question of interest in this chapter is whether those in poorer health are more likely to be employed in part-time or casual employment. It is hypothesised that individuals in poorer health are more likely to obtain these forms of employment.

Form of employment in this chapter refers to the nature of employment arrangements, namely whether persons are employed on a part time (less than 35 hours per week) or full time basis and what their contract of employment is. The specific contracts of employment focused on in this chapter are casual and permanent[24]. Form of employment is relevant to interactions between health and labour market outcomes over the life course because certain forms of employment have negative implications particularly in terms of earnings over the life course.

The chapter is structured as follows. Section 5.2 discusses background with particular reference to forms of employment in Australia. The modelling approaches to be used are discussed in section 5.3. Section 5.4 sets out the sample and explanatory variables for the econometric analyses and Section 5.5 presents and examines the results. The chapter concludes with a discussion of results and summary.

5.2 Background

5.2.1 Form of Employment in Australia

[24] See Table A-3 in the Appendix for a definition of these forms of employment

There is a growing body of literature analysing the existence (or not) of causal effects of form of employment on health (see for example Ferrie, 1999; De Witte, 1999; Benavides *et al.* 2000; Virtanen *et al.* 2005; Richardson *et al.* 2012) but the reverse relationship (causal effect of health on form of employment) is also relevant and has been under-examined.

De Lange *et al.* (2004; 2005) and Dalgard *et al.* (2009) suggest that there is a reverse relationship between (mental) health and job characteristics. It cannot be assumed that the causal relationship is unidirectional and De Lange *et al.* (2005) suggest there is good reason to pursue research on the causal relationship between health and form of employment. This combined with the cross sectional evidence in chapter 3 supports further investigation into the effect of health on form of employment.

The Australian labour market has a high incidence of part time and casual employment compared to other developed countries (Wooden and Warren, 2004; Richardson and Law, 2009). In 2010, 2.24 million people were employed on casual terms representing about 20 per cent of all employed people (ABS, 2011a**)**. It was estimated that 2.8 million people were employed on a part-time basis in 2012, representing 30 per cent of all employees (ABS, 2012). With this relatively high incidence of part time and casual employment Australia therefore provides a good case study with which to determine whether those in poor health are more likely be employed in these forms of employment.

The high proportion of part-time work suggests that those in poor health in Australia are less likely to be restricted from choosing part-time hours compared with other countries. Poor health has been linked with fewer hours of work (Currie and Madrian, 1999; Pelkowski and Berger; 2004, Cai *et al.* 2014). This is in line with the theory which states that onset of poor health may change preferences and change relative utility derived from income and leisure (Lumsdaine and Mitchell, 1999). Poor health may reduce both the capacity and preference to work for long hours or even normal full-time hours. These arguments predict that poor health is associated with a lower probability of labour force participation or, for participants, a lower number of hours supplied. The growth in part-time employment in recent decades should increase the probability that a person suffering ill health can find a job fitting with their preferences (or capability) for fewer hours. In the case that a part-time job is not available, the individual may choose not to participate at all rather than work more hours than is preferred (or feasible given their capabilities).

While the studies of the effect of health on hours worked go some way towards contributing to the analysis of health effects on job characteristics, a distinction must be drawn between consideration of continuous measures of hours worked as opposed to distinguishing between part time and full time employment. There are specific characteristics associated with part time employment which make it desirable to determine the causal effect of health on the likelihood of obtaining this specific form of employment.

Part-time and casual jobs fall under the category of what is known as flexible work. Flexible employment has been linked in the literature with higher job insecurity, lower income, limited rights and benefits and powerlessness compared with full-time permanent employment (Benach and Muntaner, 2007). Flexible work has also been linked with adverse health outcomes (see for example Ferrie, 1999; De Witte, 1999; Benavides *et al.* 2000; Virtanen *et al.* 2005) although the evidence on this relationship may be ambiguous given that a recent Australian paper found that form of employment has no effect on (mental) health (Richardson *et al.* 2012).

These forms of employment have a somewhat different character in the Australian setting compared with other countries. There are some characteristics of the Australian labour market which are unique or unusual. In Australia, health care and unemployment benefits are not linked to employment history. There are also protections in the industrial relations system for casual employees. Casual employees are paid what is called a ‘casual loading’ to compensate them for lack of permanency and leave entitlements-their hourly pay rate is higher than that of a permanent worker in the same job. Employers are also as obligated to contribute to superannuation accounts of casual workers as they are to permanent workers. Unfair dismissal protection covers both permanent and casual workers as does anti-discrimination legislation (Richardson *et al.* 2012).

A final characteristic in Australia-it is likely that many Australians employed part-time or casually (or as part-time casuals) prefer this form of employment. Wooden and Warren (2004) found that part-time casuals are no less satisfied with their jobs than part-time permanent or full-time permanent employees. Only full-time casual male employees report lower levels of job satisfaction and this may be because these workers are involuntarily in this form of employment[25]. Casual or part-time work may be preferred as providing more work/life balance and those employed casually may have made the rational decision to trade permanency and leave entitlements for a higher hourly rate of pay and more flexibility of hours worked.

Despite these positive characteristics and protections, casual and part-time work does have some negative implications in Australia especially for lifetime earnings and career path. This is a concern if those in poor health are more likely to obtain these forms of employment. Poor health is associated with less time spent in the labour force to begin with (see chapter 3) therefore any negative impact from form of employment obtained is an added concern. It is important to determine whether those in poor health experience additional disadvantage through form of employment in the time they do spend in paid work.

5.2.2 Implications of Part-time and Casual Employment

The profile in chapter 3 suggested that a higher proportion of those with poor health are in part-time or casual employment. The type of jobs offered on part-time or casual terms is one potential source of disadvantage for persons in these forms of employment. There are some jobs, higher level jobs, which are not offered on part-time or casual terms. Table 26 shows the cross sectional relationship between form of employment and occupation. Occupation is given by the hierarchical ANZSCO classification. The eight major occupational groups at the highest level of aggregation can be classified and distinguished by skill level measured by the formal education and/or training and experience usually required to enter the occupation (see Table A-11 in the Appendix).

[25] Benach & Muntaner (2007) argue that those who “involuntarily” work in a temporary position are more likely to be dissatisfied than their permanent coworkers compared with those “voluntarily” in temporary work

Table 26: Occupation Worked by Form of Employment, 2010, Per cent

Occupation	Full-time	Part-time	Permanent	Casual	Self employed
Managers	87.4	12.6	54.7	4.2	41.1
Professionals	74.6	25.4	74.5	8.9	16.6
Technicians and Trades Workers	86.7	13.3	61.3	12.9	25.8
Community and Personal Service Workers	46.4	53.6	56.9	35.7	7.4
Clerical and Administrative Workers	65.9	34.1	73.4	14.4	12.2
Sales Workers	43.5	56.5	46.6	44.0	9.4
Machinery Operators and Drivers	84.9	15.1	63.8	23.3	12.9
Labourers	57.2	42.8	45.7	38.9	15.4
Total (%)	69.8	30.2	61.7	19.8	18.5
Total (000's)	7903.6	3419.7	6983.7	2245.5	2094.1

Source: ABS Labour Market Statistics, Cat No. 6105.0, July 2012

Table 26 shows that part-time and casual workers are concentrated in lower skilled occupations and this is particularly evident for casuals[26]. The occupations with the largest shares of part-time workers are Community and Personal Service Workers, Sales workers, Clerical and Administrative workers and Labourers. Casual workers are most highly represented in Sales, Community and Personal Service work, Labourers and as Machinery Operators and Drivers. This highlights a degree of occupational concentration in part-time and casual work in Australia. Occupational segregation of part-time work has also been found in international literature (Prowse,

[26] This occupational segregation is also apparent when disaggregating by gender. See Table A-12 and Table A-13 in the Appendix for Occupation Worked by Form of Employment by Gender.

2005; O’Dorchai *et al.*, 2007). Managers have a low level of permanent employment reflecting the larger share of managers who are self employed relative to other occupations. Almost all (93 per cent) of managers who are employees are on permanent/continuing contracts.

The profile in chapter 3 found that those in fair/poor health who are working are concentrated in lower skilled occupations. This reinforces the concern that part-time and casual work has negative implications for those in poor health through occupational concentration of these forms of employment. The type of occupational concentration of part-time and casual work has negative implications in terms of income and career prospects. Lower skilled occupations are lower paid and have more limited career progression (Francesconi, 2001).

In addition to the negative implications of occupational segregation, the literature and economic theory suggests that part-time and casual work both are associated with a lower likelihood of training. Employees on casual contracts have been found to be less likely than their permanent counterparts to receive training (Arulampalam and Booth, 1998; Forrier and Sels, 2003; Draca and Green, 2004; Richardson and Law, 2009). Human capital theory suggests that employers invest in training differently depending on employment contract of employees. Casual employees are less likely to receive training in the first place compared with those employed in permanent full-time positions (Arumpalam and Booth, 1998; Draca and Green, 2004). Those who do receive training receive a much lower rate than permanent full-time employees (Draca and Green, 2004; Richardson and Law, 2009). The training they do receive is mostly specific training (only of use in the current job) as employers do not want to waste investment in general training (which can be used in future employment elsewhere) on casuals who they feel will not stay on in the job (or who they do not plan to retain). Permanent employees receive general training as they tend to stay longer on the job and the investment by employers can be recouped over time. This was supported in Richardson and Law (2009) where it was found that it was the expectation that the employee will continue working with the firm that influenced the extent of job related training.

As with casual employment, those working part-time are less likely to receive training compared with fulltime employees (Arulampalam and Booth, 1998; Harley and Whitehouse, 2001; Almeida-Santos and Mumford, 2004; Richardson and Law, 2009; Bassanini *et al.* 2005). Part-time employees receive less in total earnings than full-time employees but they also get less enrichment of human capital i.e. training. Part-time work also has other marginalizing effects. These have been studied extensively and include lower hourly wages (Wilkins *et al.* 2010), lower wage growth (Chalmers and Hill, 2007; Francesconi and Gosling, 2005; Olsen and Walby, 2004; Myck and Paull, 2001), fewer fringe benefits (Rodriguez, 2002) and fewer opportunities to be hired for or promoted to higher level jobs (Francesconi, 2001; Russo and Hassink, 2005). A lower likelihood of training and promotion has implications for lifetime earnings and career progression through effects on the accumulation of human capital.

This discussion has highlighted negative implications for life-time earnings associated with part-time and casual employment. These forms of employment lead to lower training, lower earnings and a negative impact on career progression through occupational segregation and also lower likelihood of training compared with a full-time permanent employee in the same job.

5.2.3 Review of Previous Work

As stated in section 5.2.1, there has been limited research undertaken on the effects of health on form of employment. Some of the research that has been conducted was described in Chapter 2, but is discussed here in the context of establishing what is known about the effects of health on form of employment. Some literature has considered the effect of health on hours worked however there are limitations to these studies. Three useful sources looking at the effect of health on hours worked are Currie and Madrian (1999), Pelkowski and Berger (2004) and Cai *et al.* (2014). Currie and Madrian (1999) reviewed the literature on the relationship between health and hours worked. The studies they reviewed do not appear to have considered reverse causation between health and hours worked, only two look to have controlled for selection into employment and Currie and Madrian concluded that ‘a glaring limitation of the existing literature is the intense focus on elderly white men, to the virtual exclusion of most other groups’ (at page 3353).

Pelkowski and Berger (2004) examined the effect of health problems on employment, annual hours worked and hourly wages. The methods used and findings of this study were discussed in detail in the literature review in chapter 2. Their findings with regards to hours worked are of relevance to the research question in this chapter. Illness was found to reduce hours worked, with the reduction being greater for men than women. They highlighted the importance of adjusting for selection bias, noting that while permanent health conditions do affect wages and hours worked, they actually have far greater effects on the likelihood that an individual is employed in the first place. It was noted in chapter 2 that the Pelkowski and Berger study did not take account of the reverse causation effect. Model estimates will be biased if there is endogeneity between health and labour market outcomes which is not accounted for.

The research in this chapter can be differentiated from those reviewed in Currie and Madrian as it looks at a more representative sample (rather than just older white men), by use of different methods (panel data methods and accounting for selection into employment, see section 5.3) and by trying to account for endogeneity between health and labour market outcomes. It differs from Pelkowski and Berger by attempting to account for reverse causation effects. The research in this thesis also differs from both Currie and Madrian and Pelkowski and Berger by looking at the Australian setting.

The third paper is that by Cai *et al.* (2014) using Australian data. They estimate the effect of health on working hours using a Tobit model to estimate the joint effect of health status and health shocks on working hours. They use a Tobit in recognition of the fact that a health shock does not necessarily result in one leaving the workforce, the individual may just reduce hours worked. Their focus is very much on response to health shocks and the degree of reduction in hours worked following a health shock. Their method differs from the approach in this thesis, particularly in the treatment of the issue of selection into employment.

The papers reviewed in this section thus far do not focus on form of employment. Their focus is on hours of work. It is useful to understand the effects of health on hours worked in terms of establishing effects of health on labour supply beyond the effect on labour force participation. As mentioned in section 5.2.1 however, there are specific characteristics associated with part time employment which make it desirable to establish the effect of health on the likelihood of part time employment as opposed to considering the average effect of health on a continuous measure such as hours worked. Hours worked can fall within a large range of values and unless analysis is undertaken on specific categories within this range (e.g. part time/full time or a consideration of those working very long hours) the value of the analysis is limited in determining the effect of health on form of employment and the implications arising from this.

One paper which has analysed effects of health on transitions between certain forms of employment is Zucchelli *et al.* (2012). They used Australian data to research the effect of health on mobility between full-time employment, part-time employment, self-employment and inactivity for older workers. They found that poor health increases the probability of transition to inactivity (defined as retired or unemployed) from all other forms of employment for older workers. It does find some evidence that poor health could push older workers into part time employment. Their method is similar to that used in this chapter however this chapter does not focus solely on older workers-it looks at the entire working age population.

The research in this thesis is concerned with accumulating disadvantage arising from health differentials. It looks at the degree to which poor health is associated with an increased likelihood of part-time work or casual work to determine likely effects on human capital formation and ongoing disadvantage associated with this. The relationship between health and participation was illustrated in chapter 4 but this chapter is concerned with whether those in poor health who do obtain employment work part-time or casually because of their health status.

This research uses different methods compared with previous research in this area and the Australian setting, with its unusual characteristics, sets it apart from previous work (with the exception of Cai *et al.* 2014 and Zucchelli *et al.* 2012). The focus on part-time work (defined as working less than 35 hours per week) rather than simply hours worked, analysis of the effect of health on contract of employment and considering the entire working age population in this context is also an addition to the literature.

5.3 Modelling Approaches

As was the case in the previous analysis in chapter 4, this analysis uses 10 waves of the HILDA data. These data cover the time period from 2001-2010.

The form of employment model is a model with a multinomial dependent variable. Two specifications of form of employment are used. In the first, the dependent variable takes on the value 0 if not-employed (unemployed or not in the labour force), 1 if employed on a part-time basis and 2 if employed full-time[27]. For the second specification, the dependent variable takes on the values 0 if not-employed, 1 if casually employed and 2 if in permanent employment. These specifications are used to answer the research question: are persons in poor health more likely to be in part-time or casual employment?[28]

Three types of models are used to examine dynamics

1) A pooled multinomial logit model with lagged not-employed and form of employment variables taking account of clustering to provide panel adjusted standard errors
2) A dynamic multilevel multinomial logit model with lagged not-employed and form of employment variables and unobserved heterogeneity but assuming initial conditions are exogenous

[27] Part-time or full-time status is determined by hours worked rather than a self report of full-time/part-time status. HILDA only contains information on number of hours worked , it does not ask whether work is full-time or part-time.
[28] Models were not estimated separately by gender as observations on a number of variables became too small for reliable estimation with disaggregation. It would also have been desirable to estimate models using a more detailed breakdown of form of employment (e.g. considering fixed term, self employed and overlap between part time and casual employment) however this disaggregation also resulted in low observation numbers and difficulty in obtaining reliable estimates.

3) A dynamic multilevel multinomial logit model with lagged not-employed and form of employment variables, unobserved heterogeneity and endogenous initial conditions

The pooled models were estimated as a prelude to the multilevel panel data models. Following estimation of the pooled models, an investigation was undertaken to determine the most suitable specification of the panel data multilevel model. The investigation began with a constant only single level model. This model can be written as:

$$y_{itj} = \beta_{0j} + e_{itj} \qquad (1)$$

where *i* are individuals, *t* is time (or survey waves, *t*=1,…,*T*), j=1, 2, … J denotes the response category(form of employment) and e_{itj} denotes the residual.

This model was then extended to a two level random intercept model which can be written as:

$$y_{itj} = \beta_{0j} + e_{itj} + u_i \qquad (2)$$

where the intercept is now composed of a fixed part given by β_{0j} and a random part given by u_i and $u_i \sim N(0, \sigma_u^2)$.

Time invariant explanatory variables were added:

$$y_{itj} = \beta_{0j} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + e_{itj} + u_i \qquad (3)$$

The model was then extended to include time variant explanatory variables and dynamics, then extended again to incorporate the Mundlak augmentation then the final specification used the Wooldridge method for dealing with initial conditions as described in chapter 4:

$$y_{itj} = \beta_{0j} + \beta_j' X_{it} + \gamma_j y_{i,t-1} + \xi_j \hat{y}_{i,1} + \lambda_j \bar{x}_i + e_{itj} + u_i \qquad (4)$$

where the ***X*** are the vector of observed individual characteristics (the explanatory variables), $y_{i,t-1}$ are lagged form of employment, $\widehat{y_{i,1}}$ denotes the initial condition and $\bar{x}_i$ are the means of time variant explanatory variables. The means of time variant explanatory variables are incorporated as a correction to account for relatively fixed underlying differences between individuals (this is the Mundlak augmentation used with panel data models).

Many of the methodological issues involved in estimating this type of model are similar to those specified for estimating the employment participation model: state dependence, unobserved heterogeneity, the role of initial conditions and choice of health measure[29]. In addition to these issues, selection into employment must be considered because form of employment is not observed unless an individual is employed and there are also modelling issues associated with estimating a panel model with a categorical dependent variable.

The concerns surrounding choice of health measure were discussed in detail in chapter 4. These are addressed by using the health index constructed in that chapter. As was the case when analysing employment participation, lagged and initial health are included in the model in order to reduce the possibility of simultaneity bias.

All the effects of state dependence are characterised through coefficients on a series of lagged dummy variables for form of employment ($\gamma_j y_{i,t-1}$). The larger the value of these coefficients, the greater the degree of state dependence in form of employment in the following period (Jenkins and Cappellari, 2008).

The previous chapter argued that it was important to control for unobserved heterogeneity in analysing the links between health and labour market outcomes. This strengthens the case for estimating a panel data model. The categorical nature of the dependent variable for form of employment means the random effects probit model from chapter 4 cannot be used. Unobserved heterogeneity is allowed for by

[29] State dependence refers to the dependent variable in the current period (form of employment) being dependent on employment status in the previous period.

using multilevel modelling as described in the series of equations set out above. Unobserved heterogeneity is given by the u_i in equations (2) to (4).

The Wooldridge method is applied to deal with the initial condition as was the case in chapter 4. Selection into employment is addressed by including not-employed as an outcome in the categorical dependent variable.

There are limited statistical estimation techniques suitable for estimating models taking the form of those set out above (i.e. a panel data model with a categorical dependent variable) and all are computationally intensive requiring a large amount of computer processing time (Haynes *et al.* 2008). Two which have gained prominence are the gllamm procedure in STATA and Markov Chain Monte Carlo (MCMC) simulation using a software package such as MLwiN (Haynes *et al.* 2008). Because the literature has not established a clear cut preferred method, this chapter estimates and compares results for dynamic longitudinal models using gllamm in STATA and MCMC using MLwiN in order to ensure that results are robust to the estimation procedure used. These are both multilevel panel data model procedures.

In the case of multilevel modelling using panel data, there is a two level structure with occasion treated as a level nested within individuals. The data consist of repeated measures over time on a number of individuals. With panel data it is likely that there are correlations across time within individuals. Multilevel models (as with other types of random effects models) explicitly model this dependency across time (Steele, 2008).

For a nominal dependent variable with repeated observations and with three or more categories a multinomial logit model is used (Haynes *et al.* 2008). In gllamm, integrals can be solved using either Gauss Hermite or adaptive quadrature (Rabe-Hesketh *et al.* 2005)[30]. MLwiN uses quasi-likelihood methods. Quasi-likelihood methods give estimates for random parameters which are biased downwards

[30] Adaptive quadrature in gllamm can give more precise estimates than those using Gauss Hermite quadrature in gllamm. Results using adaptive quadrature in gllamm were compared with results using Gauss Hermite quadrature in glamm as an additional robustness check. The results did not differ therefore those using Gauss Hermite quadrature are reported as computational time for adaptive quadrature is more than twice as long.

therefore the recommended estimation procedure in MLwiN involves estimating the model using marginal-quasi likelihood (MQL) to obtain starting values. These starting values are then used in performing MCMC simulation which provides unbiased parameter estimates (Rodríguez and Goldman, 2001). The advantage of simulation (using MLwiN) over both quadrature methods in gllamm is computational time (Haynes *et al.* 2008)[31].

With panel data, it is important to account for clustering in order to obtain correct standard errors. Ignoring clustering can result in underestimation of standard errors leading to false conclusions about relationships between predictors and the dependent variable. Estimating a pooled model with standard errors adjusted for clustering can address this but it does not provide any information on the degree of between-individual variation in repeated measures. Multilevel modelling provides correct standard errors by allowing for between-individual variation but it also enables an assessment of the statistical significance and degree of between-individual variation by providing an estimate of between-individual variance (Steele, 2008). Estimates of between-individual random effects can also be extracted from the results obtained using multilevel models and these can be analysed to determine how unobserved differences vary between individuals both overall and for persons with specific characteristics.

The next section discusses the estimating sample and explanatory variables included.

5.4 Sample and Explanatory Variables

The sample used for the econometric analyses was restricted to those aged between 15 and 64 years excluding full-time students. Summary statistics for most of the variables included in the analyses in this chapter can be found in Table 2 in chapter 3. Table 27 sets out and defines the variables used in the form of employment models.

[31] Despite this advantage, as stated earlier there is no established preferred method therefore models are estimated using both MLwiN and gllamm as a robustness check.

Table 27 : Variables Used in Form of Employment Models

Variable	**Description of Variable**
Form of employment specification 1[a]	0 if not employed, 1 if employed part time, 2 if employed full time
Form of employment specification 2[b]	0 if not employed, 1 if employed casually, 2 if in permanent employment
Not employed at t-1	1 if not employed in previous year, 0 otherwise
Part time at t-1[a]	1 if employed part time at t-1, 0 if not employed or employed full time
Casual at t-1[b]	1 if employed casually at t-1, 0 if not employed or employed in permanent employment
Not employed at t=1	1 if not employed in initial wave of data, 0 otherwise
Part time at t=1[a]	1 if employed part time in initial wave of data, 0 if not employed or employed full time
Casual at t=1[b]	1 if employed casually in initial wave of data, 0 if not employed or employed in permanent employment
Post GFC	1 if observation is from 2008 or later, 0 otherwise
Lagged health index	Health index score from previous year
Initial health	Health index score from initial wave of data
Health shock	1 if health somewhat worse or much worse than last year, 0 otherwise
Female	1 if female, 0 otherwise
Lagged health index*female	Interaction term between health index score from previous year and female
Has children aged 0-4	1 if has children aged 0-4, 0 otherwise
Has children aged 5-14	1 if has children aged 5-14, 0 otherwise

Variable	Description of Variable
Has children aged 0-4*female	Interaction term between presence of young children in household and female
Married/De Facto	1 if married or has partner, 0 otherwise
Partner is employed	1 if has partner in employment, 0 otherwise
Weekly non labour income ($100's)	Real weekly non labour income divided by 100
Partner wage	Real hourly wage of partner, takes value 0 if has no partner
Rural	1 if lives in rural area, 0 otherwise
Migrant	1 if migrant, 0 if Australian born
Experience	Years in employment since leaving full time education
Experience squared	Years in employment since leaving full time education squared
Economic inactivity	Years not employed since leaving full time education
Economic inactivity squared	Years not employed since leaving full time education squared
Unemployment rate	Unemployment rate calculated by age, sex, state of residence and year
Education	Measured by dummy variables reflecting highest educational attainment
Degree or above	1 if has degree or above, 0 otherwise
Advanced diploma/diploma	1 if has advanced diploma or diploma, 0 otherwise
Certificate	1 if has certificate I/II/III or IV, 0 otherwise
Year 12	1 if has year 12, 0 otherwise
Year 11 or below	Reference category, 1 if has year 11 or below

Notes: [a]Variables included only in the models using the first specification of form of employment. [b]Variables included only in the models using the second specification of form of employment Partner wage rate and non-labour income are inflated to the value in the year 2010 by the RBA annual inflation rate over the period (2001-2010) derived from the ABS Consumer Price Index.

After taking account of missing values, the estimation sample for form of employment models comprises 51,941 person-wave observations for 9,694 individuals for the specification comparing not-employed, part-time and full-time employment[32]. The estimation sample reduces to 43,651 person-wave observations for 8,951 individuals for the second specification of form of employment (comparing "not employed, casual and permanent employment)[33]. Due to the inclusion of lagged form of employment variables (and lagged health featuring as an explanatory variable), the estimating sample comprises data from waves 2 to 10 of HILDA.

Many of the variables included in the analyses are those commonly used in labour supply models and many of these were included in the modelling in chapter 4. Some variables were explained in more detail in the previous chapter while some other variables do require further explanation.

Age was not included as it was very highly correlated with experience and experience is considered more likely to be causal than age. As was the case in the example of employment participation in chapter 4, lagged and initial health are included in order to reduce the possibility of simultaneity bias.

For comparison purposes, an alternative specification was estimated which included a variable indicating a health shock. This measure used self-reported information contained in HILDA and is based on responses to the question on health compared to 12 months ago. A health shock is defined as somewhat worse or much worse health compared to 12 months ago. A dummy variable was created with value 1 if a health shock occurred and 0 otherwise. The health shock measure is included for comparison. Nonetheless, it should be noted that, as made explicit in chapter 4, this measure is flawed and results using the health index are considered to be superior.

Due to the multinomial nature of the dependent variable, each specification included two lagged form of employment variables to capture state dependence. In the case of the specification comparing not-employed, part-time and full-time, lagged not-

[32] Observations are assumed missing at random.
[33] The lower estimating sample for the second specification arose from excluding the self-employed. Form of employment is not observed for the self-employed in the second specification of form of employment.

employed (unemployed or not in the labour force) and lagged part-time variables were included with full-time being the base case. In the case of the specification comparing not-employed, casual and permanent, lagged not-employed and lagged casual were included with permanent being the base case.

Table 28 and Table 29 document the total number of form of employment transitions over the 9 waves of HILDA included in the estimating sample (waves 2 to 10)[34]. Table 28 contains the employment transitions for the first specification of form of employment while Table 29 contains the transitions for the second specification. Both tables illustrate a high degree of state dependence (persistence) in form of employment, particularly for not-employed, full-time and permanent. This supports the inclusion of the variables to capture state dependence.

Table 28: Number (and Percentage) of Transitions over Waves 2 to 10 of the HILDA Survey, Estimating Sample Form of Employment Specification I

	Not Employed	**Part-time**	**Full-time**	**Total**
Not Employed	6,815 (80.38)	1,090 (12.86)	573 (6.76)	8,478 (100)
Part-time	891 (10.88)	5,853 (71.49)	1,443 (17.63)	8,187 (100)
Full-time	768 (3.53)	1,316 (6.04)	19,700 (90.43)	21,784 (100)
Total	8,474 (22.04)	8,259 (21.48)	21,716 (56.48)	38,449 (100)

Table 29: Number (and Percentage) of Transitions over Waves 2 to 10 of the HILDA Survey, Estimating Sample Form of Employment Specification II

	Not Employed	**Casual**	**Permanent**	**Total**
Not Employed	6,827 (84.34)	682 (8.42)	586 (7.24)	8,095 (100)

[34] Note that while Table 28 and Table 29 contain all transitions over waves 2 to 10 of HILDA for the estimating sample for both specifications, the total observations in each table are lower than that for the econometric models. This reflects the unbalanced nature of the panel. Transitions can only be observed where there are observations in consecutive waves for each individual.

Casual	525 (13.82)	2,280 (60)	995 (26.18)	3,800 (100)
Permanent	781 (4.16)	741 (3.95)	17,258 (91.9)	18,780 (100)
Total	8,133 (26.51)	3,703 (12.07)	18,839 (61.41)	30,675 (100)

Two variables representing the initial period outcome (initial period form of employment indicators) were derived for each individual and included in the model specification dealing with initial conditions. These were initial not-employed and initial part-time employment indicators for the first specification and initial not-employed and initial casual employment for the second specification.

The next section presents results from estimating the three types of models set out at the beginning of section 5.3.

5.5 Results

This section presents results from estimating form of employment models. It considers the results from the two specifications of form of employment, the first comparing not-employed, part-time and full-time employment and the second comparing not-employed, casual and permanent employment. It begins by presenting estimates using the first specification which check the robustness of results from multinomial form of employment models to the choice of model specification and identify the preferred model to be used (section 5.5.1). It then analyses and interprets these results using sample estimates and scenarios using predicted probabilities obtained from the preferred model (section 5.5.2). The results from the second specification of form of employment are then presented and discussed (section 5.5.3) with the final part of the section analysing and interpreting results from this second specification using sample estimates and scenarios (section 5.5.4).

5.5.1 Form of Employment Specification I

Table 30 presents the parameter estimates obtained using multilevel modelling (gllamm) from the results from the first specification of form of employment (that comparing not-employed, part-time and full-time employment) using the three different estimators described at the beginning of section 5.3[35,36]. The effect of not being employed at t-1 or being employed part-time at t-1 are both highly significant in all three specifications providing strong evidence of state dependence[37]. This indicates that dynamics are relevant. The parameter estimates for both variables are positive in sign suggesting that being out of work or part-time in the preceding year increases the likelihood of being part-time or not-employed in the current year relative to full-time employment.

Table 30: Multinomial Logit Parameter Estimates (and Standard Errors) for Outcomes of not-employed and Part-time Relative to Full-time Employment, Pooled vs. Multilevel gllamm

	Pooled (1)		**Multilevel gllamm (2)**		**Multilevel gllamm (3)**	
	Not Employed	*Part-time*	*Not employed*	*Part-time*	*Not employed*	*Part-time*
Not employed at t-1	4.090*** (0.0635)	2.559*** (0.0569)	3.716*** (0.0776)	2.193*** (0.0723)	3.113*** (0.0797)	1.661*** (0.0758)
Part-time at t-1	2.113*** (0.0562)	3.558*** (0.0480)	1.640*** (0.0715)	3.096*** (0.0650)	1.133*** (0.0705)	2.473*** (0.0620)
Not employed at t=1					1.811*** (0.0986)	1.597*** (0.0937)
Part-time at t=1					1.371*** (0.0896)	1.748*** (0.0801)
Post GFC	0.0226 (0.0437)	0.0496 (0.0366)	0.0355 (0.0484)	0.0576 (0.0420)	0.133** (0.0603)	0.152*** (0.0557)
Lagged health index	-0.029*** (0.003)	- 0.0163*** (0.003)	-0.031*** (0.003)	-0.019*** (0.003)	-0.035*** (0.003)	-0.022*** (0.003)

[35] Multilevel models were estimated using 8 and 12 quadrature points. The results were not sensitive to choice of quadrature points therefore results reported use 8 quadrature points.
[36] As a comparison a model with dependent variable hours worked was also estimated to check any difference in findings. Results from the hours worked model correspond with those from the not employed/part-time/full-time model with persons in better health significantly more likely to work more hours. The categorical form of employment model is preferred in this chapter as it more clearly distinguishes form of employment and it is the implications arising from different forms of employment which is of interest in this chapter.
[37] In the following discussion, results are classed as significant if they are statistically significant at the conventional 5% level or better.

	Pooled (1)		Multilevel gllamm (2)		Multilevel gllamm (3)	
	Not Employed	*Part-time*	*Not employed*	*Part-time*	*Not employed*	*Part-time*
Initial health	-0.008*** (0.002)	0.002 (0.002)	-0.012*** (0.003)	-0.002 (0.002)	-0.009*** (0.003)	-0.001 (0.003)
Female	-0.550*** (0.206)	0.0765 (0.205)	-0.416* (0.233)	0.209 (0.231)	-0.436* (0.260)	-0.0179 (0.253)
Lagged health index*female	0.0141*** (0.0030)	0.0115*** (0.0028)	0.0164*** (0.0033)	0.0140*** (0.0032)	0.0163*** (0.0036)	0.0155*** (0.0035)
Has children aged 0-4	-0.156 (0.115)	-0.0215 (0.0926)	-0.146 (0.125)	-0.00176 (0.102)	-0.285* (0.154)	0.0583 (0.123)
Has children aged 5-14	-0.0673 (0.0504)	0.205*** (0.0403)	0.0623 (0.0576)	0.346*** (0.0489)	0.365*** (0.0918)	0.419*** (0.0780)
Has children aged 0-4*Female	2.639*** (0.137)	1.491*** (0.115)	3.037*** (0.153)	1.876*** (0.131)	3.211*** (0.169)	2.076*** (0.145)
Married/De Facto	0.698*** (0.0709)	0.0643 (0.0692)	0.743*** (0.0811)	0.100 (0.0793)	0.792*** (0.144)	-0.0581 (0.128)
Partner is employed	-1.044*** (0.0772)	-0.0779 (0.0716)	-1.184*** (0.0872)	-0.211** (0.0825)	-1.077*** (0.120)	-0.246** (0.110)
Weekly non labour income ($100's)	0.0260*** (0.0047)	0.0169*** (0.0039)	0.0275*** (0.0049)	0.0182*** (0.0043)	0.0197*** (0.0044)	0.0135*** (0.0042)
Partner wage	0.0082*** (0.0016)	0.0055*** (0.0013)	0.0094*** (0.0018)	0.0067*** (0.0015)	0.0062*** (0.0018)	0.0055*** (0.0016)
Experience	-0.091*** (0.007)	-0.024*** (0.006)	-0.128*** (0.0085)	-0.063*** (0.008)	-0.092*** (0.015)	-0.072*** (0.014)
Experience squared	0.0026*** (0.0001)	0.0010*** (0.0001)	0.0035*** (0.0002)	0.0019*** (0.0002)	0.0032*** (0.0002)	0.0018*** (0.0002)
Economic inactivity	0.225*** (0.0077)	0.111*** (0.0072)	0.295*** (0.0104)	0.181*** (0.0100)	0.193*** (0.0191)	0.146*** (0.0184)
Economic inactivity squared	-0.004*** (0.0002)	-0.002*** (0.0003)	-0.005*** (0.0003)	-0.003*** (0.0003)	-0.005*** (0.0003)	-0.003*** (0.0003)
Unemployment rate	0.0348*** (0.0105)	0.0367*** (0.00935)	0.0576*** (0.0115)	0.0606*** (0.0103)	0.0480*** (0.0143)	0.0460*** (0.0128)
Degree or above	-0.484*** (0.0632)	-0.268*** (0.0528)	-0.651*** (0.0752)	-0.433*** (0.0663)	-2.492*** (0.435)	-1.989*** (0.323)
Advanced	-0.208** (0.0813)	-0.154** (0.0658)	-0.294*** (0.0947)	-0.239*** (0.0809)	-1.589*** (0.423)	-0.780** (0.348)

	Pooled (1)		Multilevel gllamm (2)		Multilevel gllamm (3)	
	Not Employed	*Part-time*	*Not employed*	*Part-time*	*Not employed*	*Part-time*
Diploma/Diploma						
Certificate	-0.231*** (0.0602)	-0.100* (0.0528)	-0.324*** (0.0705)	-0.199*** (0.0646)	-1.104*** (0.238)	-0.389* (0.204)
Year 12	-0.0156 (0.0662)	-0.0437 (0.0600)	-0.0397 (0.0775)	-0.0646 (0.0723)	-0.583* (0.317)	-0.401 (0.269)
Time averaged characteristics						
Experience					-0.0124 (0.0127)	0.0261** (0.0118)
Economic inactivity					0.0877*** (0.0171)	0.0263 (0.0166)
Unemployment rate					-0.0013 (0.0271)	0.0097 (0.0241)
Has children aged 0-4					0.601*** (0.158)	0.206 (0.136)
Has children aged 5-14					-0.899*** (0.128)	-0.467*** (0.110)
Married/De facto					0.0098 (0.182)	0.261 (0.167)
Partner is employed					-0.235 (0.174)	0.0230 (0.159)
Weekly non labour income ($100’s)					0.0461*** (0.0103)	0.0342*** (0.0090)
Partner wage					0.0112*** (0.0031)	0.0049* (0.0026)
Degree or above					1.961*** (0.447)	1.688*** (0.335)
Advanced Diploma/Diploma					1.338*** (0.439)	0.570 (0.363)
Certificate					0.841*** (0.254)	0.179 (0.219)
Year 12					0.499 (0.333)	0.287 (0.285)
Constant	-1.218***	-2.735***	-0.832***	-2.341***	-1.760***	-3.093***

	Pooled (1)		Multilevel gllamm (2)		Multilevel gllamm (3)	
	Not Employed	*Part-time*	*Not employed*	*Part-time*	*Not employed*	*Part-time*
	(0.213)	(0.210)	(0.242)	(0.240)	(0.319)	(0.308)
Between individual variance			1.152*** (0.0934)		1.730*** (0.1082)	
Sample	51,941		51,941		51,941	
Individuals	9.696		9,696		9,696	
Pseudo R squared	0.5123		0.5136		0.5215	
BIC	50419.51		50012.48		49166.86	

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students

The significance of the between individual variance (the level 2 variance from inclusion of a random intercept) provides a statistical test of whether a panel data model is to be preferred. If the between individual variance is statistically significant then a significant proportion of total variance in the form of employment model is explained by panel level variance (there is unobserved heterogeneity). The between individual variance is strongly significant in both panel models (columns 2 and 3 of Table 30) indicating that there is statistically significant unobserved heterogeneity.

A likelihood ratio (LR) test to compare the fit of the model with individual effects against a model without individual effects was also conducted to test the hypothesis that there are no between individual effects. The LR test statistic provided overwhelming evidence of group effects providing further justification for preferring a panel data (multilevel) model.

A comparison of the magnitude of the between individual variance in moving from the most simple model given by equation (2) (a constant only random intercept model) and the more complex model given by equation (4) incorporating significant covariates and the Wooldridge method found that between individual variance is reduced from 10.07 to 1.73. The inclusion of the relevant explanatory variables has explained a large amount of between individual variance however the remaining unexplained variance, while lower, is still statistically significant.

The Bayesian Information criterion (BIC) is provided in the model results for each specification in Table 30 as a criterion for model selection with the lowest BIC reflecting the preferred model. A comparison of BIC indicated a parsimonious model is to be preferred, with the lowest BIC being for the Wooldridge estimator.

Part-time employment and being out of work in the initial period is also highly significant. This suggests (as was the case in chapter 4) that initial conditions do play a role and cannot be ignored. There is a higher likelihood of non-employment or part-time employment post global financial crisis

The time averaged variables play an important role with many of these being highly significant (though more so for the not-employed outcome). This suggests that the relatively fixed underlying differences between individuals are significant determinants of form of employment.

Lagged health has a negative effect though it is small in magnitude. Poorer health is associated with a higher likelihood of non-employment relative to full-time employment. Better health increases the likelihood of full-time employment among persons who are employed. The effect of health differs by gender with health having a smaller effect on the likelihood of form of employment for women (taking account of the interaction between female and health). Although the magnitude of the effect of health appears small in a single year, once the compound effect is taken into account over time (both in terms of any prolonged poor health but also negative implications arising from part time employment and non-employment) this effect of health on form of employment becomes more important.

Looking at the results from the parameter estimates in Table 30, the remaining variables have the expected effects. Employment experience significantly increases the likelihood of full-time employment, as does higher education. This is consistent with human capital arguments given that costs in foregone income in leaving employment or working part-time are likely to be higher for those with greater levels of human capital obtained either on the job or via education.

Women with young children are far less likely to be in full-time employment. This is consistent with what is known about the effect of domestic responsibilities on women's ability and/or choice to engage in paid work. Partner wage and non labour income are both linked with a lower likelihood of full-time employment.

Persons who are married or in a de facto relationship are more likely to be not in work, however having an employed partner increases the likelihood of full-time employment. This suggests that the partner labour force status variable is likely to be capturing other partner characteristics for example partnering preferences (e.g. professionals are more likely to marry professionals) but also that the respondent and their partner face the same local labour market.

The results from the estimates presented in Table 30 indicate that dynamics are relevant, unobserved heterogeneity is important and that initial conditions do play a role. A panel data model is to be preferred when estimating form of employment models. There is evidence supporting the hypothesis that those in poorer health are more likely to be employed part-time relative to full-time employment. There is also evidence that, as expected, poor health is associated with a higher likelihood of non-employment, suggesting health selection out of employment.

MCMC estimates for the models presented in columns 2 and 3 of Table 30 appear in Table A-15 in the Appendix. The estimates are very close to those provided by gllamm suggesting findings are robust to the estimation procedure used[38].

Table 31 presents results using the measure of self-assessed health shock alongside the original results from column 3 of Table 30 for comparison purposes. These

[38] The much faster processing time when using the MCMC simulation procedure also allowed estimation of a more complex model with two random intercept terms, one for the not-employed outcome and one for the part-time outcome. The parameter estimates were very close to those in the model with a single random intercept. These results showed that the random intercept was higher amongst the not-employed compared with part-time. There is a higher degree of unobserved heterogeneity amongst persons who are not employed (random intercept is 2.558 compared with 1.701 for part-time)..

results suggest that the effects of health become larger for those not-employed when using the alternative health measure (see column 2)[39]. A health shock is associated with an increased probability of non-employment (relative to full-time employment) but does not have a significant effect on the likelihood of part-time employment[40].

Table 31: Multinomial Logit Parameter Estimates (and Standard Errors) for Outcomes of not-employed and Part-time Relative to Full-time Employment, Comparison Specifications Estimated using gllamm

	Health Index (1)		**Health shock (2)**	
	Not Employed	*Part-time*	*Not employed*	*Part-time*
Not employed at t-1	3.113*** (0.0797)	1.661*** (0.0758)	3.221*** (0.0806)	1.703*** (0.0768)
Part-time at t-1	1.133*** (0.0705)	2.473*** (0.0620)	1.111*** (0.0698)	2.453*** (0.0623)
Not employed at t=1	1.811*** (0.0986)	1.597*** (0.0937)	1.834*** (0.101)	1.623*** (0.0959)
Part-time at t=1	1.371*** (0.0896)	1.748*** (0.0801)	1.377*** (0.0896)	1.785*** (0.0808)
Post GFC	0.133** (0.0603)	0.152*** (0.0557)	0.165*** (0.0590)	0.168*** (0.0548)
Lagged health index	-0.035*** (0.003)	-0.022*** (0.003)		
Health shock			0.797*** (0.105)	0.0997 (0.107)
Initial health	-0.009*** (0.003)	-0.001 (0.003)	-0.0242*** (0.0022)	-0.0106*** (0.0021)
Female	-0.436* (0.260)	-0.0179 (0.253)	0.626*** (0.0722)	1.078*** (0.0633)
Lagged health index*female	0.0163*** (0.0036)	0.0155*** (0.0035)		
Health shock*female			-0.276** (0.135)	-0.0717 (0.133)

[39] It must be kept in mind in comparing health measures that the estimate for the health index reflects the effect of a 1 unit change in the 0-100 index with higher values representing better health. The health shock measure is a dummy variable with value 1 representing an adverse shock to health.
[40] Zucchelli *et al.* (2010) also found (using Hazard models) that the effects of health are larger using the alternative measure in their study on the effects of health shocks on labour market exits.

	Health Index (1)		Health shock (2)	
	Not Employed	*Part-time*	*Not employed*	*Part-time*
Has children aged 0-4	-0.285* (0.154)	0.0583 (0.123)	-0.356** (0.153)	0.161 (0.122)
Has children aged 5-14	0.365*** (0.0918)	0.419*** (0.0780)	0.396*** (0.0910)	0.425*** (0.0781)
Has children aged 0-4*Female	3.211*** (0.169)	2.076*** (0.145)	3.285*** (0.169)	2.041*** (0.144)
Married/De Facto	0.792*** (0.144)	-0.0581 (0.128)	0.757*** (0.142)	-0.0535 (0.127)
Partner is employed	-1.077*** (0.120)	-0.246** (0.110)	-1.055*** (0.118)	-0.236** (0.108)
Weekly non labour income ($100's)	0.0197*** (0.0044)	0.0135*** (0.0042)	0.0199*** (0.0048)	0.0133*** (0.0042)
Partner wage	0.0062*** (0.0018)	0.0055*** (0.0016)	0.0049*** (0.0016)	0.0043*** (0.0015)
Experience	-0.092*** (0.015)	-0.072*** (0.014)	-0.0836*** (0.0146)	-0.0676*** (0.0139)
Experience squared	0.0032*** (0.0002)	0.0018*** (0.0002)	0.0032*** (0.0002)	0.0018*** (0.0002)
Economic inactivity	0.193*** (0.0191)	0.146*** (0.0184)	0.1992*** (0.0190)	0.1547*** (0.0186)
Economic activity squared	-0.005*** (0.0003)	-0.003*** (0.0003)	-0.0048*** (0.0003)	-0.0033*** (0.0003)
Unemployment rate	0.0480*** (0.0143)	0.0460*** (0.0128)	0.0408*** (0.0143)	0.0404*** (0.0125)
Degree or above	-2.492*** (0.435)	-1.989*** (0.323)	-2.992*** (0.417)	-2.165*** (0.320)
Advanced Diploma/Diploma	-1.589*** (0.423)	-0.780** (0.348)	-1.626*** (0.414)	-0.775** (0.350)
Certificate	-1.104*** (0.238)	-0.389* (0.204)	-1.205*** (0.243)	-0.449** (0.206)
Year 12	-0.583* (0.317)	-0.401 (0.269)	-0.813** (0.316)	-0.400 (0.268)
Time averaged characteristics				
Experience	-0.0124	0.0261**	-0.0211*	0.0201*

	Health Index (1)		Health shock (2)	
	Not Employed	*Part-time*	*Not employed*	*Part-time*
	(0.0127)	(0.0118)	(0.0123)	(0.0115)
Economic inactivity	0.0877*** (0.0171)	0.0263 (0.0166)	0.0855*** (0.0171)	0.0240 (0.0168)
Unemployment rate	-0.0013 (0.0271)	0.0097 (0.0241)	-0.0148 (0.0273)	0.0124 (0.0242)
Has children aged 0-4	0.601*** (0.158)	0.206 (0.136)	0.591*** (0.159)	0.133 (0.137)
Has children aged 5-14	-0.899*** (0.128)	-0.467*** (0.110)	-0.915*** (0.128)	-0.438*** (0.110)
Married/De facto	0.0098 (0.182)	0.261 (0.167)	0.0474 (0.182)	0.276* (0.167)
Partner is employed	-0.235 (0.174)	0.0230 (0.159)	-0.260 (0.175)	0.0114 (0.159)
Weekly non labour income ($100’s)	0.0461*** (0.0103)	0.0342*** (0.0090)	0.0433*** (0.0097)	0.0345*** (0.0088)
Partner wage	0.0112*** (0.0031)	0.0049* (0.0026)	0.0125*** (0.0032)	0.0061** (0.0026)
Degree or above	1.961*** (0.447)	1.688*** (0.335)	2.371*** (0.429)	1.835*** (0.331)
Advanced Diploma/Diploma	1.338*** (0.439)	0.570 (0.363)	1.279*** (0.431)	0.551 (0.364)
Certificate	0.841*** (0.254)	0.179 (0.219)	0.909*** (0.259)	0.217 (0.221)
Year 12	0.499 (0.333)	0.287 (0.285)	0.696** (0.333)	0.293 (0.285)
Constant	-1.760*** (0.319)	-3.093*** (0.308)	-2.936*** (0.293)	-3.957*** (0.265)
Between individual variance	1.730*** (0.1082)		1.834*** (0.1116)	
Sample	51,941		52,882	
Individuals	9,696		9,521	
Pseudo R squared	0.5215		0.5234	
BIC	49166.86		49945.07	

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 wave s of HILDA. 3) Excludes full-time students.

Apart from differences in the effect of the health measure on form of employment in Table 31, there are few differences in the results between the two models. There are minor differences in the effect of initial health and differences in the effect of gender (and the interaction between gender and health). The differences in the effect of initial health are understandable given that this variable has a different relationship with the health index than it does with the health shock measure. The reason behind the difference in the effect of gender in the two models is less clear[41].

Analysing the diagnostics towards the bottom of Table 31 suggests that the model using the health index is to be preferred. The BIC is lower for this model and the level of between individual variance is also lower suggesting that inclusion of the health index explains a greater amount of between individual variance compared with the health shock measure. Aside from this, the health index measure is the preferred measure of health for the reasons set out in chapter 4.

The parameter estimates provided in Table 30 and Table 31 are the log odds. Findings can be more sensibly interpreted by calculating predicted probabilities. The next section analyses the results from the preferred model (that from column 1 of Table 31) by reporting predicted probabilities.

5.5.2 Analysis of Specification I Results

To aid interpretation of the results from the form of employment model, the average predicted probabilities of each form of employment by selected characteristics of interest are reported in this section. The numbers presented in the tables of results in the previous section do not have a straightforward interpretation in terms of the magnitude of the effects of the explanatory variables on form of employment. Average predicted probabilities present a much clearer picture of the relationships.

[41] One explanation is that the interaction term between health and gender is different in the model using the health shock measure and this has influenced the estimate of the effect of gender.

These enable more accurate quantitative estimates of the magnitude of effects across dimensions of interest and comparisons by characteristics such as gender, particularly useful in identifying the differences by key variables.

Table 32: Observations (and Percentage) in Each Health Index Quintile for Estimating Sample by Form of Employment

Health quintile	Not Employed	Part-time	Full-time	Total
1 (lowest)	4,418 (43.34)	1,739 (17.06)	4,037 (39.60)	10,194 (100.00)
2	1,895 (18.83)	1,895 (18.83)	6,273 (62.34)	10,063 (100.00)
3	1,522 (15.64)	2,052 (21.09)	6,157 (63.27)	9,731 (100.00)
4	1,447 (15.77)	2,232 (24.32)	5,498 (59.91)	9,177 (100.00)
5 (highest)	1,258 (15.55)	2,230 (27.56)	4,602 (56.89)	8,090 (100.00)
Total	10,540 (22.30)	10,148 (21.47)	26,567 (56.22)	47,255 (100.00)

The key characteristic of interest in this thesis is health. This is analysed by comparing predicted probabilities of form of employment by health index quintiles where the lowest quintile reflects those in the worst health. Table 32 reports the number of observations in each health index quintile by form of employment for the estimating sample from the form of employment model presented in the previous section. A large proportion of persons in the lowest health index quintile were not employed and this represents just over 40 per cent of all persons who were not employed. Persons in part-time and full-time employment were more evenly distributed amongst the health index quintiles however the full time employed represent a much lower proportion of those in the lowest health index quintile in comparison with those in the other health quintiles.

Although those in the lowest health quintile are less likely to be employed, almost 40 per cent still work full time. This raises the question of how unhealthy they are.

Intersection between health measures was considered in chapter 3 and chapter 4, finding that work limiting conditions are closely linked to poor health regardless of the health measure used, that there is a linear relationship between self assessed health and the mean score of the health index (with those in poor health having a very low mean health index score) and that persons experiencing work limiting conditions have a much lower mean score compared with those with conditions not limiting work or who have no long term condition at all.

Table 33 uses the estimating sample from the form of employment model to show the number of persons with a long term condition limiting work, a condition having no impact on work or having no health condition by health index quintile. This goes further than viewing the mean score, illustrating that the vast majority of persons with a work limiting long term condition are in the lowest health index quintile. This goes some way towards explaining why the relationship between health and form of employment is not a linear one in Table 32. The larger than expected proportion employed in full time work within the lowest health index quintile can perhaps be explained by the continuous nature of the health index. While the lowest health quintile includes those who are likely the sickest, it also covers a range of values and those on the higher end of this range may be more capable of employment (and longer hours of work).

Table 33: Type of Long Term Condition by Health Index Quintile, Estimating Sample from Form of Employment Model

Health quintile	**Long term limiting type or amount of work**	**Long term condition has no impact**	**No long term condition**	**Total**
1 (lowest)	5,980	1,282	2,932	10,194
2	940	1,242	7,881	10,063
3	147	569	9,015	9,731
4	21	248	8,908	9,177
5 (highest)	0	52	8,038	8,090
Total	7,088	3,393	36,774	47,255

5. The Effects of Health on Form of Employment

The predicted probabilities presented in this section are a combination of sample estimates and counterfactuals. It is important to keep in mind the distinction between these two concepts. The results of sample estimates are influenced by characteristics of persons who fall within the sample selected. For example, if we look at the predicted probabilities of form of employment by health quintile, the predicted probabilities will be influenced by health quintile but they are also influenced by the education, age and other characteristics of persons which differ by health quintile and these sample characteristics also have an effect on probability of a specific form of employment.

Counterfactual analysis provides the expected predicted probabilities if everybody in the sample had the same selected characteristic (e.g. gender) holding all other variables at the average for the sample. These estimates are not as heavily influenced by sample characteristics but it must be noted that it is possible that few people in the sample will have the exact characteristics used in the counterfactual, plus the parameter estimates upon which the predicted probabilities are based are derived from the sample therefore counterfactuals should be used for suggestive purposes only.

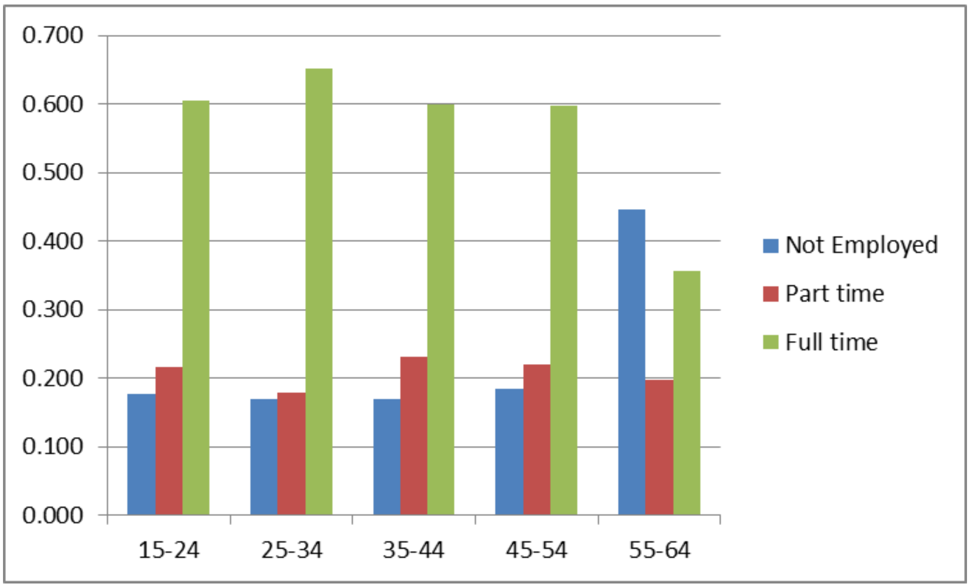

Figure 3: Average Predicted Probability of Form of Employment by Age

The analysis using predicted probabilities begins with Figure 3 (and Table A-16 in the Appendix)[42]. This demonstrates the relationship between age and average predicted probability of form of employment in the estimating sample from the form of employment model. The probability of non-employment and of full-time employment varies little until the oldest age group is reached. Those aged 25-34 have the highest rates of employment by a small margin.

The magnitude of associations between health and form of employment can be assessed from the predicted probabilities presented in Figure 4, Figure 5 and Figure 6 (for corresponding tables see Table A-17, Table A-18 and Table A-19 in the Appendix). These figures present the average predicted probabilities of form of employment by three different health measures: the health index, SF-36 Physical Functioning and SF-36 Mental Health. Each compares the probability of form of employment for those in the lowest quintile of health with those in the highest quintile of health.

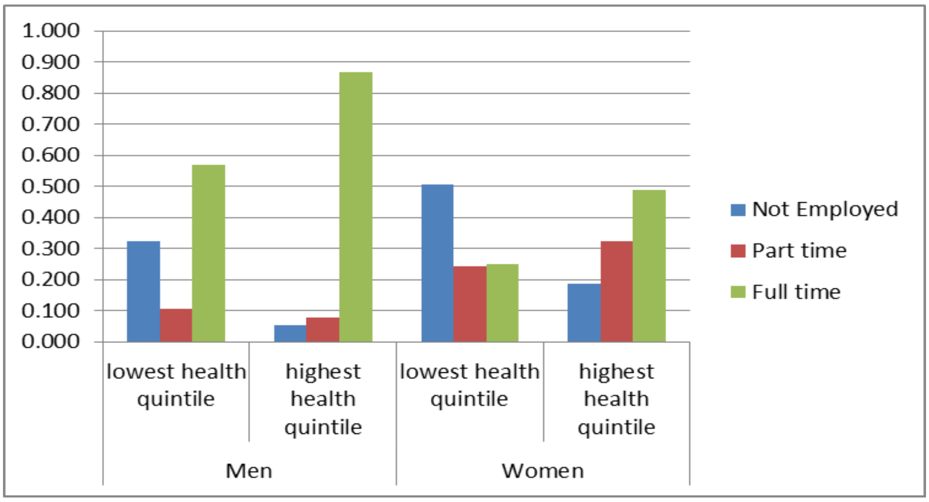

Figure 4: Average Predicted Probability of Form of Employment by Health Index Quintile and Gender

The results show that both men and women in the lowest health index quintile have a higher probability of non-employment and lower probability of full-time employment compared with persons in the highest health index quintile. Men in poor health have a higher probability of part-time employment. It appears that women in

[42] Throughout this section, tables corresponding with the figures showing predicted probabilities appear in the Appendix.

the lowest health quintile have a lower probability of part-time employment compared with those in the highest quintile however this is not inconsistent with the parameter estimates which found that poorer health was associated with a higher likelihood of part-time employment. The increased likelihood of employment for persons in better health translates to an increase for both part time employment and full time employment but the relative effects are what is captured in the analysis and rates of increase by health differ between part time and full time employment.

The relationships between physical functioning and form of employment in Figure 5 and that between mental health and form of employment in Figure 6 are very similar to the results obtained using the health index. Men and women in the lowest quintile for both physical functioning and mental health have a higher probability of non-employment and lower probability of full-time employment compared with persons in the highest quintile of both of these measures. The relationship is stronger for physical functioning than for mental health, mental health does not have as strong an effect on probability of form of employment compared with the other health measures (particularly for women). The similarities between results using different measures of health support the previously discussed findings of intersection between health measures.

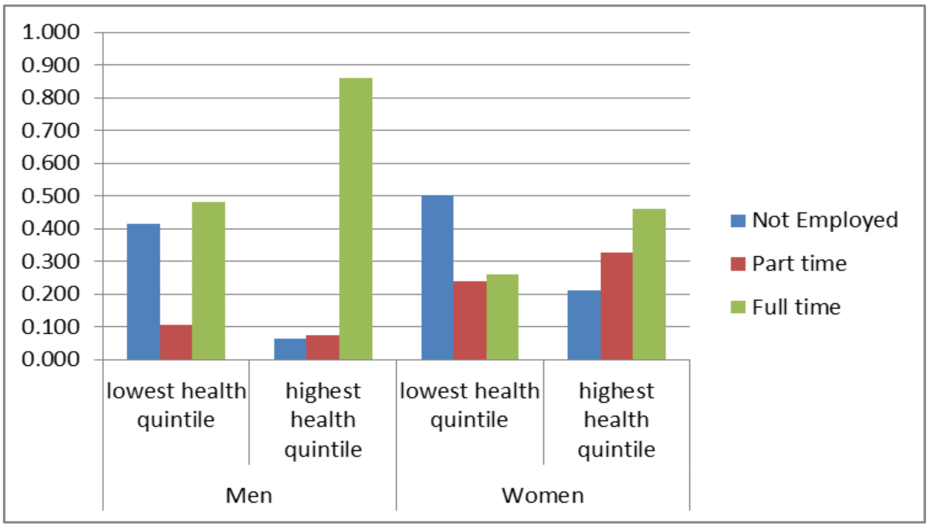

Figure 5: Average Predicted Probability of Form of Employment by Physical Functioning Quintile and Gender

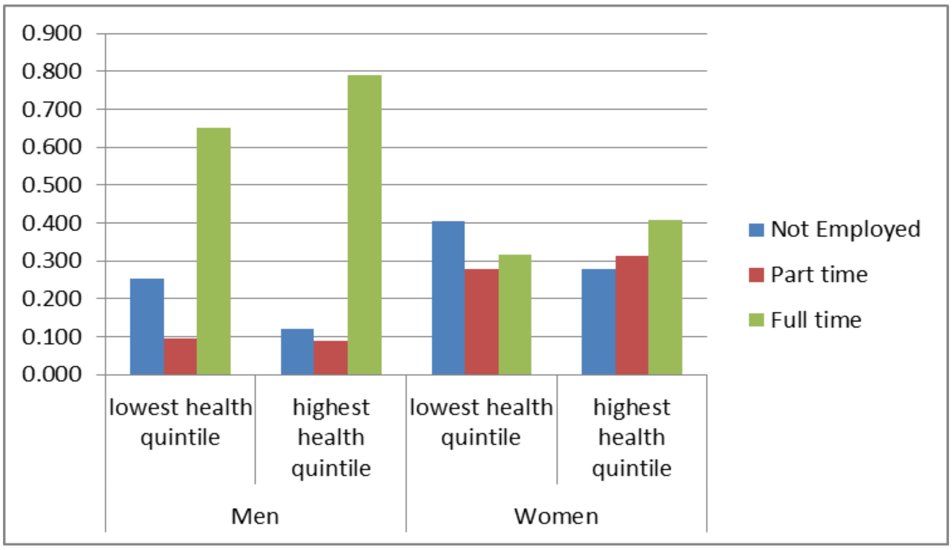

Figure 6: Average Predicted Probability of Form of Employment by Mental Health Quintile and Gender

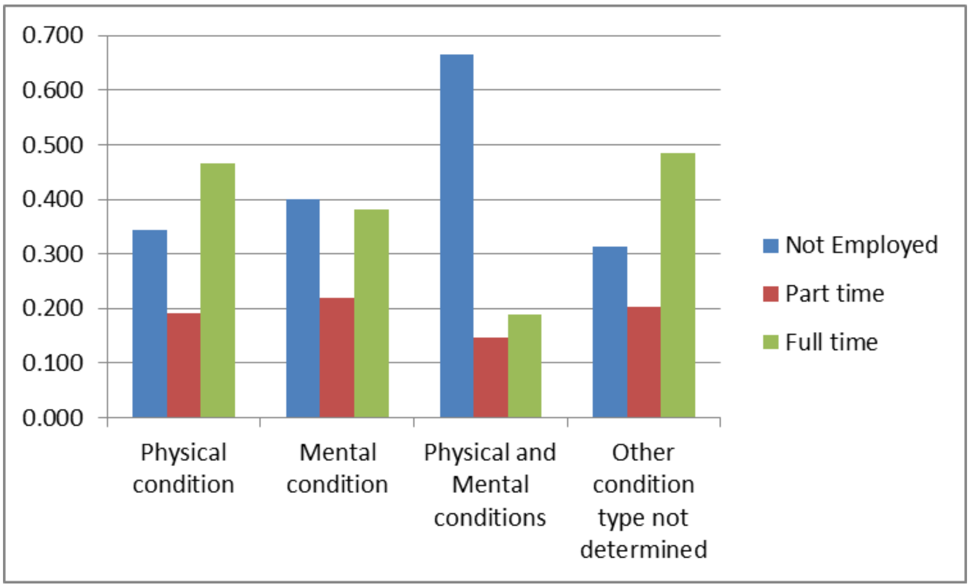

Figure 7: Average Predicted Probability of Form of Employment by Type of Long Term Condition

The relationship between health and form of employment might be expected to be stronger for those persons experiencing both physical and mental health conditions. Figure 7 shows this to be the case (see Table A-20 in the Appendix for the corresponding table). Persons who have both a physical and a mental long term health condition have a far higher predicted probability of non-employment and lower probability of either part-time or full-time employment compared with persons with physical long term condition or mental long term condition only (though the reduction in the probability of full-time employment is more marked). This is likely to be capturing the effect of comorbid health conditions to some degree[43].

The relationship between average predicted probability by type of long term condition distinguishing persons with conditions limiting work, those not limiting work ability and those with no health condition was also analysed by gender. The results were as expected and appear in Table A-22 in the Appendix. Persons with a work limiting health condition had a much higher probability of non-employment and much lower probability of full-time employment regardless of gender. The predicted probability of form of employment did not differ greatly between persons with a long term condition not impacting work ability and persons who did not have a long term condition.

Duration of health condition can also be expected to affect probability of form of employment. The relationship between average predicted probability of form of employment and duration of long term health condition can be roughly inferred from Table A-23 in the Appendix. Prolonged impairment of health has greater implications for disadvantage than a transitory experience, with health effects of longer duration likely to exacerbate the disadvantage in terms of form of employment and ability to remain employed. Table A-23 shows that longer duration is associated with a higher probability of non-employment. Results must be interpreted with caution however due to the correlation between duration of long term condition (or any health condition for that matter) and age (note that Figure 3 showed that age is associated with a higher probability of non-employment). The estimates are based on people being assigned average parameter values rather than individual specific values and therefore do not account for differences by age. The duration variable also does not distinguish between more serious long term conditions and those not having a great impact on work capacity (such as sight impairments requiring glasses). It simply identifies the duration of the long term condition the person has experienced the longest. The results are however very suggestive.

---

[43] The data used for Figure 7 was also disaggregated by gender (see Table A-21). The relationship was found to be the same by gender as for Figure 7 although the effect of physical only and mental only health conditions differed by gender reflecting the higher average probability of non-employment and higher average probability of part-time employment among women.

The preceding discussion presented predicted probabilities using sample estimates. As discussed earlier, these are influenced by the specific traits of persons having the characteristic of the variable being analysed. The remainder of this section deals with counterfactuals. These are the expected predicted probabilities if everybody in the sample had the same selected characteristic holding all other variables at the average for the sample. Counterfactuals are presented for a key scenario, an analysis of the effect of health index quintile on probability of form of employment. These provide estimates of the relationship between health and form of employment which are not influenced by the traits of those with a given level of health.

Figure 8 assesses the magnitude of associations between health and form of employment setting all observations to have the same health (chosen to be the means of each health index quintile) and averaged across all observations. It can be compared and contrasted with Figure 4 (and Table A-17 in the Appendix) which showed this relationship using sample estimates. It is apparent from Figure 8 that the relationship between health index and form of employment has narrowed considerably compared with that seen in Figure 4. This suggests that a great deal of difference between probability of form of employment can be explained by the characteristics of persons belonging in a specific health quintile (e.g. age, education).

Calculating the probabilities in Figure 8 amongst the employed only finds that men in the lowest health quintile are 2.8 per cent more likely to be employed part time compared with those in the highest health quintile. Women in the lowest health quintile are 1 per cent more likely to be employed part time. Despite the lower estimates provided by the counterfactual compared with sample estimates, poorer health is still associated with a lower probability of full-time employment and higher probability of part-time employment (particularly for men) and a higher probability of non-employment.

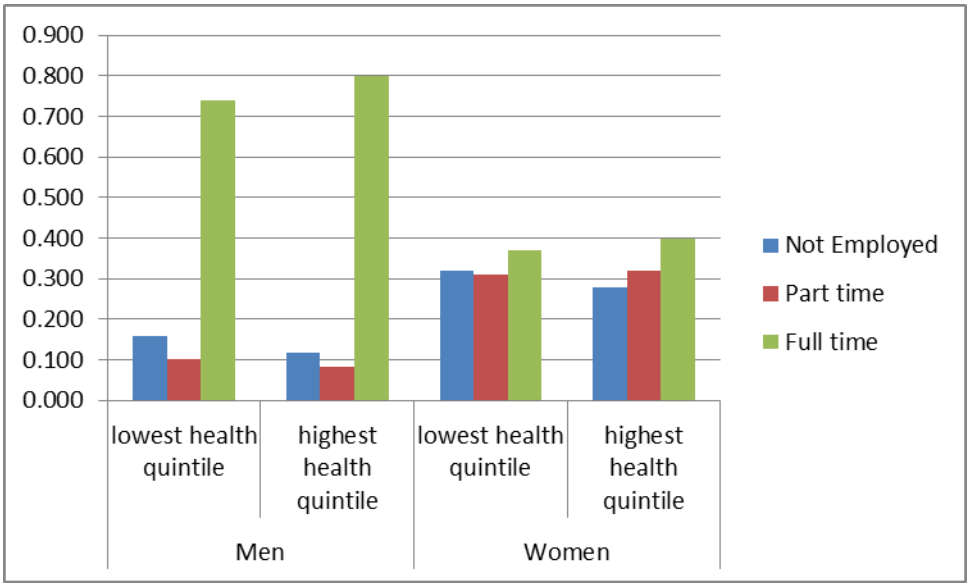

Figure 8: Average Predicted Probability of Form of Employment by Health Index Quintile and Gender

The preceding discussion has established clear relationships between health and form of employment through interpreting the results presented in section 5.5.1 via predicted probabilities estimated using the preferred model of form of employment. This discussion found further evidence that persons in poor health are less likely to employed. Amongst persons who are employed, those in better (poorer) health have a greater (lower) probability of full-time employment. The next section presents the parameter estimates from estimating models using the second specification of form of employment-that comparing not-employed, casual and permanent.

5.5.3 Form of Employment Specification II

Table 34 presents results for the second specification of form of employment (that comparing not-employed, casual and permanent) using the three different estimators set out at the beginning of section 5.3. The effect of not being employed at t-1 or being employed casually at t-1 are both highly significant in all three specifications providing strong evidence of state dependence. This indicates that dynamics are again relevant. As was the case in the earlier results, the effect of form of employment in the previous year appears overstated when initial conditions are ignored and when the data are pooled. The positive sign on the parameter estimates suggests that being out of work or casual in the preceding year increases the likelihood of being casually employed or not-employed in the current year relative to permanent employment.

Table 34: Multinomial Logit Parameter Estimates (and Standard Errors) for Outcomes of not-employed and Casual Relative to Permanent Employment, Pooled vs. Multilevel gllamm

	Pooled (1)		**Multilevel gllamm (2)**		**Multilevel gllamm (3)**	
	Not Employed	*Casual*	*Not employed*	*Casual*	*Not employed*	*Casual*
Not employed at t-1	3.873*** (0.0597)	2.467*** (0.0626)	3.425*** (0.0762)	2.043*** (0.0784)	2.968*** (0.0784)	1.633*** (0.0816)
Casual at t-1	1.714*** (0.0592)	3.302*** (0.0524)	1.097*** (0.0745)	2.713*** (0.0671)	0.792*** (0.0756)	2.306*** (0.0673)
Not employed at t=1					1.811*** (0.103)	1.595*** (0.103)
Casual at t=1					1.079*** (0.0964)	1.427*** (0.0914)
Post GFC	-0.0836* (0.0443)	-0.172*** (0.0431)	-0.129** (0.0529)	-0.242*** (0.0521)	-0.0275 (0.0631)	-0.140** (0.0652)
Lagged health index	-0.033*** (0.0028)	-0.017*** (0.0028)	-0.037*** (0.0033)	-0.020*** (0.0033)	-0.038*** (0.0035)	-0.021*** (0.0035)
Initial health	-0.011*** (0.0022)	-0.001 (0.0023)	-0.020*** (0.0028)	-0.010*** (0.0028)	-0.015*** (0.0030)	-0.007** (0.0029)
Female	-1.129*** (0.221)	-0.518** (0.229)	-1.228*** (0.264)	-0.614** (0.269)	-1.101*** (0.283)	-0.592** (0.283)
Lagged health index*female	0.0188*** (0.0031)	0.0109*** (0.0031)	0.0218*** (0.0037)	0.0136*** (0.0037)	0.0205*** (0.0039)	0.0132*** (0.0039)
Has children aged 0-4	-0.212* (0.117)	-0.206** (0.0961)	-0.247* (0.137)	-0.254** (0.117)	-0.403** (0.163)	-0.264* (0.138)
Has children aged 5-14	-0.127** (0.0511)	0.0633 (0.0499)	-0.0725 (0.0633)	0.122** (0.0621)	0.196** (0.0981)	0.138 (0.0970)
Has children aged 0-4*Female	2.030*** (0.134)	0.663*** (0.118)	2.484*** (0.161)	1.104*** (0.145)	2.535*** (0.173)	1.163*** (0.155)
Married/De Facto	0.660*** (0.0729)	-0.0145 (0.0774)	0.771*** (0.0899)	0.104 (0.0925)	0.943*** (0.150)	0.0367 (0.144)
Partner is	-0.798***	-0.0845	-1.023***	-0.300***	-0.975***	-0.245**

	Pooled (1)		Multilevel gllamm (2)		Multilevel gllamm (3)	
	Not Employed	*Casual*	*Not employed*	*Casual*	*Not employed*	*Casual*
employed	(0.0669)	(0.0715)	(0.0819)	(0.0847)	(0.117)	(0.115)
Rural	0.340*** (0.0664)	0.311*** (0.0668)	0.431*** (0.0844)	0.411*** (0.0837)	0.436*** (0.0880)	0.406*** (0.0873)
Migrant	0.173*** (0.0535)	0.0111 (0.0568)	0.271*** (0.0693)	0.104 (0.0713)	0.217*** (0.0751)	0.0632 (0.0767)
Experience	-0.111*** (0.0075)	-0.064*** (0.0074)	-0.181*** (0.0097)	-0.135*** (0.0096)	-0.141*** (0.0162)	-0.155*** (0.0169)
Experience squared	0.0029*** (0.0002)	0.0014*** (0.0002)	0.0045*** (0.0002)	0.0029*** (0.0002)	0.0039*** (0.0002)	0.0024*** (0.0002)
Economic inactivity	0.208*** (0.0081)	0.0872*** (0.0091)	0.302*** (0.0114)	0.179*** (0.0121)	0.195*** (0.0209)	0.159*** (0.0211)
Economic inactivity squared	-0.004*** (0.0002)	-0.002*** (0.0003)	-0.005*** (0.0003)	-0.004*** (0.0004)	-0.005*** (0.0003)	-0.003*** (0.0004)
Unemployment rate	0.0330*** (0.0108)	0.0285*** (0.0099)	0.0586*** (0.0122)	0.0568*** (0.0112)	0.0510*** (0.0150)	0.0492*** (0.0137)
Degree or above	-0.328*** (0.0654)	-0.507*** (0.0676)	-0.626*** (0.0850)	-0.790*** (0.0849)	-1.671*** (0.467)	-1.210*** (0.330)
Advanced Diploma/Diploma	-0.110 (0.0851)	-0.237*** (0.0842)	-0.265** (0.109)	-0.395*** (0.107)	-1.157** (0.451)	-0.236 (0.391)
Certificate	-0.221*** (0.0631)	-0.143** (0.0613)	-0.364*** (0.0802)	-0.273*** (0.0772)	-0.984*** (0.242)	-0.158 (0.220)
Year 12	-0.0649 (0.0690)	-0.206*** (0.0672)	-0.162* (0.0885)	-0.279*** (0.0853)	-0.342 (0.349)	-0.0984 (0.285)
Time averaged characteristics						
Experience					-0.0002 (0.0138)	0.0566*** (0.0149)
Economic inactivity					0.0792*** (0.0188)	-0.0058 (0.0187)
Unemployment rate					-0.0136 (0.0288)	-0.0098 (0.0261)
Has children aged 0-4					0.600*** (0.170)	0.272* (0.155)
Has children aged 5-14					-0.808*** (0.137)	-0.348** (0.135)

	Pooled (1)		Multilevel gllamm (2)		Multilevel gllamm (3)	
	Not Employed	*Casual*	*Not employed*	*Casual*	*Not employed*	*Casual*
Married/De facto					-0.168 (0.194)	0.164 (0.190)
Partner is employed					-0.0164 (0.167)	-0.0797 (0.165)
Degree or above					1.250*** (0.480)	0.600* (0.346)
Advanced Diploma/Diploma					1.030** (0.470)	-0.0562 (0.411)
Certificate					0.757*** (0.260)	-0.0457 (0.240)
Year 12					0.178 (0.367)	-0.192 (0.305)
Constant	0.126 (0.226)	-1.110*** (0.227)	1.221*** (0.276)	-0.0465 (0.274)	0.0996 (0.356)	-1.058*** (0.343)
Between individual variance			2.0383*** (0.1319)		2.477*** (0.1419)	
Sample	43,689		43,689		43,689	
Individuals	8,951		8,951		8,951	
Pseudo R squared	0.4775		0.4890		0.4980	
BIC	42754.72		41839.26		41378.26	

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students and the self employed.

The between individual variance is strongly significant in both multilevel models (columns 2 and 3 of Table 34) indicating that there is statistically significant unobserved heterogeneity. . An LR test was conducted and this provided strong evidence of group effects. As was the case with results from the first specification of form of employment, the combination of significant between individual variance and the result from the LR test provide strong justification for preferring a panel (multilevel) model.

The BIC is again lowest for the model which includes the Wooldridge estimator (column 3 of Table 34), indicating this model is to be preferred. Casual employment and non-employment in the initial period are both highly significant in column 3, lending further support for preferring a model accounting for the initial condition. Initial conditions do play a role in modelling this specification of form of employment and they cannot be ignored.

As was the case with specification 1 results in Table 30, the time averaged variables in Table 34 play an important role with many of these being highly significant (though more so for the not-employed outcome). This again suggests that relatively fixed underlying differences between individuals are significant determinants of form of employment (in particular non employment).

Lagged health has a significant negative effect though this effect is small in magnitude. The effect of health on the likelihood of casual employment is smaller than that found in analysing effects on part-time employment. Nonetheless, better health increases the likelihood of permanent employment amongst persons who are employed. This effect differs by gender with health again having a smaller effect on the likelihood of form of employment for women (taking into account the interaction between female and health). As was stated in section 5.5.1, while the magnitude of the effect of health appears small in a single year (the results in Table 34 are for the effect at year t), once the compound effect is taken into account over time (both in terms of any prolonged poor health but also negative implications arising from casual employment and non-employment) the effect of health on form of employment becomes more important.

Looking at the results from the parameter estimates in Table 34, better initial health is associated with a lower likelihood of casual employment. Surprisingly, other things equal, women are found to be less likely than men to be casual relative to permanent employment however for women with young children the opposite is true. Men with young children are more likely to be in permanent employment. Employment experience and higher education have the expected effects with both significantly increasing the likelihood of permanent employment, consistent with the human capital arguments set out earlier. Living in a rural area increases the likelihood of casual employment.

The results of the estimates in Table 34 support the results in section 5.5.1 by finding that dynamics are relevant, unobserved heterogeneity is important and that initial conditions do play a role in modelling form of employment. A panel data model is to be preferred. There is some evidence supporting the hypothesis that those in poor health are more likely to be in casual employment relative to permanent employment. While many of the findings with regards to non-employment replicate those in the analysis of part time/full time employment, the analysis here makes a contribution through identifying the effect of health on the likelihood of casual employment and permanent employment, both forms of employment which have implications for health related disadvantage.

MCMC estimates for the models presented in columns 2 and 3 of Table 34 appear in Table A-24 in the Appendix. As was the case with the first specification of form of employment, the estimates are very close to those provided by gllamm suggesting findings are robust to the estimation procedure used[44].

Comparison specifications were also estimated using the alternative health measure, the measure of health shock (table unreported). The results show little difference compared with those in Table 34, with a health shock not found to have a significant effect on the likelihood of casual employment. There are few differences in the results between the two models and analysing the diagnostics suggests that the model using the health index is to be preferred.

The parameter estimates provided in Table 34 are the log odds. As stated in section 5.5.1, findings can be more sensibly interpreted by calculating predicted probabilities. The next section analyses the results from Table 34 by reporting predicted probabilities.

[44] As was the case with the first specification of form of employment, a more complex model was also estimated using MCMC and obtaining separate random intercepts for not-employed and casual. The parameter estimates again did not differ greatly from the model with a single random intercept. The estimated random intercept was higher for those not employed indicating greater unobserved heterogeneity compared with casual (3.16 for not employed compared with 2.63 for part-time).

5.5.4 Analysis of Specification II Results

To aid interpretation of the results presented in section 5.5.3, the average predicted probabilities of each form of employment by selected characteristics are reported in this section. This discussion follows a similar format to that in section 5.5.2 with the key characteristic of interest being health and this is analysed by comparing predicted probabilities of form of employment (using the specification comparing not-employed, casual and permanent employment) by health index quintiles.

Since health deteriorates at later ages, it is relevant to note that the probability of permanent employment at first rises, then decreases with age (see Figure 9). The probability of casual employment is highest amongst persons aged 15 to 24 (despite the exclusion of full-time students).

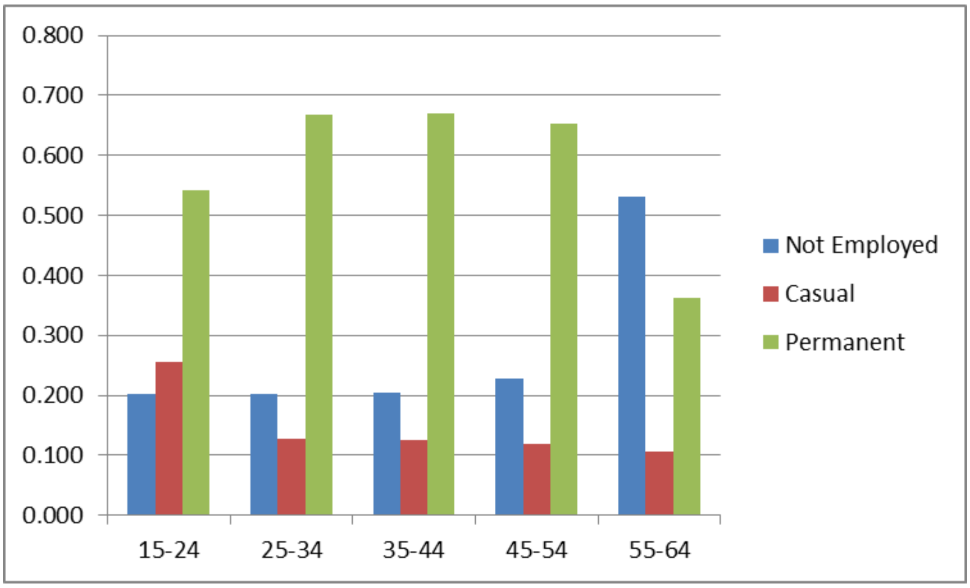

Figure 9: Average Predicted Probability of Form of Employment by Age

Figure 10, Figure 11 and Figure 12 (and Table A-26, Table A-27 and Table A-28 in the Appendix) assess the magnitude of associations between health and form of employment using the same health measures discussed in section 5.5.2 in relation to the first specification of form of employment. These figures present the average predicted probabilities of form of employment by health index quintile (Figure 10), SF-36 physical functioning quintile (Figure 11) and SF-36 mental health quintile (Figure 12).

5. The Effects of Health on Form of Employment

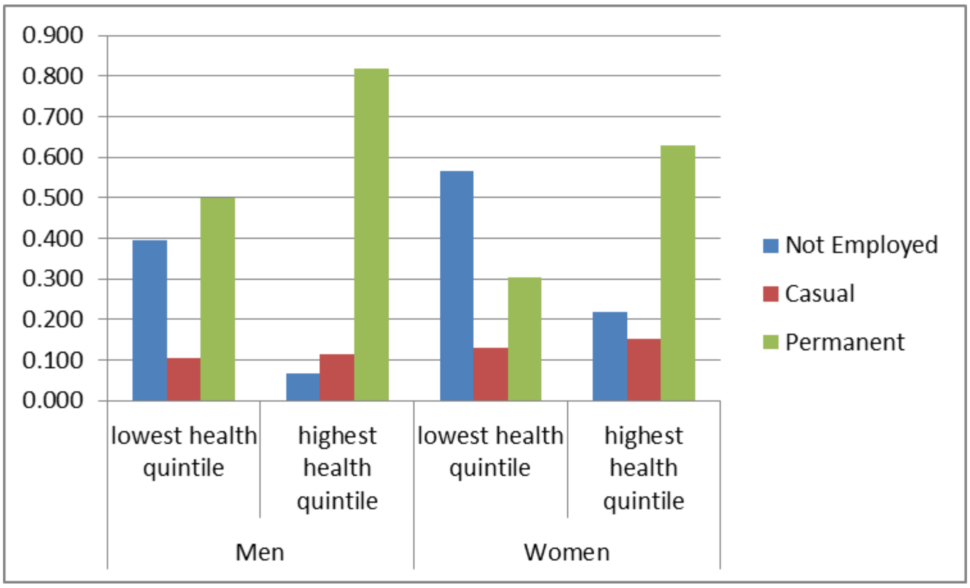

Figure 10: Average Predicted Probability of Form of Employment by Health Index Quintile and Gender

Both men and women in the lowest health index quintile have a substantially lower predicted probability of permanent employment compared with persons in the highest health index quintile. They have only a slightly lower probability of casual employment.

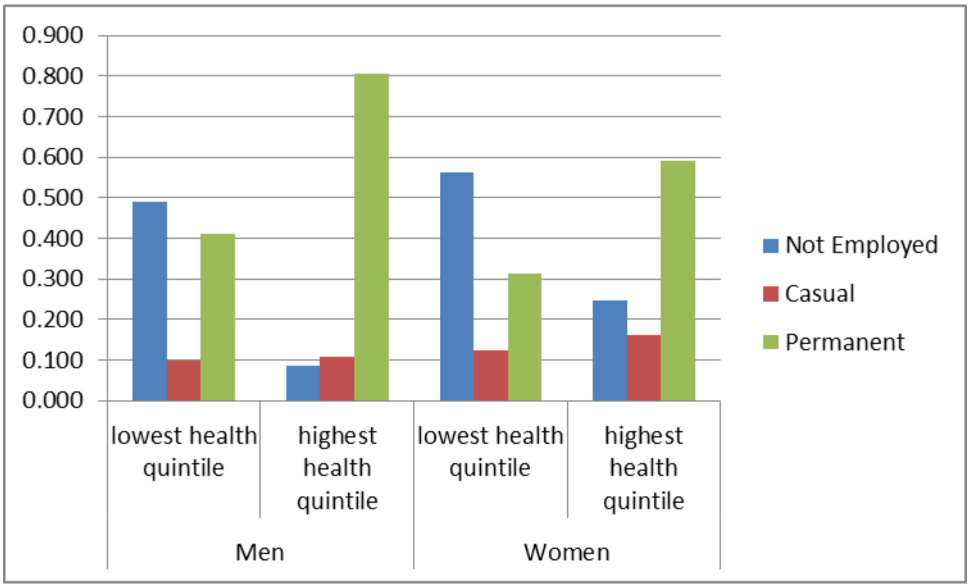

Figure 11: Average Predicted Probability of Form of Employment by Physical Functioning Quintile and Gender

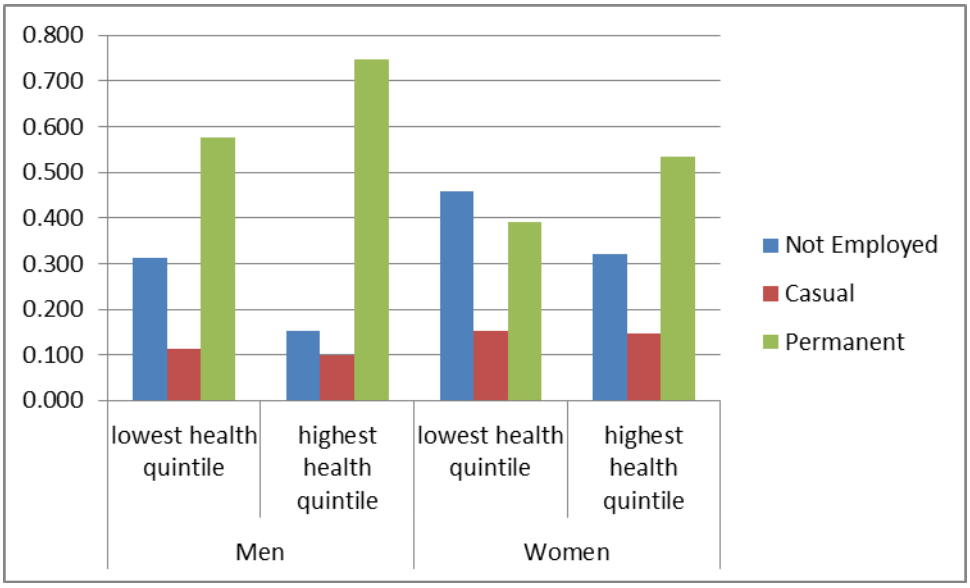

Figure 12: Average Predicted Probability of Form of Employment by Mental Health Quintile and Gender

After converting the figures in Figure 10 to compare probability of casual employment and probability of permanent employment poorer health is associated with a higher likelihood of casual employment amongst employed persons. Men in the lowest health index quintile are 7.2 per cent more likely to be casually employed compared with those in the highest quintile. The relationship is smaller for women.

The relationship between physical functioning and form of employment in Figure 11 and that between mental health and form of employment in Figure 12 are again very similar to the results obtained using the health index. Men and women in the lowest quintile for both physical functioning and mental health have a lower probability of permanent employment compared with persons in the highest quintile of both of these measures. The relationship is again not as strong for mental health as for the other measures however there is still a clear relationship between mental health and probability of form of employment. The probability of casual employment by health quintile for both measures mirrors that from Figure 10 where the difference in probability of casual employment for persons in better health is much lower than that found for permanent employment.

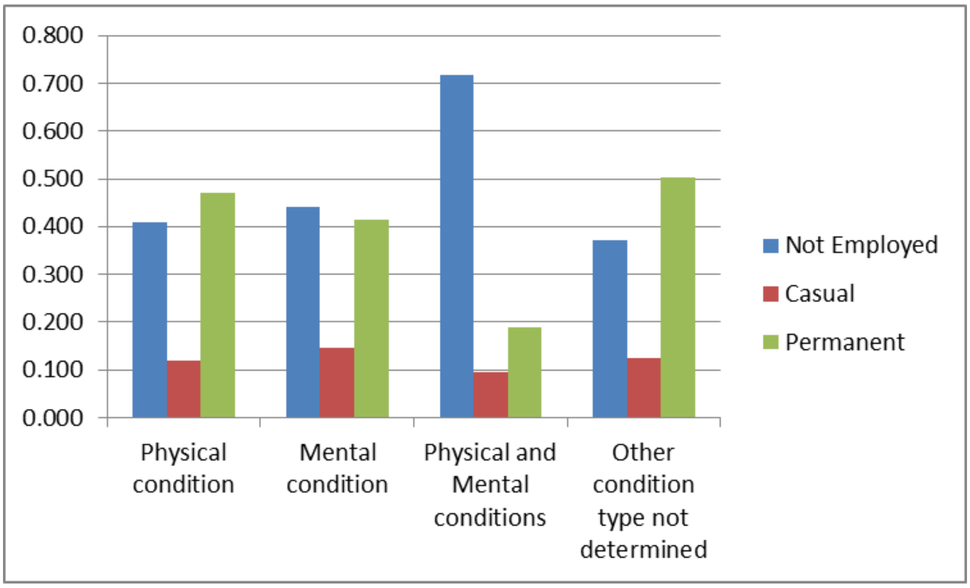

Figure 13: Average Predicted Probability of Form of Employment by Type of Long Term Condition

Figure 13 (and Table A-29 in the Appendix) shows that the relationship between health and employment is more greatly impacted for persons experiencing both physical and mental health conditions. Persons experiencing both types of long term condition have a much lower probability of both casual and permanent employment compared with persons which physical or mental long term conditions only

Distinguishing long term conditions by whether they are work limiting or do not limit work finds the expected relationship (see Table A-30 in the Appendix). Persons with a condition limiting their work ability had a much higher probability of non-employment and a much lower probability of permanent employment regardless of gender. The predicted probability of form of employment did not differ greatly between persons with a long term condition not impacting work ability and persons who did not have a long term condition though persons with no long term condition had a slightly lower probability of non-employment and slightly higher probability of employment (particularly permanent employment).

The remainder of this section reports counterfactuals for the same scenario dealt with in section 5.5.2. Figure 14 replicates Figure 8 from section 5.5.2 using the second specification of form of employment. Figure 14 shows a relationship between health and form of employment but as was found in section 5.5.2, the relationship is not as strong as that seen in the sample estimate.

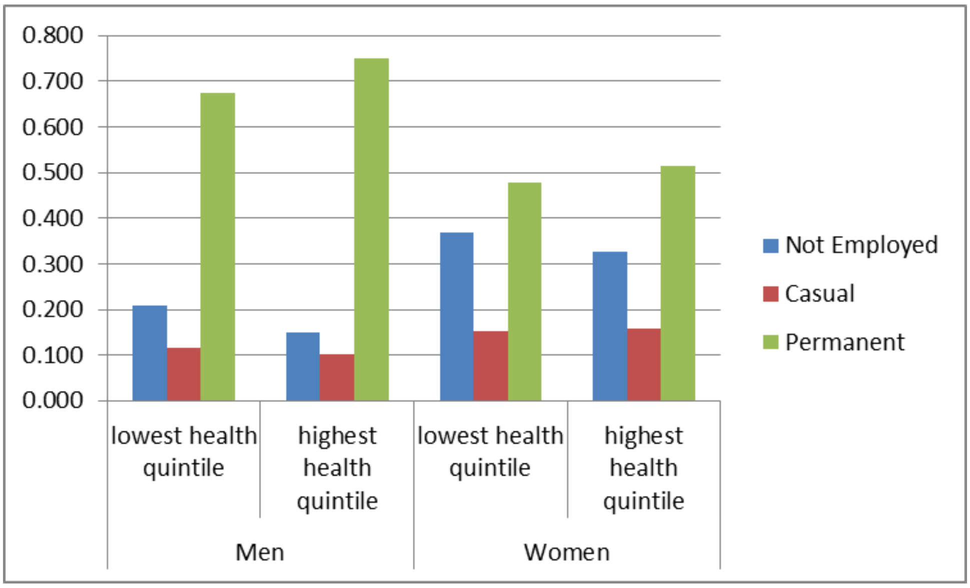

Figure 14: Average Predicted Probability of Form of Employment by Health Index Quintile and Gender

Converting the probabilities presented in Figure 14 to consider the employed only finds that men in the lowest health quintile are 2.8 per cent more likely to be employed casually compared with those in the highest health quintile (the comparable figure is 7.2 per cent using the sample estimate). Women in the lowest health quintile are 1.1 per cent more likely to be casually employed than women in the highest health quintile. Nevertheless, despite the smaller estimates, poorer health is still associated with a lower probability of permanent employment amongst employed persons.

The preceding discussion has expanded on that from section 5.5.2 to provide further evidence of clear relationships between health and form of employment. Using a second specification of form of employment, the results in section 5.5.3 were interpreted via predicted probabilities estimated using the preferred model of form of employment identified in that section. This discussion found that poor health results in a lower probability of permanent employment. The results further support the hypothesis that persons in poor health are more likely to be employed on casual terms.

5.6 Discussion and Conclusions

Most previous research on the relationship between form of employment and health assumes that any causal relationship is unidirectional such that form of employment affects health. This chapter has estimated the determinants of form of employment in order to test the hypothesis that persons in poor health are more likely to be employed on part-time or casual terms, or not employed at all. Controls for selection into employment, state dependence, initial conditions, unobserved heterogeneity and measurement error in health were included in the models to better determine causality. The results can only be taken as suggestive of causal effects however, because even with using lagged health, the timing of changes in health cannot be said to exactly match changes in form of employment.

The results of the dynamic, multilevel multinomial logit models estimated in this chapter suggest it is important to control for selection into employment given that form of employment is only observed for persons who are employed. Failure to control for selection overstates the effect of health on form of employment. Incorporating non-employment as an outcome in form of employment models shows that individuals in poorer health or experiencing a health shock are less likely to be employed.

The results also provide strong evidence that dynamics should be included and that initial conditions cannot be ignored when modelling form of employment. Failure to account for these also risks overstating the magnitude of the determinants of form of employment. By controlling for these modelling issues the models are a better fit and offer more reliable results.

Among persons who are employed, health has a statistically significant effect on form of employment with persons in poor health being significantly more likely to be in part-time or casual employment. The results from this chapter establish that the relationship between health and form of employment at least flows in the direction from health to form of employment, even if the literature finds inconsistent evidence of the relationship flowing in the other direction[45]. Moreover the association is subject to unobserved heterogeneity, requiring panel data estimation. This suggests that it is important to control for individual differences when modelling relationships between health and labour market outcomes and there are reciprocal relationships at play which must be considered when conducting research into the effect of form of employment on health.

The findings in this chapter support those on the effect of health on hours worked (Currie and Madrian 1999; Pelkowski and Berger 2004; Cai *et al.* 2014) and the suggestion that health may have a causal effect on job characteristics (De Lange *et al.* 2004, 2005; Dalgard *et al.* 2009). The element of choice is important, with part time and casual work having the potential to offer flexibility to accommodate health impairments. Part time and casual employment could function as a means to participate in the labour market for those who might not be capable of working in full time or permanent positions.

The effect of health on form of employment was found for both men and women. There are gender differences in the size of the relationships, with health having a larger effect on the likelihood of part time and casual employment for men. The magnitude of the effects (estimated using counterfactuals to simulate the effect of differing health) were similar for both part time and casual employment amongst employed persons, with men in poor health 2.8 per cent more likely to be employed part time compared with those in the best health. Men in poor health were also 2.8 per cent more likely to be casually employed compared with those in the best health. For women in poor health the comparable figures were a 1 per cent greater likelihood of part time employment and a 1.1 per cent greater likelihood of casual employment.

The similar magnitude of estimated effects between part time and casual is interesting, especially given the overlap between these forms of employment. Sample estimates of the magnitude of effects differ from those obtained using counterfactuals with the estimated effect of health on casual employment for the employed being larger for average predicted probabilities obtained via sample estimates. This

[45] While there is evidence in the international literature of form of employment affecting health, Richardson *et al.* (2012) find no effect of form of employment on mental health in Australia.

suggests there are some differences in characteristics of those employed part time and casual but the overlap is an important consideration and an area for future research to consider in order to disentangle the effect of health on part time employment, casual employment and those employed in a combination of the two. The research in this chapter has provided a starting point for further analysis and the findings in this chapter do contribute to understanding the degree of health related disadvantage.

Periods out of the workforce and an increased probability of part-time and casual employment for persons in poorer health have negative implications in terms of career progression and lifetime earnings. Despite part time and casual employment offering flexibility to those who face health related obstacles in participating in employment, these forms of employment are also associated with occupational segregation and fewer training opportunities. The effects of health on form of employment add to the disadvantage already experienced by individuals with impaired health in comparison with their healthier counterparts.

6. The Effect of Health on Occupation

6.1 Introduction

The cross sectional profile presented in chapter 3 suggested that there is a relationship between health and occupation. As discussed in the previous chapter, cross sectional analysis cannot identify causal effects. This chapter presents econometric findings from estimating panel data models designed to determine the effect of health on occupation obtained.

The association between health and occupation identified in chapter 3 masks the complex interactions which may occur in the relationship between health and occupation. Health might influence the occupation obtained (and whether employment is obtained in the first place) but changes in health might also affect occupation. This chapter aims to answer two questions-1) do those in poor health work in different occupations than those in good health, and 2) what effect does a change in health (for better or worse) have on level of occupation. This may tell us how people adapt to their limitations and what types of jobs make this harder or easier.

The chapter is structured as follows. The background and theory on the relationship between health and occupation are set out in section 6.2. Section 6.3 discusses classification/measurements of occupation and ways in which occupation can be analysed. Section 6.4 sets out methods, data and modelling approaches used to answer the research questions of interest. Section 6.5 discusses the sample and explanatory variables used in the analyses. Section 6.6 presents results from the econometric analyses and section 6.7 concludes with a discussion of results and summary.

6.2 Background

Occupation is important because different occupations are associated with differences in income and varying career prospects (Yamaguchi, 2010). Occupations also differ in their exposure to risk of unemployment and specific health hazards. There are causal relationships linking educational attainment, occupation and income. Educational attainment affects occupational position and through this, affects income. The relationship between health and occupation is less clear than that between education and occupation as health can affect both. Along with this, the role of health selection into employment in the first place must be kept in mind - occupation is not observed for all persons experiencing poor health.

Although studies have investigated how poor health affects hours of work and labour force participation, there are few which have examined the effect of health during working age (and the effect of changes in health) on occupation. The reverse relationship has been investigated with a number of studies examining the effect of occupation on health (for recent examples see Sindelar *et al.* 2007; Chau & Khlat, 2009; Fletcher & Sindelar, 2009; Gueorguieva *et al.* 2009). These studies suggest a strong relationship between greater physical job demands and poorer health (especially cumulated physical job demands), that there are occupation-related health differences which persist with age and that blue collar work at labour force entry is associated with declining health later in life. There is also some suggestion that status of occupation is associated with health beyond the distinction between work which is physically demanding and that which is not. A social gradient in health is found when analysing the relationship between occupation status and health (Ferrie *et al.* 2002; Gueorguieva *et al.* 2009; Toivanen, 2011).

Studies which have examined effects of health and effects of changes in health on occupation include Pelkowski and Berger (2003), Cohiden *et al.* (2009), De Raeve *et al.* (2009) and Halleröd and Gustaffson (2011). Pelkowski and Berger (2003) used the US Health and Retirement Study to investigate the propensity of workers to change employers and occupations following the onset of health problems. They found that workers with health problems are more likely than healthy workers to remain with their current employer (as opposed to switching employers). Among those who switched employers, those with health problems are more likely to change occupations than healthy workers, presumably to adapt to their health challenges.

The authors do attempt to control for endogeneity of health however they do not control for selection into employment or consider in their model to what degree persons which health problems leave employment following onset of a health problem.

Cohiden *et al.* (2009) used French data to estimate the prevalence of common mental disorders according to occupation and whether these problems affected work by a) hindering the individual in their work or b) causing them to stop working. They found that prevalence of mental health problems is consistently higher among those in the lowest occupational categories. The study does rely on self reports of the effect on work and is limited to people working at the time of the survey. It also does not appear to use panel data.

De Raeve *et al.* (2009) used Dutch panel data to gain insight into relationships between changes in mental health and characteristics of work arrangements and occupational mobility. They found evidence for a possible causal relationship between deterioration in mental health and subsequent change in working time arrangements or occupational mobility. The results suggested that workers adapt to the onset of a health problem by changing jobs within the company or by changing jobs from one company to another. This study did not consider those not working and the role of selection into employment.

Halleröd and Gustaffson (2011) used Swedish panel data and growth curve modelling to undertake an empirical analysis of the direct relationship between changes over time in socioeconomic status and changes in morbidity. The structural relationship and changes over time were simultaneously estimated using structural equation modelling. They found that initial health affects occupational mobility. Initial morbidity had a negative impact on change of occupational position, suggesting health based selection into less prestigious jobs. With regards to the reverse relationship, they found that more prestigious jobs are related to initially good health and to a less rapid deterioration in health. Change in occupation was found to be related to change in health, with people who move into higher status occupations experiencing slower deterioration in health.

Halleröd and Gustaffson (2011) appear to have provided the most rigorous analysis to date of the causal effects of health on occupation. They did however limit their sample to those who were part of the labour force and therefore do not account for selection into employment.

While some of these previous studies focus specifically on mental health or physical health measures, the focus in this chapter is on general health as measured using the health index constructed in chapter 4. The direction of the likely effect of health on occupation (after taking into account selection into employment) is not clear from the literature although it can be theorised. Some studies assessing the effect of poor health in childhood have found that those with poor health more likely to move down the social scale and less likely to move up (Manor *et al.* 2003; van de Mheen *et al.* 1998). This corresponds with the theory that persons with poor health have lower levels of human capital both via lower educational attainment and lower work capacity resulting in employment in lower status, lower skilled and lower paid occupations. The results from chapter 5 found that persons in poor health are more likely to be in part time and casual employment. The occupational segregation in these forms of employment also supports the theory that persons with poor health are more likely to be employed in lower status occupations.

A recent area of interest for researchers has been the degree to which workers who develop health problems are accommodated in their current employment (Burkhauser *et al.* 1995; Daly & Bound, 1996; Krause *et al.* 1998; Campolieti, 2004**).** The job accommodation literature has found that people with health problems who are not accommodated in their current job select into less physically demanding jobs **(**Daly & Bound, 1996; Krause *et al.* 2001**)**. This fits with the theory that some persons who cannot find employment which accommodates their health problems will opt out of work altogether. Those who do work select into jobs which allow them to manage their health[46].

[46] Note that within the job accommodation literature, selecting from a lower status, physically demanding manual job into a job which is less physically demanding does not necessarily reflect a switch into a higher status non-manual job. Changes in job demands may reflect a job requiring fewer hours, more breaks and less physical demands while still being a manual job of a similar status. A more complex job change from manual to non-manual work is likely to require retraining and given the time to completion of any retraining, there will be a substantial lag between onset of poor health and obtaining a higher skilled, less physically demanding job.

Compared with research into the health-occupation relationship, much less research has examined the degree to which individuals change jobs in order to extend their working life following the onset of poor health. Job change can allow a worker to adapt to their health problem by adjusting the demands of their employment (Daly and Bound, 1996; Bound *et al.* 1999). The ability of an individual to adapt to a health problem depends on the type of job they are employed in at the time of onset of poor health. The physical demands of manual jobs suggest that these types of jobs are less likely to be able to accommodate health problems **(**Krause *et al.* 2001**)**. However, this literature had not considered a representative sample and focuses only on persons with health impairments. It also has limited control for selection into employment. Workers who cannot adapt to the onset of a health problem by adjusting their job demands are likely to leave employment. Conversely, an improvement in health may enable a person who was not working to gain employment without having to consider the need for a job which will accommodate their health problems or likewise, may be able to change jobs to a more demanding occupation.

Establishing the effect of health during working age on occupation is important for three reasons. First, the relationship between occupation and income and the relationship between occupation and career opportunities (reinforcing the link between occupation and income) suggest that if poor health increases the likelihood of lower skilled, lower status work then persons with poorer health will not have access to the same income or the same career opportunities that an otherwise equivalent person in good health would have. This has implications for lifetime earnings. Second, the relationships between poor health and low income and lack of career opportunities are subject to reinforcing mechanisms. There is not only one way causality given that lower income and poorer jobs can have a negative effect on health (Smith, 1999). There could be a vicious circle given that ill health can damage earning ability, which further undermines the health situation (Halleröd and Gustaffson, 2011). There could also be a vicious cycle in another sense given that employment in lower skilled, lower status jobs has been found to affect health adversely. If these are the occupations in which persons in poor health obtain employment, reinforcing mechanisms from the reverse relationship between occupation and health have further implications for both lifetime earnings and the ability to continue working later in life.

This chapter adds to the contributions of previous analyses of the effect of health and changes in health (both good and bad) on occupation by considering the Australian setting. It can be differentiated from past work by its use of complex panel data analysis using representative data, with methods to control for both selection into employment and the endogeneity of health.

It is hypothesised that poor health leads to a higher probability of non-employment (as found in the literature and in results from chapters 4 and 5). The aim of this chapter is to determine whether persons in poor health are more likely to work in lower status jobs after controlling for selection into employment. It also studies the effect of health on physical job demands to determine whether people in poor health are more likely to be employed in non-manual jobs in order to accommodate their health problems. The descriptive statistics in chapter 3 suggested that a higher proportion of people in poor health work in physically demanding jobs however this may be attributed to the effect of work on health. The analysis in this chapter aims to isolate the health effect on the likelihood of manual vs non-manual employment.

Apart from determining the effect of health (and changes in health) on occupation, this chapter also aims to determine the degree to which persons who experience poor health change jobs in order to adapt and what type of job they change to. This chapter will determine the effect of health on the degree of job change for the working age population after selection into employment is accounted for.

The analyses in this chapter use panel data and methods to address the modelling issues highlighted in chapter 4, with a specific aim to determine effects after accounting for selection into employment, something which does not seem to be addressed in the literature to date.

The next section discusses ways in which occupation can be measured/classified in order to undertake econometric analyses of the effect of health on occupation.

6.3 Classification of Occupation/Measures of Occupation

There are a number of measures available for measuring/classifying occupation. These can be grouped into three categories: prestige measures, socioeconomic indices and class measures. Choice of measure used depends on the exact aspect the researcher is interested in.

Prestige scales are derived by asking panels of experts or population samples for subjective judgements about the prestige of occupations (McMillan, 2010). Prestige measures include the Standard International Occupational Prestige Scale (SIOPS) and the Australian ANU scale. In Australia, the initial ANU1 scale was developed in the 1960s. SIOPS is the international measure. It was generated from prestige studies conducted in sixty countries (Ganzeboom & Treiman, 1996). Both measures are based on occupational prestige but it has been noted that prestige measures are strongly correlated with commonly used categorical occupation classifications (Erikson & Goldthorpe, 1993). Blue collar workers typically have a low score on the prestige scales while white collar workers score more highly. Prestige measures have two advantages: 1) there is a clear assumption about an occupation hierarchy and 2) they capture changes within occupational classes (Halleröd & Gustaffson, 2011).

The continuous nature of prestige scales means that it is easy to identify the lowest socioeconomic group plus prestige tends to be stable over time and across countries (McMillan, 2010). It must be noted though that the studies used to create available prestige measures are quite dated now. The labour market has undergone considerable change since these measures were developed and this has raised questions regarding the validity of traditional prestige scales (McMillan, 2010). Prestige scales are also less commonly used now than socioeconomic indices (Ganzeboom & Treiman, 2003).

Socioeconomic indices scale occupations according to the education, income and other socioeconomic characteristics of population samples. These are a more direct way of tapping into the human resources and economic rewards associated with occupations (McMillan, 2010). Socioeconomic indices include the International

Socioeconomic Index (ISEI) and the Australian Socioeconomic Index for 2006 (AUSEI06). The most commonly used measure is the ISEI which allows researchers to assign scores to the International Standard Classification of Occupations (ISCO). In Australia, this same approach was used to form the basis of the AUSEI06 which is the latest version of the ANU scale (McMillan, 2010). The AUSEI06 was generated from Australian Census data and can assign scores to ANZSCO codes (McMillan *et al.* 2009). The scale ranges from 0 to 100 with medical practitioners at the top of the scale and labourers at the bottom.

In the socioeconomic indices, scaling procedures assign scores to occupations using methods which maximise the role of occupation as an intervening variable between education and income (McMillan, 2010). This means that these indices are more so a measure of socioeconomic status than a pure measure of occupation.

The final commonly used available measure is the Erikson-Goldthorpe-Portocarero (EGP) schema also known as the Goldthorpe class measure. This is arguably the most commonly used occupational measure in the social sciences (Goldthorpe 1980; Erikson *et al.* 1979; Erikson & Goldthorpe, 1993). The schema is composed of 11 categories (see Table 35) which can be collapsed into a smaller set of classes.

Table 35: EGP Schema

I	Service class: Higher grade professionals, administrators & officials; managers in large industrial establishments; large proprietors
II	Service class: Lower grade professionals, administrators & officials; higher grade technicians; managers in small industrial establishments; supervisors of non-manual employees
IIIa	Routine non-manual employees, higher grade

IIIb	Routine non-manual employees, lower grade
IVa	Small proprietors, artisans, etc. with employees
IVb	Small proprietors, artisans, etc. without employees
IVc	Farmers & small holders; other self-employed workers in primary prodn
V	Lower grade technicians; supervisors of manual workers
VI	Skilled manual workers
VIIa	Semi- & unskilled manual workers (not in agriculture, etc.)
VIIb	Agricultural workers & other workers in primary production

Source: Rose (2005)

The idea behind the EGP schema is that class categories are produced by similar market and work conditions. It is well established internationally and forms the basis of the National Statistics Socio-economic Classification in the United Kingdom which is the official class measure of the UK Office for National Statistics (Rose *et al.* 2005). A version has also been developed for Europe (Rose & Harrison, 2009). The EGP has been mapped onto the ISCO so that the only data requirements to produce the measure are occupational data coded to ISCO, a variable indicating whether or not the respondent is self employed and a variable indicating the number of employees the respondent supervises (Ganzeboom & Treiman, 1996).

The descriptive statistics presented in chapter 3 and the literature reviewed in the previous section highlighted two aspects of occupation which are associated with health: occupational status and physical job demands (identified in the literature as blue collar work)[47]. These are closely linked but both correspond with different

[47] This is not to say that these are the only aspects of occupation which have a relationship with health. Job stress and work schedules are other possibilities, as are other conditions of work which might

occupational measures. Both will be analysed to determine the effects of health on occupation. The specific effects of being in a particular type of occupation based on physical demands (e.g. manual vs. non-manual employment) are captured by the EGP schema. Use of the EGP schema allows for controlling for movements into and out of employment (i.e. selection into employment) given that is a categorical measure-the addition of a "not employed" category can be used to control for selection. The disadvantage of using the EGP schema is that the only changes over time that can be observed are changes within broad occupational categories.

The AUSEI06 is also used as a measure of occupation in the analyses in order to capture the effects of health on occupational status, with results from analysing this compared with those using the EGP schema. The AUSEI06 has two advantages over the EGP schema: first, there is a clear assumption about an occupational hierarchy with the index being continuous and ranging from 0 to 100; second, the AUSEI06 captures changes within occupational classes. The main disadvantage of the AUSEI06 is that it is only observed for persons initially employed (persons who become unemployed or leave the labour force retain their previous occupational status) and therefore does not allow the same degree of modelling of the selection effect and it is important to explicitly consider this.

While there is no consistent recommended approach to collapsing categories of the EGP schema, it appears common to collapse the 11 categories into three classes[48]. Classes 1 and 2 are combined to form a "salariat" class, classes IIIa, IV and V combine to form an "intermediate" class and classes IIIb, VI and VII combine to form a "working class" (Rose, 2005; Harrison & Rose, 2006). This approach was adopted and modified for the analysis in this chapter. The EGP schema was generated using the ISCO, a variable identifying self employment and a variable identifying those who are supervisors. Table 36 shows the EGP categories generated using this method and the number and percentage of respondents in each of these categories.

---

have a physical toll. The degree to which these might be subject to reverse relationships, with health affecting these outcomes, is a matter for further research.

[48] Collapsing categories increases the number of observations within each category. Observation numbers on a number of variables are far too small for reliable estimation with EGP categories disaggregated into the 11 categories.

Table 36: EGP Schema Categories in HILDA Waves 1 to 10

EGP	Frequency	Per cent
I Higher controllers	5,429	6.55
II Low controllers	28,459	34.32
III Routine non-manual	12,656	15.26
IV Self employed with employees	6,176	7.45
V Self employed without employees	10,719	12.93
VI Skilled manual	12,525	15.10
VII Semi-skilled manual	4,196	5.06
VIII Self employed farm workers	2,770	3.34
Total	82,930	100.00

It is apparent from comparing Table 35 with Table 36 that the EGP categories generated using the ISCO to EGP conversion routine in Stata are not an exact match to the EGP schema. They are however the closest possible match given the data available. The method used to generate the EGP schema using HILDA creates eight occupational categories, grouping some of those presented in Table 35. This grouping of categories results from the mapping of the EGP onto the ISCO which is dependent on level of detail of occupation available[49]. The categories in Table 36 are then combined in a similar fashion to that described above to generate a two class occupation measure.

The class measure has been modified in this chapter to take account of one of the specific major aspects of occupation found to be associated with health in the literature-physical job demands. This is captured via a manual/non-manual classification of occupation rather than a three class measure. Classes I, II and III from Table 36 are combined to form a “non-manual” classification and classes VI, VII and VIII are combined to form a “manual” classification. Classes IV and V are excluded due to inability to identify level of physical job demands for these groups. This classification mirrors the high SEP/low SEP classification used by Hyde *et al.*

[49] Four digit ANZSCO provides the most disaggregated EGP schema, HILDA has occupation available at the 2 digit level. This grouping does not affect the analysis given that categories are further collapsed in a manner which does not require separation of the grouped categories.

(2006) in their study comparing the effects of low childhood socioeconomic position and low adult socioeconomic position on self rated health.

The non-manual/manual classification also includes a “not employed” category to allow for the effects of selection into employment when undertaking modelling. Table 37 shows this classification and the numbers/percentages of respondents in each of category of this combined measure.

Table 37: Non-Manual/Manual Classification of Occupation in HILDA Waves 1 to 10

	Freq.	**Percent**
Not employed	47,228	41.70
Manual	19,491	17.21
Non-Manual	46,544	41.09
Total	113,263	100.00

The next section discusses the methods and modelling approaches which were used to analyse the EGP schema and AUSEI06 measures of occupation.

6.4 Methods, Data and Modelling Approaches

As was the case in the analyses in chapters 4 and 5, the analysis in this chapter uses 10 waves of the HILDA data covering the time period 2001-2010.

There are two specifications of occupation used, the EGP schema and the AUSEI06 discussed in the previous section. The occupation model using the EGP schema is a model with a multinomial dependent variable. The EGP specification has a dependent variable taking on the value 0 if not employed, 1 if in a manual occupation and 2 if in a non-manual occupation.

The modelling approach using the EGP uses the same process as in the previous chapter. Three types of models are used to examine dynamics and establish the preferred modelling approach

1) A pooled multinomial logit with lagged not employed and occupation variables taking account of clustering to provide panel adjusted standard errors
2) A dynamic multilevel multinomial logit with lagged not employed and occupation variables and unobserved heterogeneity but assuming initial conditions are exogenous
3) A dynamic multilevel multinomial logit with lagged not employed and occupation variables, unobserved heterogeneity and endogenous initial conditions

The modelling approach using the AUSEI06 differs in that the dependent variable is continuous (ranging from 0-100). As with the modelling approach using the EGP, both pooled and panel models are estimated to establish the preferred model. Given that non employment is not included as an outcome in the specification using the AUSEI06, job characteristics can also be included in the model for this specification. In order to allow comparisons between specifications, the AUSEI06 models are estimated both with and without job characteristics.

These model specifications are used to answer the research question of interest: what is the effect of health on occupation?[50]

The model building process followed was similar to that in chapter 5 for both specifications of occupation. Pooled models were estimated as a prelude to the multilevel panel data models. An investigation was then undertaken to determine the most suitable specification of the panel data model beginning with a constant only model, then introducing a random intercept, time invariant then time variant explanatory variables, then the final specification using the Wooldridge method for dealing with initial conditions. The final model using the EGP measure of occupation is specified as:

$$y_{itj} = \beta_0 + \beta_j' X_{it} + \gamma_j y_{i,t-1} + \xi_j \hat{y}_{i,1} + \lambda_j \bar{x}_i + e_{itj} + u_i \qquad (1)$$

[50] Models were not estimated separately by gender as observations on a number of variables became too small for reliable estimation with disaggregation. It would also have been desirable to estimate models using a more detailed breakdown of occupation using the EGP schema however this disaggregation also resulted in low observation numbers and difficulty in obtaining reliable estimates

where j=1, 2, … J denotes the response category (occupation), *i* are individuals (i=1,…, n) and *t* is time (or survey waves, $t = 1,\ldots, T$). The X are the vector of observed individual characteristics (the explanatory variables). Lagged occupation dummy variables are denoted by the $y_{i,t-1}$, $\widehat{y_{i,1}}$ is initial occupation, and $\overline{x_i}$ are the equivalent of the Mundlak augmentation (the average of the time variant Xs). A random intercept is given by the u_i (where $u_i \sim N(0, \sigma_u^2)$) and e_{itj} represents the error term. The equation for the model using the AUSEI06 differs from equation (1) in that the dependent variable is continuous rather than categorical. The model using the AUSEI06 measure is specified as:

$$y_{it} = \beta_0 + \beta' X_{it} + \gamma y_{i,t-1} + \xi \hat{y}_{i,1} + \lambda \bar{x}_i + e_{it} + u_i \qquad (2)$$

The methodological issues involved in estimating these types of models are those set out in chapters 4 and 5: state dependence, unobserved heterogeneity, the role of initial conditions, choice of health measure and selection into employment[51].

The concerns surrounding choice of health measure were discussed in detail in chapter 4. These are addressed by using the health index constructed in that chapter. As was the case in chapters 4 and 5, lagged health is included in the model rather than current health in order to reduce the possibility of simultaneity bias.

In previous chapters, lagged and initial health were included with lagged health being the lag of the health index constructed in chapter 4. The literature suggests that including both initial period health and lagged health allows the estimated coefficient on health to be interpreted as a deviation from an underlying health stock represented by initial health. This suggests that a model containing initial period health and lagged health captures the effects of changes in health.

An alternative specification is to include a variable indicating a health shock. This was done in chapter 5 as a comparison model. This measure used self reported information contained in HILDA and is based on responses to the question on health

[51] State dependence refers to the dependent variable in the current period (occupation) being dependent on employment status in the previous period.

compared to 12 months ago. A health shock is defined as somewhat worse or much worse health compared to 12 months ago. A dummy variable was created with value 1 if a health shock occurred and 0 otherwise. This variable can be used to determine the effect of worsening health on occupation.

Likewise, a measure was constructed from the same question in HILDA to identify an improvement in health. A health improvement was defined as somewhat better or much better health compared to 12 months ago. A dummy variable was created with value 1 if a health improvement occurred and 0 otherwise. This variable was used to determine the effect of improving health on occupation.

The three approaches described above (using lagged and initial health, using health shock variable and using improved health variable) are used to determine the effect of health and changes in health on occupation. The health shock and health improvement measures are included for comparison purposes. Nonetheless, it should be noted that, as made explicit in chapter 4, these measures have been subject to criticism and results using the health index are considered to be superior.

All the effects of state dependence are characterised through coefficients on a series of lagged dummy variables for occupation ($\gamma_j y_{i,t-1}$) for the EGP schema and lagged AUSEI06 for the AUSEI06 specification. The larger the value of these coefficients, the greater the degree of state dependence in occupation in the following period (Jenkins & Cappellari, 2008).

Unobserved heterogeneity was allowed for by using multilevel modelling as discussed in chapter 5. Unobserved heterogeneity is given by the u_{ij} in equation (1) and u_i in equation (2).

The Wooldridge method was used to handle endogenous initial conditions as was the case in chapters 4 and 5 and as discussed in detail in chapter 4.

Selection into employment was addressed by including not employed as an outcome in the categorical dependent variable used to model the EGP specification of occupation. The analysis sample for the model using the AUSEI06 measure comprises only persons who were employed at some time during the time period covered by the HILDA data. As such, estimates from this model could be affected by selection bias. People who were employed in at least one of the years covered by HILDA are likely to have characteristics which distinguish them from persons who were not and it would be incorrect to assume that their responses to a change in health are the same. Sample selection bias is corrected for in the AUSEI06 models using a two-stage procedure following Vella and Verbeek (1999) and Orme (2001). This is based on the widely used method pioneered by Heckman (1979) and involves analysis of the probability that a person with particular characteristics is represented in the sample prior to analysis of the AUSEI06 models. The initial employment model from chapter 4 was estimated and from this a generalised residual is obtained. This is then included as a term in the AUSEI06 models, controlling for selection bias.

Identification conditions must be satisfied in a selective model like the AUSEI06 models in this chapter. The model is identified by including different explanatory variables in the employment equation and the equation using the AUSEI06 as the dependent variable, each equation has variables which do not appear in the other equation. The employment equation includes different variables via the controls for state dependence and ignition conditions. The AUSEI06 includes different variables via lagged and initial AUSEI06 but also by including job characteristics in later specifications of the model, along with the inclusion of the generalised residual to control for selection.

Given that the model to be estimated for the EGP specification is a panel data model with a categorical dependent variable, the estimation procedures used in this chapter is the same as those used in chapter 5. The modelling was undertaken using the gllamm procedure in Stata and Markov Chain Monte Carlo (MCMC) simulation using MLwiN. Results from both procedures are compared in order to establish robustness of results.

For the AUSEI06 specification of occupation, the xtmixed multilevel modelling procedure in Stata was used. This procedure was chosen as this is the equivalent multilevel modelling procedure in Stata when the dependent variable is continuous and multilevel modelling was preferred for both specifications of occupation to ensure some consistency when presenting and discussing results.

In addition to the models estimating effects of health on occupation, job change models are also analysed. The models set out above estimate the effect of health and the effect of changes in health on occupation but they cannot establish the effects of health (or changes in health) on occupational changes. The job change models use the heckprob modelling procedure in Stata.

The heckprob command controls for endogeneity resulting from selection into employment. The procedure uses maximum likelihood to fit probit models with sample selection. It provides consistent, asymptotically efficient estimates for all parameters in the model. The use of the heckprob command allows correlation between error terms of the two equations (the employed equation used to control for selection and the job change equation used to establish the determinants of job change).

The job change models are pooled probit models however they incorporate panel adjusted standard errors in order to account for the panel nature of the data. Given that the EGP measure is a broader occupational measure, job changes are measured using job change variables derived from the AUSEI06 in order to maximise the number of job changes observed. The job change variables comprise three dummy variables: lower AUSEI06, same AUSEI06 and higher AUSEI06. In each case, the variables are coded to represent a change in AUSEI06 between t and t-1. Lower AUSEI06 represents a lower AUSEI06 ranking at time t compared with t-1, higher AUSEI06 represents a higher AUSEI06 ranking at time t compared with t-1 and same AUSEI06 represents the same AUSEI06 ranking at time t and t-1.

6.5 Sample and Explanatory Variables

As with previous econometric analyses in this thesis, the sample used for the econometric analyses in this chapter was restricted to those aged between 15 and 64 years excluding full time students. Table 38 sets out and defines the variables used in the models of occupation[52].

After taking account of missing values, the estimating sample for the EGP models comprises 38,774 person-wave observations for 7,735 individuals[53]. The estimating sample for the AUSEI06 models comprises 38,632 person-wave observations for 7,757 individuals. The estimating sample is lower than that in chapter 5 due to a larger number of persons identified as self-employed when using the EGP measure of occupation and the exclusion of the non-employed when using the AUSEI06 measure of occupation. Due to the inclusion of lagged occupation variables (and lagged health included as an explanatory variable), the estimating sample comprises data from waves 2 to 10 of HILDA.

Table 38: Variables used in Occupation Models

Variable	**Description of Variable**
Dependent variables	
EGP	0 if not employed, 1 if employed in a manual occupation, 2 if employed in a non-manual occupation
AUSEI06	Australian Socioeconomic Index scaled from 0 to 100
Variables appearing in both specifications of occupation	
Post GFC	1 if observation is from 2008 or later, 0 otherwise
Female	1 if female, 0 otherwise
Post GFC*female	Interaction term between post GFC and female
Lagged health index	Health index score from previous year
Initial health	Health index score from initial wave of data
Health shock^	1 if health somewhat worse or much worse than last year, 0 otherwise
Health improvement^	1 if health somewhat better or much better than last year, 0 otherwise
Lagged health	Interaction term between health index score from previous year

52 Summary statistics for many of these variables can be found by referring to Table 2 in Chapter 3.
53 These observations are assumed missing at random.

index*female	and female
Has children aged 0-4	1 if has children aged 0-4, 0 otherwise
Has children aged 5-14	1 if has children aged 5-14, 0 otherwise
Has children aged 0-4*female	Interaction term between presence of young children in household and female
Married/De Facto	1 if married or has partner, 0 otherwise
Partner is employed	1 if has partner in employment, 0 otherwise
Weekly non labour income ($100's)	Real weekly non labour income divided by 100
Partner wage	Real hourly wage of partner, takes value 0 if has no partner
Rural	1 if lives in rural area, 0 otherwise
Migrant	1 if migrant, 0 if Australian born
Migrant*lagged health index	Interaction term between health index score from previous year and migrant
Migrant*lagged health index*female	Interaction term between health index score from previous year, migrant and female
Father's occupation	AUSEI06 occupational status scale, father's occupation when respondent was aged 14
Experience	Years in employment since leaving full time education
Experience squared	Years in employment since leaving full time education squared
Economic inactivity	Years not employed since leaving full time education
Economic inactivity squared	Years not employed since leaving full time education squared
Unemployment rate	Unemployment rate calculated by age, sex, state of residence and year
Education	Measured by dummy variables reflecting highest educational

	attainment
Degree or above	1 if has degree or above, 0 otherwise
Advanced diploma/diploma	1 if has advanced diploma or diploma, 0 otherwise
Certificate	1 if has certificate I/II/III or IV, 0 otherwise
Year 12	1 if has year 12, 0 otherwise
Year 11 or below	Reference category, 1 if has year 11 or below
Variables appearing only in model using EGP schema	
Not employed at t-1	1 if not employed in previous year, 0 otherwise
Manual at t-1	1 if employed manually at t-1, 0 if not employed or employed in a non-manual occupation
Not employed at t=1	1 if not employed in initial wave of data, 0 otherwise
Manual at t=1	1 if employed manually in initial wave of data, 0 if not employed or employed in a non-manual occupation
Variables appearing only in model using AUSEI06	
AUSEI06 at t-1	Australian Socioeconomic Index ranged from 0 to 100, value from previous year
AUSEI06 at t=1	Ranking on Australian Socioeconomic Index in initial wave of data
Hours worked	Hours worked per week in all jobs
Job tenure	Job tenure in years in main job
Union member	1 if member of a union, 0 otherwise
Private sector	1 if employed in the private sector, 0 otherwise
Generalised residual	Correction for sample selection bias

Notes: ^Variables included in comparison models only. Partner wage rate and non-labour income are inflated to the value in the year 2010 by the RBA annual inflation rate over the period (2001-2010) derived from the ABS Consumer Price Index.

Explanatory variables included in the regressions using the EGP schema measure of occupation are those used in the form of employment regressions apart from adjustments to variables to control for state dependence and inclusion of a variable measuring parental occupation. A measure of father's occupation was included as this is a measure of childhood SES which is known to affect adult outcomes.

Table 39 documents the total number of occupational transitions (using the EGP measure) over the 9 waves of HILDA included in the estimating sample (waves 2 to 10). This table illustrates a high degree of state dependence, most particularly for non-manual employment. This supports the inclusion of the variables to capture state dependence (lagged non employed and lagged manual employment).

Table 39: Number (and Percentage) of Transitions over Waves 2 to 10 of the HILDA Survey, Estimating Sample EGP

	Not Employed	Manual	Non-Manual	Total
Not Employed	5,887 (85.1)	346 (5.0)	682 (9.9)	6,915 (100.0)
Manual	352 (6.4)	4,601 (84.1)	521 (9.5)	5,474 (100.0)
Non-Manual	789 (5.0)	452 (2.9)	14,492 (92.1)	15,733 (100.0)
Total	7,028 (25.0)	5,399 (19.2)	15,695 (55.8)	28,122 (100.0)

Table 40: Number (and Percentage) of Transitions over Waves 2 to 10 of the HILDA Survey, Estimating Sample EGP, Persons Aged over 45

	Not Employed	Manual	Non-Manual	Total
Not Employed	3,604 (91.77)	123 (3.13)	200 (5.09)	3,927 (100.00)
Manual	169 (8.07)	1,745 (83.29)	181 (8.64)	2,095 (100.00)
Non-Manual	364 (5.80)	157 (2.50)	5,757 (91.70)	6,278 (100.00)
Total	4,137 (33.63)	2,025 (16.46)	6,138 (49.90)	12,300 (100.00)

The level of persistence in occupation raises questions as to whether there are sufficient transitions in occupation, particularly amongst the sample which post dates the age at which health shocks are likely to occur. Table 40 documents the number of occupational transitions using the EGP measure amongst persons aged over 45, the portion of the sample with a higher likelihood of health shocks. The percentage of transitions is lower for those previously not employed compared with the whole sample in Table 39. The percentage of transitions from manual and non manual employment are similar in both tables and lower than the percentage and number of transitions found in the form of employment tables in the previous chapter, lending weight to use of comparison measures of occupation which are less broad and likely to capture a greater degree of occupational transition.

The explanatory variables included in the regressions using the AUSEI06 measure of occupation differ from those using the EGP schema in that job characteristics are included as well as the generalised residual from the two step procedure discussed in the previous section which acts as a control for selection into employment.

The job change models include the same explanatory variables as those used in the AUSEI06 occupation models. The only exception is the omission of the lagged AUSEI06 variable in the job change models compared with the AUSEI06 models.

6.6 Results

This section presents estimates from the model specifications set out in section 6.4. It considers the results from two specifications of occupation, the first using the EGP schema and the second using the AUSEI06. It begins by presenting estimates using the EGP schema which check the robustness of results from multinomial occupation models to the choice of model specification (section 6.6.1). The results from estimates using the AUSEI06 are then presented and discussed (section 6.6.2) with the section concluding by comparing results from the two specifications of occupation. The final part of this section presents statistics analysing job changes and the results from estimating job change models (section 6.6.3).

6.6.1 Results using EGP Schema

Table 41 presents the parameter estimates obtained using gllamm to estimate the model using the EGP schema and the three different estimators described at the beginning of section 6.4. The results presented compared a pooled model (column (1)) with multilevel gllamm assuming exogenous initial conditions (column (2)) and multilevel gllamm with endogenous initial conditions (column (3)). The EGP model produced parameter estimates for the not employed and manually employed outcomes to be interpreted relative to non-manual employment (the reference category for the model).

The effect of not being employed at t-1 or being employed in a manual occupation at t-1 are both highly significant in all three specifications providing strong evidence of state dependence[54]. This indicates that dynamics are relevant when modelling occupation. As was the case in the last two chapters, this effect again appears overstated when initial conditions are assumed to be exogenous and when data are pooled. After controlling for initial conditions and the panel nature of the data the size of the effect remains substantial. The parameter estimates for both variables are positive in sign suggesting that being out of work or manually employed in the preceding year increases the likelihood of being "not employed" or in a manual occupation in the current year relative to non-manual employment.

Table 41: Multinomial Logit Parameter Estimates (and Standard Errors) for Outcomes of "Not employed" and Manual Relative to Non-Manual Employment

	Pooled (1)		**Multilevel gllamm (2)**		**Multilevel gllamm (3)**	
	Not employed	*Manual*	*Not employed*	*Manual*	*Not employed*	*Manual*
Not employed at t-1	3.629*** (0.062)	2.401*** (0.082)	3.357*** (0.080)	2.161*** (0.098)	2.577*** (0.089)	1.245*** (0.107)
Manual at t-1	2.180*** (0.075)	4.729*** (0.081)	1.949*** (0.094)	4.530*** (0.102)	0.887*** (0.112)	2.858*** (0.114)

[54] In the following discussion, results are classed as significant if they are statistically significant at the conventional 5% level or better.

	Pooled (1)		Multilevel gllamm (2)		Multilevel gllamm (3)	
	Not employed	*Manual*	*Not employed*	*Manual*	*Not employed*	*Manual*
Not employed at t=1					1.827*** (0.118)	1.893*** (0.141)
Manual at t=1					2.112*** (0.149)	3.184*** (0.145)
Post GFC	-0.106 (0.079)	-0.053 (0.070)	-0.108 (0.085)	-0.066 (0.074)	-0.044 (0.102)	-0.076 (0.097)
Female	-1.229*** (0.231)	-0.807*** (0.283)	-1.522*** (0.257)	-1.036*** (0.302)	-1.421*** (0.306)	-0.903** (0.357)
Post GFC*Female	0.216** (0.101)	0.101 (0.114)	0.213* (0.109)	0.116 (0.121)	0.243** (0.120)	0.264* (0.135)
Lagged health index	-0.025*** (0.003)	-0.004 (0.003)	-0.027*** (0.003)	-0.005 (0.004)	-0.028*** (0.004)	-0.003 (0.004)
Initial health	-0.011*** (0.002)	0.005* (0.003)	-0.014*** (0.003)	0.003 (0.003)	-0.012*** (0.003)	-0.001 (0.004)
Lagged health index*female	0.017*** (0.003)	-0.005 (0.004)	0.019*** (0.004)	-0.005 (0.004)	0.018*** (0.004)	-0.006 (0.005)
Has children aged 0-4	-0.121 (0.118)	0.010 (0.081)	-0.120 (0.125)	-0.001 (0.088)	-0.305* (0.165)	0.001 (0.134)
Has children aged 5-14	-0.240*** (0.056)	-0.122** (0.057)	-0.265*** (0.061)	-0.138** (0.062)	-0.0404 (0.108)	-0.212* (0.112)
Has children aged 0-4*Female	1.756*** (0.137)	0.161 (0.153)	1.967*** (0.149)	0.351** (0.164)	2.204*** (0.174)	0.605*** (0.191)
Married/De Facto	0.642*** (0.076)	0.126 (0.085)	0.716*** (0.084)	0.198** (0.093)	0.921*** (0.163)	0.242 (0.169)
Partner is employed	-1.044*** (0.083)	-0.142 (0.100)	-1.167*** (0.090)	-0.227** (0.106)	-1.150*** (0.131)	-0.385*** (0.144)
Weekly non labour income ($100’s)	0.010*** (0.003)	-0.008 (0.006)	0.011*** (0.003)	-0.008 (0.006)	0.013*** (0.003)	-0.0002 (0.005)
Partner wage	0.003 (0.002)	-0.007** (0.003)	0.002 (0.002)	-0.007** (0.003)	0.001 (0.002)	0.0002 (0.003)
Rural	0.202*** (0.067)	0.517*** (0.070)	0.255*** (0.075)	0.583*** (0.078)	0.277*** (0.091)	0.529*** (0.097)

	Pooled (1)		**Multilevel gllamm (2)**		**Multilevel gllamm (3)**	
	Not employed	*Manual*	*Not employed*	*Manual*	*Not employed*	*Manual*
Migrant	0.374 (0.268)	-0.455 (0.339)	0.472 (0.297)	-0.418 (0.361)	0.488 (0.352)	-0.327 (0.425)
Migrant*Lagged health index	-0.003 (0.004)	0.005 (0.005)	-0.005 (0.004)	0.004 (0.005)	-0.005 (0.005)	0.002 (0.006)
Migrant*Lagged health index*female	-0.0001 (0.0017)	0.0046** (0.0019)	0.0013 (0.0018)	0.0059*** (0.0021)	0.0009 (0.0022)	0.0051** (0.0025)
Father's occupation	-0.003** (0.0011)	-0.007*** (0.0013)	-0.004*** (0.0012)	-0.008*** (0.0014)	-0.005*** (0.0015)	-0.008*** (0.0018)
Experience	-0.076*** (0.0079)	-0.032*** (0.0089)	-0.099*** (0.0091)	-0.052*** (0.010)	-0.089*** (0.0179)	-0.094*** (0.0198)
Experience squared	0.0021*** (0.0002)	0.0005*** (0.0002)	0.0026*** (0.0002)	0.0010*** (0.0002)	0.0027*** (0.0002)	0.0014*** (0.0003)
Economic inactivity	0.187*** (0.0084)	0.0065 (0.0106)	0.217*** (0.0102)	0.0317*** (0.0121)	0.151*** (0.0206)	0.0498** (0.0235)
Economic inactivity squared	-0.003*** (0.0003)	0.0004 (0.0003)	-0.003*** (0.0003)	0.0001 (0.0003)	-0.003*** (0.0004)	-0.0004 (0.0004)
Unemployment rate	0.0462*** (0.0126)	0.0020 (0.0139)	0.0521*** (0.0130)	0.0066 (0.0142)	0.0485*** (0.0172)	0.0259 (0.0179)
Degree or above	-0.691*** (0.0712)	-1.819*** (0.0956)	-1.024*** (0.0900)	-2.197*** (0.113)	-2.229*** (0.499)	-2.160*** (0.494)
Advanced Diploma/Diploma	-0.354*** (0.0879)	-1.063*** (0.0979)	-0.575*** (0.102)	-1.315*** (0.113)	-1.554*** (0.526)	-1.956*** (0.520)
Certificate	-0.245*** (0.0716)	-0.176*** (0.0642)	-0.303*** (0.0801)	-0.226*** (0.0728)	-1.245*** (0.293)	-0.922*** (0.315)
Year 12	-0.139* (0.0776)	-0.539*** (0.0807)	-0.261*** (0.0879)	-0.667*** (0.0913)	-0.503 (0.392)	-0.420 (0.378)
Time averaged characteristics						
Experience					-0.0037 (0.0151)	0.0309* (0.0162)
Economic inactivity					0.0866*** (0.0182)	0.0192 (0.0207)
Unemployment					0.0140	-0.0402

	Pooled (1)		Multilevel gllamm (2)		Multilevel gllamm (3)	
	Not employed	*Manual*	*Not employed*	*Manual*	*Not employed*	*Manual*
rate					(0.0328)	(0.0347)
Has children aged 0-4					0.673*** (0.186)	0.213 (0.196)
Has children aged 5-14					-0.738*** (0.149)	-0.147 (0.159)
Married/De facto					-0.0787 (0.205)	0.130 (0.221)
Partner is employed					-0.315* (0.189)	-0.0267 (0.222)
Weekly non labour income ($100's)					0.0033 (0.0118)	-0.0327** (0.0157)
Partner wage					0.0067** (0.0029)	-0.0114** (0.0052)
Degree or above					1.243** (0.512)	0.168 (0.524)
Advanced Diploma/Diploma					1.011* (0.541)	0.772 (0.534)
Certificate					1.036*** (0.312)	0.798** (0.332)
Year 12					0.236 (0.412)	-0.165 (0.401)
Constant	-0.360 (0.253)	-1.496*** (0.270)	0.388 (0.296)	-0.789** (0.310)	-0.497 (0.398)	-1.413*** (0.441)
Between individual variance			0.744*** (0.102)		2.229*** (0.179)	
Sample	38,774		38,774		38,774	
Individuals	7,735		7,735		7,735	
Pseudo R squared	0.6183		0.6200		0.6360	
BIC	30158.01		30046.36		29106.09	

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students

As was the case in chapter 5, the significance of the between individual variance (from inclusion of a random intercept) provides a statistical test of whether a panel data model is to be preferred. The between individual variance is significant in both panel models in Table 41 (Columns 2 and 3) indicating that there is statistically significant unobserved heterogeneity and that a panel data model should be preferred when modelling occupation.

Following the same process as chapter 5, an LR test was also conducted to test the hypothesis that there are no between individual effects for the model of occupation using the EGP schema. The LR test statistic again provided overwhelming evidence of group effects adding to the justification for preferring a panel data (multilevel) model.

A comparison of the BIC shows that the model with the lowest BIC in Table 41 is for the model incorporating the Wooldridge estimator (column 3). Manual employment and being out of work in the initial period is also highly significant. This suggests (as with the previous two chapters) that initial conditions do play a role and that the preferred model specification is the model which accounts for this. A number of the time averaged variables are also statistically significant suggesting that the relatively fixed underlying differences between individuals are significant determinants of occupation.

Lagged health has a significant negative effect but only for the non-employment outcome. Poorer health is associated with a higher likelihood of non-employment relative to non-manual employment. As was the case in chapter 5, this effect differs by gender with health having a smaller effect on the likelihood of non-employment for women (taking into account the interaction term between female and health). This suggests health selection plays a lesser role for women. This can be attributed to women having other reasons for not being in the labour force.

Among persons who are employed, health does not have a significant effect on manual/non-manual employment as measured using the EGP schema apart from for female migrants. Female migrants in poorer health appear more likely to be employed in manual occupations however the effect is very small and while statistically significant, is not of practical significance. This suggests that after taking account of differing educational attainment and other factors affecting occupation, health does not have a significant effect on the likelihood of being employed in either manual or non-manual employment.

Two mechanisms may be at work in terms of any relationship between health and occupation. It was theorised at the beginning of this chapter that persons in poor health might choose non-manual employment in order to adapt to their impaired health. It was also noted that poor health (particularly if the onset is earlier in life) is associated in the literature with a higher likelihood of moving down the social scale. Non-manual occupations, as coded in the EGP, include the higher status occupations. This restricts the ability to choose these occupations given that the higher status occupations require higher skills and education, especially given the association between poor health and lower education. This, combined with the physical demands of manual occupations, might explain why there is no significant *causal* health effect on occupation after accounting for selection into employment and other factors denoted by the explanatory variables. Having said this, the EGP schema only captures broad occupations, health may have an effect on occupation within these broad categories and this will not be apparent using this specification of occupation.

The remaining variables in Table 41 appear to have the expected effects. Women are less likely to be out of work or in manual employment (and more likely to be in non-manual employment) but women with young children are much less likely to be employed and if employed, more likely to be employed in manual occupations. Employment experience increases the likelihood of non-manual employment, as does higher education. Non labour income increases the likelihood of non employment relative to non-manual employment. Father’s occupation is significant suggesting that higher childhood SES lowers the likelihood of non-employment and manual employment (though the magnitude of this effect is small).

Women appear less likely to be employed post GFC. Living in a rural area increases the likelihood of non employment or manual employment, reflecting a higher proportion of manual employment in rural areas and higher unemployment rates. Having an employed partner is associated with a lower likelihood of non-employment and manual employment but being married or in a de facto relationship increases the likelihood of non-employment. This is what was seen in chapter 5 and suggests that partner labour force status variable is capturing other partner characteristics (e.g. partner selection or both partners facing the same labour market).

The results from the estimates presented in Table 41 indicate (as was the case with chapter 5) that dynamics are relevant, there is unobserved heterogeneity and that initial conditions need to be accounted for. A panel data model is to be preferred when estimating occupation models. The estimates support the hypothesis that poor health is associated with a higher likelihood of non-employment (as found in the literature and in results from chapters 4 and 5). This provides further evidence that there is health selection out of employment. Results presented thus far also find that poor health is not linked with an increased probability of being in a specific occupation.

MCMC estimates for the models presented in columns 2 and 3 of Table 41 using gllamm appear in Table A-31 in the Appendix. The estimates are very close to those provided by gllamm (as was the case in Chapter 5) suggesting findings are robust to the estimation procedure used[55].

The models were also run using two alternative specifications of health to compare with the results presented in Table 41 (see Table A-32 in the Appendix). As discussed in section 6.4, the preferred model is that presented in Table 41 using the preferred health measure (the health index). The results using the alternative health measures are mainly for comparison only. Column 1 of Table A-32 presents results

[55] As in chapter 5, the much faster processing time when using the MCMC simulation procedure also allowed estimation of more complex model with two random intercept terms, one for the “not employed” outcome and one for the manual employment outcome. The parameter estimates were very close to those in the model with a single random intercept. These results showed that the random intercept was lower amongst the “not employed” compared with the manually employed. There is a higher degree of unobserved heterogeneity amongst persons who are manually employed (random intercept is 2.065 for not employed compared with 3.856 for manual).

using the measure of self-assessed health shock while column 2 presents results using a measure of self assessed health improvement.

Results using the measure of self-assessed health shock again find a significant effect of health on the likelihood of non-employment[56]. This adds to the evidence that persons who experience a health shock are more likely to select out of employment if they cannot adjust to their health problem. The results in Table A-32 suggest a larger effect on the likelihood of non-employment for those experiencing a health shock compared with the results using the lagged health index in Table 41[57]. For women, the interaction between health and gender in column 1 of Table A-32 is significant suggesting that women experiencing a health shock are more likely to be employed in a manual occupation relative to non-manual employment. This may provide some evidence supporting the claim by Hallerod and Gustafsson (2012) that there is health selection into less prestigious jobs and also supports the finding that poor health is associated with a movement down the social scale but in this case it is only observed for women.

As with the previous chapter, it must be kept in mind in comparing health measures that the two measures being compared are not on the same scale. The estimate for the health index reflects the effect of a 1 unit change in the 0-100 index with higher values representing better health. The health shock measure is a dummy variable with value 1 representing an adverse shock to health. It is unsurprising that the magnitude of the effect of a health shock is larger given that a value of 1 for the health shock measure represents a greater change in health than a change in the value of the health index. The health shock measure is much more a measure of a more serious change in health and a change which may be more likely to prompt a change in behaviour.

[56] The model was also estimated using an alternative measure of self-assessed health shock with value 1 if the individual suffered an injury or illness in the previous 12 months and 0 otherwise. Results using the alternative specification of health shock were very similar to those in column 1 of Table A-32.

[57] This again corresponds with Zucchelli *et al.* (2010) who found that the effect of health on labour market exits is larger using a self-assessed health shock measure compared with the health index measure.

Results using the measure of self-assessed health improvement find no significant effect of an improvement in health on the likelihood of non-employment or manual/non-manual employment. This is unexpected however it may be explained by voluntary vs. involuntary labour market activity. An adverse health shock cannot be ignored and requires a response whereas an improvement in health just makes it possible to shift into employment or to a more desired occupation (in this case, from manual to non-manual work). Any such positive shift will be likely to occur at a more leisurely pace.

Apart from differences in the effect of the health measures Table A-32 compared with Table 41, there are few differences in the results between the models in Table A-32 and that in Table 41 and these are only minor differences in the effects of some explanatory variables. There are minor differences in the effect of initial health, having children aged 0-4, the interaction term between post GFC and female and differences in the effect of gender (and the interaction between gender and health). The minor differences in the effect of initial health can be attributed to the different relationship between initial health and the health index compared with the self-assessed health change measures in Table A-32. The remaining differences are possibly caused by the use of different health measures in the interaction between health and gender in the different specifications which then have a flow on effect to the results from the gender variable and interaction terms containing gender.

The parameter estimates provided in Table 41 and Table A-32 are the log odds from estimating panel data multinomial logit models of the determinants of occupation. Results from these estimates suggest that persons in poor health are less likely to be employed but amongst those who are employed, health does not have a significant effect on the likelihood of being employed in manual or non-manual occupations in the broad classification used. This finding does differ when an alternative health measure is used-women who experience a health shock were found to be more likely to be employed in a manual occupation using the self assessed measure of health shock. This offers some evidence in support of poor health being associated with lower paid and lower status jobs but it does raise questions as to how women manage the physical demands of these jobs in conjunction with worsening health. It differs from the expected finding that people seek jobs which allow them to adapt to their impaired health, with non-manual jobs seeming far more likely to allow the necessary adjustments[58]. The criticisms of measures such as this health shock measure as discussed in chapter 4 and the results from the diagnostics (the BIC) also indicate that results using the health index are to be preferred. The next section analyses the results from using an alternative measure of occupation, the AUSEI06.

6.6.2 Results using AUSEI06

As discussed in both section 6.3 and section 6.6.1, the EGP schema only captures changes between broad occupational classifications. The low number of transitions between broad occupational categories could explain the lack of a significant effect of health on occupation when using the EGP schema. The AUSEI06 assumes a less rigid occupational hierarchy than the EGP, ranging from 0-100 and this wider range is more likely to capture changes within occupational classes. Estimates using the AUSEI06 may therefore be more able to determine the effect of health (and changes in health) on occupation within the broad occupational categories comprising the EGP measure used earlier in this chapter.

Table 42 documents the number of transitions in AUSEI06 ranking for the sample which post dates the age when persons are most likely to experience a health shock. The number of occupational transitions is much higher than those observed when using the EGP schema (see Table 40). The number of transitions are also high compared with the number of transitions observed for form of employment in the previous chapter, increasing confidence that results using the AUSEI06 contain enough within individual variation in occupation choice that any effects of health on occupation will be able to be identified in the analysis.

Table 42: Number (and Percentage) of Transitions over Waves 2 to 10 of the HILDA Survey, Estimating Sample AUSEI06, Persons Aged over 45

	Lower AUSEI06	**Same AUSEI06**	**Higher AUSEI06**	**Total**
Lower	223	703	910	1,836

[58] The expected relationship between health and physical job demands may differ in the case of poor mental health where physical job demands might not pose the same impediment to employment.

AUSEI06				
	(12.15)	(38.29)	(49.56)	(100.00)
Same AUSEI06	686	5,390	675	6,751
	(10.16)	(79.84)	(10.00)	(100.00)
Higher AUSEI06	887	708	255	1,850
	(47.95)	(38.27)	(13.78)	(100.00)
Total	1,796	6,801	1,840	10,437
	(17.21)	(65.16)	(17.63)	(100.00)

Table 43 presents the parameter estimates obtained using pooled models (column 1) and multilevel modelling (column 2) from the model using the AUSEI06. Models were estimated both with and without the correction for selection bias described in section 6.4.

The effect of occupational status in the previous year (AUSEI06 at t-1) is highly significant for both the pooled and multilevel specifications in Table 43. This provides strong evidence of state dependence and again supports the inclusion of dynamics when modelling occupation. As with previous estimates presented in this thesis, the effect appears overstated when the data are pooled and initial conditions are not accounted for. After controlling for initial conditions and the panel nature of the data a substantial degree of state dependence remains. The parameter estimate is positive suggesting a higher ranking on the AUSEI06 index in the preceding year is associated with a higher ranking in the current year.

Table 43: Estimates (and Standard Errors) of Determinants of Occupational Status (Dependent Variable AUSEI06 score 0-100)-Pooled vs. Multilevel Linear Regression with and without Controlling for Selection

	Pooled (1)		**Multilevel (2)**	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*

	Pooled (1)		Multilevel (2)	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
AUSEI06 at t-1	0.734*** (0.006)	0.733*** (0.006)	0.337*** (0.008)	0.337*** (0.008)
AUSEI06 at t=1			0.344*** (0.009)	0.343*** (0.009)
Post GFC	0.244 (0.175)	0.277 (0.176)	0.691*** (0.237)	0.744*** (0.237)
Female	3.137*** (0.861)	3.350*** (0.868)	3.353*** (1.039)	3.725*** (1.048)
Post GFC*Female	-0.380 (0.244)	-0.377 (0.244)	-0.541** (0.264)	-0.530** (0.265)
Lagged health index	0.015 (0.010)	0.006 (0.010)	0.018 (0.011)	0.0058 (0.012)
Initial health	0.002 (0.007)	-0.007 (0.008)	-0.007 (0.011)	-0.020* (0.011)
Lagged health index*female	-0.023** (0.011)	-0.022* (0.011)	-0.023* (0.014)	-0.022 (0.014)
Has children aged 0-4	0.140 (0.216)	0.801*** (0.305)	0.100 (0.281)	0.899** (0.372)
Has children aged 5-14	0.058 (0.136)	-0.074 (0.141)	0.013 (0.209)	0.018 (0.209)
Has children aged 0-4*Female	-0.863*** (0.322)	-0.791** (0.322)	-0.847** (0.381)	-0.759** (0.381)
Married/De Facto	-0.00481 (0.235)	0.276 (0.252)	0.690* (0.369)	1.145*** (0.395)
Partner is employed	0.062 (0.217)	-0.408 (0.260)	0.0816 (0.281)	-0.454 (0.326)
Weekly non labour income ($100’s)	0.007 (0.007)	0.015* (0.008)	-0.0004 (0.008)	0.010 (0.009)
Partner wage	0.011*** (0.003)	0.013*** (0.003)	0.004 (0.004)	0.005 (0.004)
Rural	-0.915***	-0.894***	-0.533*	-0.487*

	Pooled (1)		Multilevel (2)	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
	(0.195)	(0.195)	(0.274)	(0.274)
Migrant	-2.256** (1.092)	-2.168** (1.096)	-1.645 (1.308)	-1.510 (1.312)
Migrant*Lagged health index	0.027* (0.015)	0.027* (0.015)	0.017 (0.018)	0.017 (0.018)
Migrant*Lagged health index*female	-0.012*** (0.004)	-0.012*** (0.004)	-0.018*** (0.007)	-0.017** (0.007)
Father's occupation	0.024*** (0.003)	0.025*** (0.003)	0.033*** (0.005)	0.033*** (0.005)
Experience	0.023 (0.027)	-0.044 (0.034)	0.116** (0.054)	0.026 (0.060)
Experience squared	-0.0002 (0.001)	0.002* (0.001)	-0.002** (0.001)	0.0006 (0.001)
Economic inactivity	-0.121*** (0.033)	-0.002 (0.050)	-0.289** (0.147)	-0.169 (0.153)
Economic inactivity squared	0.0020 (0.0016)	-0.0001 (0.0017)	0.0039* (0.0023)	0.0008 (0.0025)
Unemployment rate	-0.110*** (0.038)	-0.087** (0.038)	-0.228*** (0.049)	-0.201*** (0.050)
Degree or above	9.374*** (0.296)	9.211*** (0.301)	14.59*** (1.715)	13.54*** (1.745)
Advanced Diploma/Diploma	5.244*** (0.287)	5.210*** (0.287)	5.914*** (1.419)	5.030*** (1.440)
Certificate	1.269*** (0.186)	1.162*** (0.189)	1.335* (0.760)	0.679 (0.782)
Year 12	2.399*** (0.234)	2.382*** (0.234)	-0.509 (1.170)	-0.840 (1.173)
Time averaged characteristics				
Experience			-0.056 (0.042)	-0.056 (0.041)
Economic			0.071	0.131

	Pooled (1)		Multilevel (2)	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
inactivity			(0.146)	(0.146)
Unemployment rate			0.271** (0.108)	0.295*** (0.108)
Has children aged 0-4			-0.486 (0.472)	-0.0958 (0.490)
Has children aged 5-14			-0.163 (0.360)	-0.506 (0.376)
Married/De facto			-0.627 (0.592)	-0.637 (0.591)
Partner is employed			-0.500 (0.559)	-0.842 (0.562)
Partner wage			0.024** (0.010)	0.030*** (0.010)
Degree or above			-3.425* (1.783)	-2.598 (1.800)
Advanced Diploma/Diploma			0.203 (1.485)	1.057 (1.500)
Certificate			0.206 (0.819)	0.722 (0.831)
Year 12			3.847*** (1.229)	4.149*** (1.231)
Constant	7.620*** (0.830)	7.130*** (0.854)	9.607*** (1.318)	8.805*** (1.349)
Generalised residual		0.852*** (0.274)		1.223*** (0.369)
Between individual variance			49.177*** (3.056)	49.046*** (3.044)
Residual variance			101.966***	101.950***
			(2.318)	(2.317)
Sample	38,632	38,632	38,632	38,632
Individuals	7,757	7,757	7,757	7,757

	Pooled (1)		**Multilevel (2)**	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
BIC	300719.0	300713.2	297512.2	297504.5

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students

Both the between individual variance and the within individual (residual) variance are significant. The variance partition coefficient is 49.178/101.964=0.482 which indicates that 48 per cent of the variance in the AUSEI06 can be attributed to differences between individuals. As was the case with previous results, the significance of the between individual variance (from inclusion of a random intercept) provides a statistical test of whether a panel data model is to be preferred. The significant between individual variance in Table 43 indicates that there is unobserved heterogeneity and provides further evidence that a panel data model should be preferred when modelling occupation. In keeping with previous analyses in this thesis, an LR test was also conducted. The LR test statistic also provided strong evidence of group effects further supporting the preference for a panel data (multilevel) model.

A comparison of the BIC shows that the model with the lowest BIC in Table 43 is for the multilevel model incorporating the Wooldridge estimator and including the correction for selection bias (though the inclusion of the correction for selection bias does not have a large impact on the BIC). Initial AUSEI06 is also highly significant adding to the evidence that initial conditions should be accounted for in modelling occupation. Some of the time averaged variables are significant suggesting (as with the results using the EGP) that relatively fixed underlying differences between individuals are significant determinants of occupation.

Comparing the results with and without the correction for selection bias (the generalised residual), in the results controlling for selection bias the main difference is in the effect of having young children. The effect is larger and is highly significant in the results controlling for selection. This suggests that after controlling for selection into employment, men with young children have a higher AUSEI06 ranking (taking into account the negative and significant estimate on the interaction between female and having young children).

There are minor differences in the effect of the gender variable between results with and without the correction for selection bias and also differences in the effect of partner labour force status and being married or in a de facto relationship (though partner labour force status still fails to be significant at the 5 per cent level). There are notable differences in the estimated effects of employment experience and time out of work (the variable labelled economic inactivity). These variables are significant when selection bias is not accounted for but are no longer significant at any level after the correction for selection bias is included. This suggests that after taking into account the probability of employment for the sample used in the AUSEI06, employment experience and time out of work are not important determinants of occupation.

The generalised residual controlling for selection bias is significant, suggesting that there is significant selection bias. This indicates that selection must be accounted for in order to avoid biased results. The preferred estimates are those which control for selection bias and the remainder of the discussion regarding Table 43 focuses on these (the estimates in the final column of Table 43).

Health does not have a significant effect on occupation apart from for female migrants (as was the case with the results from Table 41). As was the case with results using the EGP schema, this suggests that after taking into account selection into employment, educational attainment and other factors affecting occupation, health does not have a causal effect on occupation (or occupational status). While the earlier results using the EGP could only capture changes between broad categories, the results in Table 43 using the AUSEI06 capture changes within occupational classes. The lack of a significant effect of health indicates that there is no evidence of a causal effect of health on occupational status after controlling for selection into employment. Persons experiencing poor health are not more likely to be employed in lower status occupations after accounting for selection into employment and this finding is not sensitive to the measure of occupation used.

The remaining variables mostly appear to have the expected effects. Women have a higher AUSEI06 ranking. Persons with higher education also have a higher occupational position. Father's occupation is linked with higher AUSEI06 in line with the literature which suggests that higher childhood SES leads to higher occupational status. Living in a rural area is weakly associated with a lower occupational position (at the 10 per cent significance level) representing the lower proportion of professional and managerial type jobs in rural areas.

Job losses look to have been higher amongst lower status occupations for men (relative to high status jobs) post GFC with the post GFC variable being significant and positive in sign suggesting post GFC is associated with higher occupational status. For women, the effect is smaller (taking into account the significant interaction between post GFC and gender). Being married or in a de facto relationship has a positive effect on AUSEI06 ranking, again suggesting this variable is capturing other partner characteristics (e.g. partner selection or facing the same labour market). A higher unemployment rate is associated with lower AUSEI06.

The results from the estimates presented in Table 43 indicate (as with previous results in this thesis) that a panel model is to be preferred in modelling relationships between health and labour market outcomes. Dynamics are again relevant, there is significant unobserved heterogeneity and initial conditions play a role. Results including the correction for sample selection bias indicate that there is sample selection bias and illustrate the importance of controlling for this. Failure to control for this bias could result in an incorrect identification of the significant determinants of occupation. Results suggest that health does not have a significant effect on occupational position as measured using the health index after controlling for selection.

The main disadvantage in using the AUSEI06 as a measure of occupation is that the AUSEI06 is only observed for persons who are employed. The selection effect cannot be explicitly modelled as an outcome when using the AUSEI06. One advantage, however, in using the AUSEI06 (compared with the EGP schema used earlier in this chapter) is that job characteristics can be included in the model[59]. Table 44 presents results including job characteristics alongside the original results from column 2 of Table 43 to enable comparisons.

Table 44: Estimates (and Standard Errors) of Determinants of Occupational Status (Dependent Variable AUSEI06 score 0-100)-Multilevel Linear Regression with and without Job Characteristics (and with and without controlling for selection)

	Without job characteristics		**With job characteristics**	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
AUSEI06 at t-1	0.337*** (0.008)	0.337*** (0.008)	0.326*** (0.008)	0.326*** (0.008)
AUSEI06 at t=1	0.344*** (0.009)	0.343*** (0.009)	0.336*** (0.009)	0.335*** (0.009)
Post GFC	0.691*** (0.237)	0.744*** (0.237)	0.667*** (0.234)	0.704*** (0.235)
Female	3.353*** (1.039)	3.725*** (1.048)	3.744*** (1.032)	4.000*** (1.040)
Post GFC*Female	-0.541** (0.264)	-0.530** (0.265)	-0.562** (0.263)	-0.553** (0.263)
Lagged health index	0.018 (0.011)	0.0058 (0.012)	0.016 (0.011)	0.007 (0.012)
Initial health	-0.007 (0.011)	-0.020* (0.011)	-0.010 (0.011)	-0.019* (0.011)
Lagged health index*female	-0.023* (0.014)	-0.022 (0.014)	-0.024* (0.014)	-0.023* (0.014)
Has children aged 0-4	0.100 (0.281)	0.899** (0.372)	0.102 (0.281)	0.680* (0.372)
Has children aged 5-14	0.013 (0.209)	0.018 (0.209)	0.101 (0.209)	0.103 (0.209)

[59] Job characteristics could not be included in the models using the EGP schema because job characteristics are not observed for the “not employed’ outcome.

	Without job characteristics		With job characteristics	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
Has children aged 0-4*Female	-0.847** (0.381)	-0.759** (0.381)	-0.151 (0.383)	-0.101 (0.383)
Married/De Facto	0.690* (0.369)	1.145*** (0.395)	0.727** (0.367)	1.056*** (0.392)
Partner is employed	0.082 (0.281)	-0.454 (0.326)	0.060 (0.281)	-0.326 (0.325)
Weekly non labour income ($100's)	-0.0004 (0.008)	0.010 (0.009)	0.007 (0.008)	0.015* (0.008)
Partner wage	0.004 (0.004)	0.005 (0.004)	0.005 (0.004)	0.006 (0.004)
Rural	-0.533* (0.274)	-0.487* (0.274)	-0.715*** (0.272)	-0.678** (0.271)
Migrant	-1.645 (1.308)	-1.510 (1.312)	-1.508 (1.307)	-1.412 (1.311)
Migrant*Lagged health index	0.017 (0.018)	0.017 (0.018)	0.020 (0.018)	0.020 (0.018)
Migrant*Lagged health index*female	-0.018*** (0.007)	-0.017** (0.007)	-0.019*** (0.007)	-0.019*** (0.007)
Father's occupation	0.033*** (0.005)	0.033*** (0.005)	0.036*** (0.005)	0.036*** (0.005)
Experience	0.116** (0.054)	0.026 (0.060)	0.078 (0.054)	0.015 (0.060)
Experience squared	-0.002** (0.001)	0.0006 (0.001)	-0.0009 (0.001)	0.0007 (0.001)
Economic inactivity	-0.289** (0.147)	-0.169 (0.153)	-0.206 (0.148)	-0.121 (0.154)
Economic inactivity squared	0.0039* (0.0023)	0.0008 (0.0025)	0.0023 (0.0023)	0.0001 (0.0024)
Unemployment rate	-0.228*** (0.049)	-0.201*** (0.050)	-0.202*** (0.048)	-0.183*** (0.049)

	Without job characteristics		**With job characteristics**	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
Hours worked			0.069*** (0.007)	0.068*** (0.007)
Job tenure			0.051*** (0.013)	0.050*** (0.013)
Union member			0.180 (0.187)	0.194 (0.187)
Private sector			-3.444*** (0.256)	-3.446*** (0.256)
Degree or above	14.59*** (1.715)	13.54*** (1.745)	13.82*** (1.686)	13.05*** (1.716)
Advanced Diploma/Diploma	5.914*** (1.419)	5.030*** (1.440)	5.746*** (1.389)	5.105*** (1.411)
Certificate	1.335* (0.760)	0.679 (0.782)	0.977 (0.760)	0.505 (0.781)
Year 12	-0.509 (1.170)	-0.840 (1.173)	-0.811 (1.164)	-1.059 (1.168)
Time averaged characteristics				
Experience	-0.056 (0.042)	-0.056 (0.041)	-0.070* (0.041)	-0.070* (0.041)
Economic inactivity	0.071 (0.146)	0.131 (0.146)	0.0645 (0.147)	0.109 (0.147)
Unemployment rate	0.271** (0.108)	0.295*** (0.108)	0.320*** (0.107)	0.336*** (0.107)
Has children aged 0-4	-0.486 (0.472)	-0.0958 (0.490)	-0.305 (0.470)	-0.024 (0.487)
Has children aged 5-14	-0.163 (0.360)	-0.506 (0.376)	-0.132 (0.359)	-0.381 (0.374)
Married/De facto	-0.627 (0.592)	-0.637 (0.591)	-0.528 (0.591)	-0.539 (0.591)
Partner is employed	-0.500 (0.559)	-0.842 (0.562)	-0.723 (0.560)	-0.965* (0.563)
Partner wage	0.024**	0.030***	0.028***	0.032***

	Without job characteristics		**With job characteristics**	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
	(0.010)	(0.010)	(0.010)	(0.010)
Degree or above	-3.425* (1.783)	-2.598 (1.800)	-3.179* (1.752)	-2.575 (1.769)
Advanced Diploma/Diploma	0.203 (1.485)	1.057 (1.500)	0.202 (1.456)	0.825 (1.472)
Certificate	0.206 (0.819)	0.722 (0.831)	0.539 (0.819)	0.912 (0.830)
Year 12	3.847*** (1.229)	4.149*** (1.231)	4.084*** (1.224)	4.313*** (1.227)
Constant	9.607*** (1.318)	8.805*** (1.349)	9.932*** (1.410)	9.379*** (1.439)
Generalised residual		1.223*** (0.369)		0.885** (0.368)
Between individual variance	49.177***	49.046***	48.573**	48.520***
	(3.056)	(3.044)	(2.916)	(2.909)
Residual variance	101.966***	101.950***	100.540***	100.528***
	(2.318)	(2.317)	(2.267)	(2.267)
Sample	38,632	38,632	38,406	38,406
Individuals	7,757	7,757	7,743	7,743
BIC	297512.2	297504.5	295297.6	295298.7

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students

Analysing the diagnostics in Table 44 suggests that the specification including job characteristics is to be preferred. The results including job characteristics have lower between individual variance and lower within individual (residual) variance compared with those which do not include job characteristics. The BIC is also lower for the results including job characteristics. The generalised residual is lower after including the job characteristics variables but remains significant, reinforcing the need to control for selection into employment.

The results with and without job characteristics (when selection into employment is corrected for) show little difference in the magnitude of the effects of the other explanatory variables, aside from the effect of having young children no longer being significant once job characteristics are included. The effect of including the generalised residual is less when comparing results including job characteristics compared with results excluding the job characteristics.

Aside from union membership the included job characteristic variables are significant determinants of occupational position. The effect of hours worked is positive and suggests that higher hours are associated with higher status occupations. Job tenure is significant and positive with longer job tenure linked with a higher AUSEI06 ranking while employment in the private sector has a negative effect on AUSEI06 ranking.

The significance of the job characteristics variables combined with the diagnostics in Table 44 support the inclusion of job characteristics in the AUSEI06 model.

As with the EGP model, the AUSEI06 model was also run using two alternative specifications of health to compare with the results presented in Table 44 (see Table A-33 in the Appendix for the comparison models). Table 44 presented results using the preferred model (using the lagged health index which is the preferred health measure), the results in Table A-33 using the measure of self-assessed health shock and self assessed health improvement are included for comparison purposes and to determine whether findings are sensitive to the measure of health used.

Results using the self-assessed health shock measure find no significant effect of a health shock on occupational status for men or women. Likewise, results using the measure of self-assessed health improvement find no significant effect of an improvement in health on occupational status. This suggests (as with the earlier discussion) that there is no causal effect of health on occupation status after controlling for selection into employment. The lack of a significant effect of health on occupation further supports the findings in section 6.6.1 that onset of poor health is more likely to result in health selection out of employment rather than occupation of employment.

Aside from the health measure, there are also few differences in the effects of the other explanatory variables in comparing the estimates from the health change models with the estimates in Table 44. Noticeable differences include the effect of the gender and migrant variables and the interaction term between migrant, female and health. As with the previous discussion in relation to the results in section 6.6.1, these differences are possibly caused by the use of different health measures in the interaction between health and gender and health and migrant status in the different specifications which then have a flow on effect to the results from the gender and migrant variables and interaction terms containing migrant status. Initial health now has a significant effect in the health change specifications in Table A-33 however the magnitude of the effect does not really differ from that in Table 44 for initial health. The difference in significance level in Table A-33 may again be attributed to the interaction between initial health and the different health measures used in this table. Initial health has a different relationship with the health index than it does with the health shock and health improvement measures.

Results in this section suggest that health and changes in health do not have a significant effect on occupation. Combining the findings from this section and the findings presented in section 6.6.1 provides some evidence that this result is not sensitive to health measure used or measure of occupation chosen. The discussion so far has analysed the effect of health and changes in health on occupation: however health (and changes in health) can also result in changes in occupation. The next section analyses determinants of job change in order to establish whether health has a significant effect on the likelihood of changing jobs.

6.6.3 Analysis of Job Change and Results from Job Change Models

Section 6.2 discussed the role of job change in enabling persons who experience a health shock to remain in employment. A limitation of much of the current literature on job change and job accommodation is the failure to properly take into account selection into employment. Most literature also only analyses a subset of the population-persons with health impairments. This section presents analyses of the working age population which control for selection into employment in order to provide unbiased estimates of the effect of health on the likelihood of changing jobs.

Before moving on to the econometric results, it is useful to consider some descriptive statistics on job change distinguishing between persons who experienced a health shock and those who did not. Table 45 and Table 46 present the number and percentage of broad occupational changes using the EGP occupational measure. Table 45 presents occupational changes for persons who did not experience a health shock while Table 46 considers those who did experience a health shock[60].

Table 45: Number (and Percentage) of Broad Occupational Changes, Persons who did not experience a Health Shock

	t=2				**t=3**			
t=1	*Not employed*	*Manual*	*Non-Manual*	*Total*	*Not employed*	*Manual*	*Non-Manual*	Total
Not employed	1,481 (83.91)	119 (6.74)	165 (9.35)	1,765 (100)	1,249 (79.1)	133 (8.42)	197 (12.48)	1,579 (100)
Manual	108 (8.48)	1,037 (81.46)	128 (10.05)	1,273 (100)	105 (9.11)	915 (79.36)	133 (11.54)	1,153 (100)
Non - Manual	172 (5.97)	116 (4.03)	2,593 (90)	2,881 (100)	205 (7.87)	94 (3.61)	2,307 (88.53)	2,606 (100)
Total	1,761 (29.75)	1,272 (21.49)	2,886 (48.76)	5,919 (100)	1,559 (29.21)	1,142 (21.39)	2,637 (49.4)	5,338 (100)

Table 45 and Table 46 both include occupation transitions at both t=2 and t=3 because occupational changes may not be immediately apparent following a health shock. There appears to be more transitions (percentage wise) to non employment for people experiencing a health shock and lower occupational changes among people experiencing a health shock who continue to work. There are more occupational

[60] The number and percentage of occupational changes were analysed using two different measures of health shock. The results did not differ greatly. Results presented in this section use the measure where a health shock is defined as somewhat worse or much worse health compared with 12 months ago as this measure had fewer missing values.

transitions at t=3 compared with t=2 (percentage wise) among those employed at t=1 for people experiencing a health shock between t=1 and t=2 however the differences observed would not be large enough to be significant especially given the low cell counts.

Table 46: Number and Percentage of Broad Occupational Changes, Persons who experienced a Health Shock between 2001 and 2002

	t=2				**t=3**			
t=1	*Not employed*	*Manual*	*Non-Manual*	*Total*	*Not employed*	*Manual*	*Non - Manual*	Total
Not employed	357 (90.61)	11 (2.79)	26 (6.6)	394 (100)	322 (92.8)	9 (2.59)	16 (4.61)	347 (100)
Manual	23 (19.17)	87 (72.5)	10 (8.33)	120 (100)	25 (23.81)	72 (68.57)	8 (7.62)	105 (100)
Non-Manual	32 (11.23)	8 2.81	245 (85.96)	285 (100)	43 (16.86)	11 (4.31)	201 (78.82)	255 (100)
Total	412 (51.56)	106 (13.27)	281 (35.17)	799 (100)	390 (55.16)	92 (13.01)	225 (31.82)	707 (100)

Table 47 and Table 48 present the number and percentage of job changes by whether individuals experience a health shock using an alternative measure of job change. These tables identify job change as lower, same or higher AUSEI06 ranking at t=2 or t=3 compared with t=1.

Table 47: Number and Percentage of Persons Experiencing AUSEI06 Change, Persons who did not experience a Health Shock

	t=2			**t=3**		
	Freq.	*Percent*	*Cum.*	*Freq.*	*Percent*	*Cum.*
Lower	1,175	20.86	20.86	897	18.21	18.21
Same	3,262	57.91	78.77	3,052	61.94	80.15
Higher	1,196	21.23	100	978	19.85	100
Total	5,633	100		4,927	100	

Table 48: Number and Percentage of Persons Experiencing AUSEI06 Change, Persons who experienced a Health Shock between 2001 and 2002

	t=2			t=3		
	Freq.	*Percent*	*Cum.*	*Freq.*	*Percent*	*Cum.*
Lower	96	19.12	19.12	91	22.25	22.25
Same	286	56.97	76.1	241	58.92	81.17
Higher	120	23.9	100	77	18.83	100
Total	502	100		409	100	

There are a larger number of occupational changes observed for employed persons both for persons experiencing a health shock and those who do not when using the AUSEI06 change variable instead of EGP transitions. This reflects the broad nature of the EGP measure. The AUSEI06 change variable is capturing changes within these broad categories.

Comparing Table 47 and Table 48 shows that there does not appear to be a significant difference between those who had a health shock and those who did not in the proportion changing jobs (to lower or higher AUSEI06) and those remaining in a job with the same AUSEI06 ranking (simplistically assuming same AUSEI06 equates to same job which may not be the case). The degree of occupational change is also quite similar at t=2 and t=3. The information in the tables presented thus far in this section does not provide support for the claim that a health shock results in job change.

Econometric modelling is required to determine causal effects. While there does not appear to be a difference by health status in the proportion experiencing a job change in the descriptive statistics presented so far, these statistics may mask causal effects because they do not control for other factors which may affect the likelihood of changing jobs. Econometric techniques are needed to determine any effect of health on job change in order to hold other factors affecting likelihood of job change constant.

Table 49 presents the results from estimating job change models. The estimates presented are conditional marginal effects. These can be interpreted as the marginal effects for the probability of lower AUSEI06 (column 1), same AUSEI06 (column 2) or higher AUSEI06 (column 3) conditional on being employed. The standard errors presented are panel adjusted.

Table 49: Estimates (and Standard Errors) for Probit Marginal Effects for the Probability of Changes in Occupation Corrected for Selection into Employment

	Lower AUSEI06	Same AUSEI06	Higher AUSEI06
Post GFC	-0.003 (0.007)	0.011 (0.010)	-0.007 (0.007)
Female	-0.013* (0.007)	0.005 (0.013)	0.012* (0.007)
Post GFC*Female	0.001 (0.010)	0.004 (0.014)	-0.005 (0.010)
Health shock	0.008 (0.011)	-0.009 (0.017)	0.001 (0.012)
Initial health	-0.0001 (0.0002)	0.0005 (0.0004)	-0.0004** (0.0002)
Health shock*female	-0.010 (0.016)	0.006 (0.023)	0.004 (0.017)
Has children aged 0-4	-0.008 (0.008)	0.007 (0.014)	0.002 (0.009)
Has children aged 5-14	-0.0006 (0.0051)	0.0012 (0.0089)	0.0005 (0.0054)
Has children aged 0-4*Female	0.031** (0.014)	-0.057** (0.023)	0.018 (0.014)
Married/De Facto	-0.002 (0.008)	0.019 (0.014)	-0.017* (0.009)
Partner is employed	-0.009 (0.008)	0.012 (0.013)	0.0001 (0.008)
Weekly non labour income ($100’s)	0.0001 (0.0002)	0.00004 (0.0004)	-0.0002 (0.0003)
Partner wage	-0.0001 (0.0001)	0.00002 (0.0002)	0.0001 (0.0001)
Rural	-0.015** (0.006)	0.026** (0.012)	-0.011 (0.007)

6. The Effect of Health on Occupation

	Lower AUSEI06	Same AUSEI06	Higher AUSEI06
Migrant	0.008	-0.012	0.004
	(0.006)	(0.011)	(0.006)
Migrant*Health shock	-0.010	0.024	-0.015
	(0.023)	(0.035)	(0.025)
Migrant*Health shock*female	0.007	-0.006	0.002
	(0.033)	(0.047)	(0.034)
Father's occupation	0.0001	-0.0001	-0.00001
	(0.0001)	(0.0002)	(0.0001)
Experience	0.001	0.004**	-0.004***
	(0.0009)	(0.001)	(0.0009)
Experience squared	-0.000001	-0.00009***	0.00007
	(0.00002)	(0.00003)	(0.00002)
Economic inactivity	0.001	-0.002	0.0002
	(0.001)	(0.002)	(0.001)
Economic inactivity squared	-0.00006	0.00014	-0.00006
	(0.00005)	(0.00009)	(0.00006)
Unemployment rate	-0.0001	-0.0017	0.0013
	(0.0013)	(0.0019)	(0.0013)
Hours worked	-0.0004**	-0.0002	0.0006***
	(0.0002)	(0.0003)	(0.0002)
Job tenure	-0.003***	0.007***	-0.003***
	(0.0003)	(0.0006)	(0.0003)
Union member	0.041***	-0.091***	0.051***
	(0.006)	(0.009)	(0.006)
Private sector	0.007	0.009	-0.015**
	(0.006)	(0.010)	(0.006)
Degree or above	-0.022***	0.053***	-0.029***
	(0.007)	(0.012)	(0.007)
Advanced Diploma/Diploma	0.003	0.010	-0.012
	(0.009)	(0.016)	(0.009)
Certificate	-0.012*	0.027**	-0.013*
	(0.007)	(0.012)	(0.007)
Year 12	0.014*	-0.030**	0.013
	(0.008)	(0.014)	(0.008)
Constant	-1.125***	-0.485***	-0.869***

	Lower AUSEI06	Same AUSEI06	Higher AUSEI06
	(0.094)	(0.110)	(0.095)
Rho	0.314***	-0.434***	0.186***
	(0.036)	(0.033)	(0.038)
Sample	48,632	48,632	48,632
Individuals	9,493	9,493	9,493

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students. 4) Standard errors are panel adjusted standard errors.

In the case of the heckprob procedure, Rho is a test statistic which determines whether the selection (employment) equation is independent from the job change equation. In this case Rho is highly significant in the results from all three models. This provides evidence that the job change equation is not independent from the selection equation and supports the use of the model accounting for selection into employment.

The results in Table 49 show that after controlling for selection into employment, almost all of the demographics do not have a significant effect on the likelihood of job change. Having a degree is significant across all three models, having a negative effect on the likelihood of changing jobs though the size of the effect is small. Job characteristics are significant determinants of job change. Hours worked has a small but significant effect, with higher hours negatively associated with the likelihood of changing to a lower status job and positively associated with the likelihood of changing to a job with a higher status job. Job tenure is also significant in all three models, having a small positive effect on remaining in a job with the same AUSEI06 ranking and a small negative effect on changing to a job with a lower or higher AUSEI06 ranking. Union membership has a small but significant positive effect on the likelihood of changing to a job with a lower or higher AUSEI06 ranking and a small negative effect on remaining in a job with the same AUSEI06 ranking.

The health shock variable is not significant in any of the three models in Table 49[61]. This suggests that there is no significant evidence that persons experiencing a health shock are more likely to change jobs compared with persons who do not experience a health shock after accounting for selection into employment. This does not mean that people who have a health shock do not change jobs in order to adapt to health impairment, just that they are not significantly more likely to change jobs compared with persons who do not experience a health shock.

The results in Table 49 also suggest that persons who experience a health shock are not more likely to remain in the same job (if we assume that same AUSEI06 equates to remaining in the same job). This does not mean that job accommodation does not play a role in enabling persons to adapt to a health shock and remain in employment. HILDA does not contain an indicator of job accommodation therefore it was not possible to explicitly model the degree of job accommodation in order to determine the role of this in enabling continued employment following a health shock.

It is possible that the combination of the job accommodation effect and the job change effect discussed in the literature cancel each other out. This could explain the lack of a significant effect of health on the likelihood of changing jobs or remaining in the same job after accounting for selection into employment.

There are of course limitations to the analyses undertaken in this chapter. Firstly, the number of transitions between occupations and health states are limited as seen in the transition tables presented earlier in the chapter. Second, modelling of health is not able to distinguish between episodic poor health and long term continuing health impairment. Finally, it is possible that persons experiencing health impairment may be among those who did not respond during later waves of the HILDA survey. Nevertheless, the analysis in this chapter still provides insight into an under-examined area-the effect of health on occupation.

---

[61] The models presented in Table 49 use the health shock measure. These models were also estimated using lagged health index and an alternative measure of health shock. Results were not substantially different. Health does not have a significant effect regardless of the health measure used.

Taking into account all the information presented in this section-the EGP estimation results, the AUSEI06 estimation results and the findings from the job change models-the main finding is that the movement out of employment (selection out of employment) is the dominant response to a health shock or to poorer health. While there may be some degree of job change or job accommodation enabling continued employment, this is dominated in the results by the selection effect. These findings illustrate the importance of accounting for selection in order to prevent bias in results when modelling the effect of health on occupation.

6.7 Conclusion

While a number of studies have examined the effect of occupation on health, the reverse relationship is under-examined. Studies which have researched the effect of health impairment on occupation have not controlled for selection into employment. The growing literature on the adverse effect of poor health on the likelihood of employment and poor health being linked with job exits emphasises the need to consider movements out of employment as a response to health when analysing employment outcomes.

This chapter has used two measures in order to determine the effect of health on occupation and the effect of changes in health on occupation. The first measure (the EGP measure) allowed modelling of the selection effect and changes within broad occupations defined by physical job demands (manual vs. non-manual employment) while the second measure (the AUSEI06) captured changes within occupational status/ranking. Both of these aspects of occupation were previously found to be associated with health but *causal* evidence on the effects of health on these outcomes was lacking.

As was the case with the analysis in chapter 5, results can be taken as suggestive of causal effects. The controls for selection into employment, state dependence, initial conditions, unobserved heterogeneity and measurement error in health allow better determination of causality however, the models cannot completely account for endogeneity. Timing of changes in health cannot be said to exactly match changes in occupation.

The results from the dynamic, multilevel models estimated in this chapter showed that (as was the case in the previous chapter) it is important to control for selection into employment given that occupation is only observed for persons who are employed. Incorporating non-employment as an outcome in the models using the EGP measure of occupation showed that individuals in poorer health or who experience a health shock are less likely to be employed. This suggests not only that persons in poor health are less likely to be in employment but that persons who cannot adapt to health impairment are more likely than those with no health problems to leave employment.

The estimates also provide strong evidence that dynamics should be included and that initial conditions should be accounted for in modelling occupation. This result combined with that from the previous two chapters strongly suggests the importance of including controls for state dependence and initial conditions when modelling relationships between health and labour market outcomes. The models estimated also found evidence of unobserved heterogeneity. Modelling occupation requires panel data estimation in order to control for individual differences.

Among persons who are employed, health (and changes in health) does not have a significant effect on occupation. This was the case for results for all specifications for both measures of occupation used. Analysing models of job change in order to determine the effect of health on likelihood of changing jobs also found that after taking into account selection into employment, persons experiencing an adverse health shock are not more likely to change occupation.

Previous literature has found that job change and job accommodation are ways in which persons can adapt to health impairment to keep working. The results in this chapter suggest that the selection out of employment is the dominant response to poor health. This is consistent with persons in poor health (or who experience onset of poor health) being more likely to leave employment than to change jobs.

The findings in this chapter have implications for lifetime earnings. Job change in response to poor health may be associated with lower income (particularly if linked with fewer hours of work to adapt to health limitations) but it still offers the opportunity to earn an income. Job change might occur within occupations and this cannot be identified in the data however it is not likely to negate the conclusion that withdrawal from employment is a common response, and one which widens the gap in lifetime earnings between people who experience poor health and those in continuous good health who do not suffer this disadvantage.

7. An Investigation of Cumulative Effects of Health Related Labour Market Disadvantage

7.1 Introduction

Chapter 3 provided cross sectional indicators of cumulative disadvantage while chapters 5 and 6 established relationships between health and some key labour market outcomes which can lead to disadvantage. The results presented in chapters 5 and 6 indicate that there is health related labour market disadvantage but they cannot establish whether and to what extent this is cumulative.

This chapter expands on the cross sectional material on cumulative disadvantage in chapter 3 and the econometric studies in chapters 5 and 6 by estimating econometric models of measures capturing advantage (or disadvantage) over the life course. Panel data modelling techniques are used to establish the effect of health on these measures and thus to better understand the extent to which health related labour market disadvantage is cumulative, the impact of this disadvantage and implications arising from this.

The specific research question of interest in this chapter is whether health related labour market disadvantage is cumulative and if so, to what degree. It is hypothesised that there is a cumulative effect and that the degree will be affected by age of onset of poor health-those with poor health early in their working life will experience a greater cumulative effect of health related labour market disadvantage.

The chapter begins in section 7.2 by reviewing the background and theory on relationships between health and labour market disadvantage. Some of the relevant research was also covered in chapter 2. Section 7.3 discusses measures of cumulative effects used in this chapter and ways in which the cumulative effect of labour market disadvantage can be analysed. Section 7.4 sets out methods, data and modelling approaches used while section 7.5 discusses the sample and explanatory variables used. Section 7.6 presents results from estimating econometric models and section 7.7 concludes with a discussion of results and summary.

7.2 Background

The review of the literature in chapter 2 revealed that poor health has been found to have a negative effect on labour market outcomes studied thus far. The pathways include reduced labour force participation, increased likelihood of unemployment and job loss, reduced hours worked, lower wages, and early retirement.

This literature suggests strongly that poor health results in labour market disadvantage. The analysis in chapters 5 and 6 expanded on the literature, with chapter 5 finding that health affects the form of employment for the working age population. The analysis in chapter 6 did not find a causal effect of health on occupation after controlling for selection into employment however poor health was strongly associated with economic inactivity. The results emphasised the need to control for unobserved heterogeneity and selection into employment in order to avoid overestimates of the effect of health on labour market outcomes.

The combination of evidence both from previous literature and from the empirical studies presented in this thesis suggests a likely cumulative effect of health. Flexible forms of employment, fewer hours of work, exiting employment and longer periods of time out of the workforce have negative effects on lifetime earnings. Poor health that leads to an initial labour market set back has the potential to then lead to subsequent and cumulating poorer labour market outcomes, particularly for persistent poor health. Cross sectional statistics presented in chapter 3 support this hypothesis however longitudinal evidence is required to establish a causal effect.

The literature on cumulative effects of poor health does provide some longitudinal evidence but as discussed in chapter 2 this evidence is limited. While there is a range of literature analysing health and socioeconomic aspects of the cumulative disadvantage of poor health, empirical evidence on cumulative *labour market* disadvantage resulting from poor health is scarce. The studies which do examine this relationship are restricted in terms of sample used and methodology. Studies confined samples to men and subsets of the working age population and even where panel data was used, methods often did not address the known econometric issues of unobserved heterogeneity, sample selection bias and endogeneity. There also does not appear to be any Australian evidence.

This chapter uses the HILDA data to test and quantify the hypothesis that poor health results in cumulative labour market disadvantage. It adds substantial new empirical results to an important topic that has attracted only limited research to date. Its contribution includes the application of appropriate contemporary econometric techniques to Australian panel data that represents the entire working age population.

Economic theory draws on the Grossman model (Grossman, 1972; 2000). According to this model poor health results in less healthy time. This results in less time spent working (reducing both earnings and the capacity for human capital accumulation). Poor health is also associated with a shorter lifespan, reducing the incentive for human capital accumulation. The wealth constraint equation in the model particularly highlights disadvantage arising from poor health. Full wealth in the Grossman model equals initial assets plus the present value of the earnings an individual would receive if they spent all their time at work. The findings of the literature on the relationship between health and employment and the findings from the analyses in the previous chapters strongly suggest that full wealth, a measure of advantage associated with lifetime earnings, is affected by health. In the model this is reflected by a reduction in hours worked over the life cycle and results in lower earnings and therefore lower wealth.

The arguments underpinning medical sociology theory relating to cumulative disadvantage are closely related to those of the relevant economic theory and stem from the cumulative disadvantage hypothesis set out by Ross and Wu (1996) and Haas *et al.* (2011). This theory argues that those who start out with good health are able to translate their initial physical productive advantage into additional opportunities for promotion, job advancement, and higher earnings through greater accumulation of human capital and psychosocial resources (Ross and Wu, 1996; Haas *et al.*, 2011). Additionally, those persons who start out with good health are more able to engage in continuous employment over time. Thus early career advantage translates into even greater advantages later in life leading to greater disparity in earnings and disparity in accumulation of wealth. Under the cumulative disadvantage hypothesis, poorer health is hypothesised to result in slower rate of growth of wealth relative to healthy persons of the same age.

Key to theory in both disciplines is the effect of health on time spent in employment and the advantage conferred on those in good health in being able to remain employed. The role of health in affecting the rate of human capital accumulation is not explicitly incorporated in the Grossman model. It is explicitly stated in the medical sociology theory of cumulative disadvantage related to health and can be inferred from the basic relationships within the Grossman model, An adverse effect of poor health, not only affecting time spent employed but also resulting in lower accumulation of human capital and therefore affecting opportunities for promotion and higher earnings underpins the hypothesis to be tested in this thesis, that there is cumulative labour market disadvantage resulting from poor health which affects lifetime earnings. This hypothesis will be tested using indicators of accumulating disadvantage.

Chapter 2 reviews the relevant literature. Two main indicators of accumulating disadvantage were examined: labour force experience and wealth. Both of these measures are related to lifetime earnings and descriptive statistics in chapter 3 find an association between health and these measures. The literature reviewed in chapter 2 does find diminished career earnings and adverse effects on years worked for those previously experiencing poor health. The populations studied tend to be restricted, for example to men or to older people, and only a few use the multiple econometric advantages available from panel data. The limited empirical evidence supports the theoretical effect of health on earnings in the Grossman model and the medical sociology literature.

The lifetime earnings of an individual cannot in practice be observed. Wealth is a stock measure which can be observed at a moment in time. It comprises the value of assets owned by an individual or household minus the debts owed and is a measure of available economic resources. As a stock measure, it is also an indicator of the cumulative income received to that point (recognising that people save at different rates from their income). It is thus a direct observation of the outcomes of the working life to date.

The majority of studies analysing the relationship between wealth and health focus on causal effects from wealth to health (see for example Headey and Wooden 2004; Cai, 2009a; Aittomaki *et al.*, 2010; Connolly *et al.*, 2010; Hajat *et al.*, 2010). Recent studies using panel data methods which consider the opposite relationship- causal effects from health to wealth- find strong evidence of health causation, that poor health causes lower wealth (Michaud and van Soest, 2008; Smith, 2009). As discussed in chapter 2 however, studies of the effect of health on wealth interpret wealth as a measure of SES rather than determining accumulating disadvantage and also confine their sample to a subset of the population.

In Australia (as in most developed countries), wealth becomes a particularly important indicator later in life as changes in the value of superannuation and net worth can act as a measure of accumulated advantage/disadvantage over the life course, representing resources accumulated over working life and available later in life to meet financial commitments and maintain a satisfactory living standard after retirement.

Levels of wealth tend to be closely associated with the stage in the household life cycle. Many younger households have relatively low wealth and relatively high income while older households are more likely to be relatively wealthy but have lower income (ABS, 2006b). Household composition also affects distribution of wealth with couples having more wealth on average than single parent families or lone person households (ABS, 2006b).

In Australia, the superannuation system is a form of compulsory saving for retirement, with almost all workers entitled to this as part of their employee benefits. This was not always the case. Superannuation became more widely available in the 1970’s through negotiation for its inclusion in industrial awards but coverage was low, with only 32 per cent of wage and salary earners having superannuation in 1974 (Australian Treasury, 2001). The 1986 National Wage Case provided for a minimum level of superannuation for employees covered by awards, with 3 per cent of wages to be paid into superannuation. The Superannuation Guarantee was introduced in 1993, mandating a minimum level of employer contribution of 4 per cent of earnings for all employees earning over $450 a month, with a charge imposed for failures to meet that minimum. The employer contribution progressively increased up to the current level of 9.5 per cent (ATO, 2015).

The superannuation system is the closest thing Australia has to a contributions based social security system. In the pre-compulsory era, superannuation fund members were generally entitled to withdraw their benefits whenever they resigned from their job (Parr *et al.*, 2007). In 1987, the government introduced preservation requirements. Following this, superannuation can only be accessed from age 55 with a tax penalty; from age 60, if you have retired, without penalties and from age 65 without restriction. The purpose of superannuation is to reduce dependence on the means tested age pension and to improve the welfare of retirees (Keegan, 2011). Persons without superannuation are solely reliant on alternative private savings and/or the government funded (and means tested) age pension in retirement.

In 2007, 90 per cent of employed people had superannuation, compared with 55 per cent in 1988 (ABS, 2009a). Employed people who were not making contributions to superannuation were mainly self-employed. Superannuation is a key individual indicator of cumulative labour market disadvantage in Australia, where levels of superannuation savings, employment and earnings level are closely linked. Factors such as hours worked, employment continuity, income level and retirement age all impact on the amount of superannuation saved (ABS, 2002a).

The close links between household net worth and labour market outcomes (and particularly between superannuation and labour market outcomes) mean these measures can be used to assess the impact of health on cumulative labour market disadvantage. The exact way in which these are measured and can be used is discussed in more detail in the next section.

This chapter uses HILDA data to test and quantify the cumulative disadvantage hypothesis using two indicators, household wealth and superannuation. Poorer health is hypothesised to result in a slower rate of growth of wealth relative to healthy persons of the same age.

The wealth measures used in this chapter will be discussed in the next section.

7.3 Measure of Wealth

This section is divided into two parts. It begins by setting out the background on wealth measures and the longitudinal data available to measure wealth in Australia. It then presents some descriptive statistics which further illustrate the health-wealth gradient observed when analysing cross sectional data.

7.3.1 Background on Wealth Measures

The analysis in this chapter will use measures of wealth obtained from the HILDA survey. While there is a fair degree of individual ownership of assets, benefits of asset ownership and resources flowing from wealth are usually shared between members of households. This supports using a household measure of wealth: household net worth. Notwithstanding this, an individual measure of wealth can be used to more accurately capture effects of labour market disadvantage over time-a household measure can mask effects of health as the measure combines other earnings and wealth accumulated by other household members[62]. Also, an individual measure such as superannuation has the unique benefit of being closely linked with labour market outcomes due to a large component of superannuation being employer contributions, and employment status and earnings levels being determinants of the level of superannuation contributions.

Given the advantages (and disadvantages) arising from use of each type of measure, the analysis of health related cumulative labour market disadvantage in this chapter will use two measures of wealth: household net worth (defined as total value of household assets minus debts) and individual superannuation. These measures will be used to test the hypothesis that those in poorer health experience a cumulative

[62] Household net worth is influenced by household composition. Lone person households have lower net worth (on average) than households composed of more than one (adult) member.

labour market disadvantage and to obtain a quantitative estimate of the degree of this cumulative disadvantage.

Household wealth is a function of a number of factors including family background, household composition, consumption and saving as well as labour market outcomes. Individual superannuation is more closely related to labour market activity, though still affected by employer contribution rates, private contributions, returns on investments and drawing down on super in emergencies. These other factors weaken the relationship between the measures of wealth and labour force experience however wealth measures remain a cumulative measure of past labour market success and the best available proxy for lifetime earnings in HILDA and resources available to draw on in retirement, a key indicator of cumulative advantage or disadvantage.

Data on the wealth of Australians is limited, with wealth data collected directly from households and individuals being rare. As a result, relatively little research has been conducted on wealth in Australia. In 2002, the (then) Department of Family and Community Services, in association with the Reserve Bank of Australia (RBA), funded the inclusion of a wealth module in Wave 2 of the HILDA survey (Headey *et al.* 2005). Currently, data on wealth has been collected at three points in time in the HILDA survey, with data available on individual and household wealth for 2002, 2006 and 2010.

The inclusion of the wealth module in wave 2 of HILDA survey in 2002 was the first large-scale survey of household wealth in Australia since World War I (Headey *et al.*, 2008). This module covers all the main components of wealth including property, superannuation, shares and other assets. It collected data on asset portfolios and debts and these data were found to be comparable with national aggregate statistics available from the ABS and the RBA (Headey *et al.*, 2008).

Most of the questions in the HILDA wealth module were answered at the household level with one person answering on behalf of the household. Household level questions covered housing, businesses, equity-type investments (e.g. shares, managed funds) and cash type investments (e.g. bonds, debentures), vehicles and collectibles such as artworks (Headey and Wooden, 2004). Questions which could not be answered accurately at a household level were asked at the individual level. Questions answered by individuals covered superannuation, bank accounts, credit card debt, HECS-HELP debt and other personal debt[63]. Respondents were asked to give exact dollar amounts in their responses, however bands were offered to persons who could not provide an exact estimate of their level of superannuation (Headey and Wooden, 2004).

Wealth is difficult to measure in surveys and previous attempts overseas have been associated with high item non-response rates and underestimates of national wealth of about 25 per cent (Juster *et al.*, 1999). The underestimates are partly due to under-reporting, partly because the wealthiest persons are under-represented in surveys and partly due to equal probability samples being poorly placed to measure wealth given that it is so concentrated at the higher end of the distribution (Headey and Wooden, 2004).

The HILDA survey also experienced these difficulties to a certain extent. While item response rates on most components of wealth were over 90 per cent, after taking into account item non-response in the components of wealth, total household wealth was only able to be directly computed for 61 per cent of all households responding in wave 2 (Headey and Wooden, 2004). Rather than dropping all missing values when analysing wealth data (and in order to avoid likely bias from doing so), an imputation process was undertaken by the staff at the RBA. Generating imputed values to replace missing values involved estimating regression models for each of the major components of wealth, using the results from these regressions to identify a ‘nearest neighbour’ from the sample of households with complete data for the relevant wealth component then using the responses of these ‘neighbours’ to replace the missing values (Headey and Wooden, 2004). Comparing HILDA wealth data including the imputed values with the RBA’s estimates of national aggregates suggests that the household wealth estimates seem reasonable, with the HILDA survey underestimating net worth by only around 10 per cent. Headey and Wooden (2004)

[63] HECS-HELP is a loan program provided by the Australian government to enable eligible students to pay their student contribution amounts for higher education.

suggest that this is likely to be almost entirely due to inadequate representation of the very wealthy.

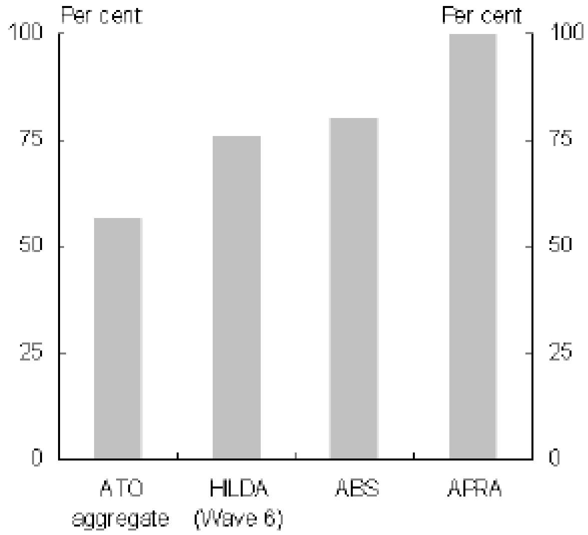

Figure 15: Aggregate Superannuation Assets in 2005-06 as a Percentage of the Average APRA Superannuation Assets in 2005-06

Source: Rothman & Tellis (2008), Chart 1

When used as an aggregate measure, HILDA estimates of superannuation are close to those provided by the ABS Survey of Income and Housing (SIH) and are much closer to Australian Prudential and Regulation Authority (APRA) estimates than the confidentialised Treasury 16 per cent sample matched super and personal income tax file (see Figure 15 and Rothman & Tellis, 2008). HILDA estimates are also consistent in broad terms and produce overall results consistent with aggregate superannuation contributions as reported by APRA and the ATO (Clare, 2012). The key advantage of HILDA superannuation data lies not only in the ability to obtain trends on individuals by different characteristics but also the availability of longitudinal individual level measures of superannuation. HILDA is the only source of longitudinal person level superannuation data in Australia.

The remainder of this section presents some descriptive statistics using these measures of wealth.

7.3.2 Overview of Wealth by Health

Between 2002 and 2010, median superannuation is estimated to have grown by 94 per cent[64]. Over the same time period, median household net worth grew by 42 per cent. These aggregate statistics mask differences in the rate of growth in wealth between persons with characteristics which influence both their level of and growth in wealth. It is more informative to consider wealth by age and health. The remainder of discussion in this section uses HILDA data to present the health-wealth gradient for key age groups.

These statistics present median superannuation and household net worth by health quintile using the health index constructed in chapter 4. After disaggregating by health quintile, the growth in median household wealth and median superannuation is higher amongst persons in lower (poorer) health quintiles. This can be partly attributed to persons in poorer health starting from a lower base so that growth in superannuation reflects a larger percentage change. It must also be noted that change between 2002 and 2010 is not as large as it might otherwise have been due to the effect of the global financial crisis. This is particularly so for older persons with higher superannuation balances and this is due to the importance of growth in superannuation from fund earnings as opposed to inflow from contributions (Davis, 2012). Prior to 2008, there were high returns from superannuation however following the global financial crisis there were negative or poor returns and this impacted heavily on persons with large balances for whom contributions play a smaller role in accumulation of wealth (Davis, 2012)[65].

In 2002, median household net worth of persons aged 25 to 65 in the best health quintile was 80 per cent higher than median household net worth of persons in the worst health quintile. The gap narrowed in 2010 to 40 per cent. A similar pattern appears for median superannuation with the gap between those in the best and worst health quintiles being larger in 2002 than in 2010. The narrowing of the health-wealth gradient between 2002 and 2010 is likely to be at least partly due to the

[64] Author's own calculations using HILDA for persons aged between 25 and 64 in 2002.

[65] The effect of the global financial crisis was also relevant for household net worth. Superannuation forms a large component of Australian household net worth. Aside from this, the global financial crisis had a negative effect on equities and house prices which also affect household net worth.

effects of the global financial crisis. Persons in better health have larger average balances of superannuation as noted and the global financial crisis had a larger negative effect on those with larger balances.

Table 50 displays the health-wealth gradient for all persons aged 25 to 45 in 2010 as well as by gender. While those in the worst health quintile clearly have lower wealth, there is not the expected clear gradient by health in Table 50. This reflects the age profile of health. The persons in the best health are younger and therefore have lower wealth. There are obvious differences by gender with median superannuation (in particular) and median household wealth in most cases being lower for women compared with men (the only exception is for household net worth for persons in the best health quintile). This reflects different patterns of labour force participation and higher likelihood of part time work for women raising children and gender related salary differences such as lower average wages for female dominated industries (Davis, 2012).

Table 50: Median Wealth by Health Index Quintile and Gender, Persons aged 25-45, 2010

	Persons	**Men**	**Women**
Superannuation			
Worst (1st) quintile	18,000	27,000	6500
2nd quintile	30,000	38,000	20000
3rd quintile	30,000	40,000	21000
4th quintile	30,000	37,970	25000
Best (5th) quintile	30,000	30,000	30000
Household Net Worth			
Worst (1st) quintile	151,015	186,100	103316
2nd quintile	234,855	247,150	222350
3rd quintile	296,595	292,444	296935
4th quintile	290,000	295,500	287668
Best (5th) quintile	374,082	358,500	382450

Notes: 1) Median wealth in 2010 Australian dollars by constructed health index quintile.

Table 51: Median Wealth by Health Index Quintile and Gender, Persons aged 46-55, 2010

	Persons	Men	Women
Superannuation			
Worst (1st) quintile	30,000	45,000	10,000
2nd quintile	65,000	85,000	45,000
3rd quintile	70,000	137,000	40,000
4th quintile	60,000	174,000	42,000
Best (5th) quintile	60,000	235,000	55,000
Household Net Worth			
Worst (1st) quintile	392,525	389,000	392,613
2nd quintile	601,883	602,305	599,000
3rd quintile	748,407	815,585	699,100
4th quintile	832,025	941,989	800,775
Best (5th) quintile	907,044	1,665,214	865,350

Notes: 1) Median wealth in 2010 Australian dollars by constructed health index quintile.

Table 52: Median Wealth by Health Index Quintile and Gender, Persons aged 56-65, 2010

	Persons	Men	Women
Superannuation			
Worst (1st) quintile	12,000	40,000	0
2nd quintile	82,000	140,000	51,500
3rd quintile	130,000	250,000	62,500
4th quintile	80,000	240,000	63,750
Best (5th) quintile	120,000	270,000	120,000
Household Net Worth			
Worst (1st) quintile	518,000	588,631	445,625
2nd quintile	829,500	895,440	753,120
3rd quintile	1,089,000	1,169,500	1,012,550
4th quintile	1,065,650	1,240,000	1,002,445
Best (5th) quintile	1,368,900	1,829,999	1,315,300

Notes: 1) Median wealth in 2010 Australian dollars by constructed health index quintile.

Table 51 and Table 52 present the health-wealth gradient for older age groups. These are the age groups with a larger prevalence of persons in poor health. There is a much clearer health-wealth gradient apparent in these tables, particularly after disaggregating wealth by gender. Persons in the lowest health quintile again have much lower wealth compared with persons in better health quintiles. This pattern appears for both men and women. The lower levels of wealth for women compared with men observed in Table 50 are even more evident in Table 51 and Table 52.

This section has discussed the wealth measures used in this chapter to determine cumulative effects of health related labour market disadvantage. The tables presented in the latter part of this section illustrate the importance of holding other factors constant in order to determine the effect of health on wealth. The next section outlines the methods and modelling approaches used to determine this relationship.

7.4 Methods, Data and Modelling Approaches

The analysis in this chapter uses release 10 of HILDA (as with previous chapters) but it does not use all 10 waves of HILDA. As discussed in section 7.3, the wealth data was only collected in waves 2, 6 and 10 therefore the analysis in this chapter makes use of the data in those select years in which wealth data is available.

Two particular sources of bias have been identified in analysing cumulative effects of health: unobserved heterogeneity and endogeneity of health (Hum *et al.*, 2008; Michaud and van Soest, 2008). Panel data techniques are used in the chapter in order to exploit the longitudinal nature of the HILDA data and to control for unobserved heterogeneity. The importance of controlling for unobserved heterogeneity was highlighted in chapters 4, 5 and 6 of this thesis but was also observed by Michaud and van Soest (2008) specifically with regards to modelling the relationship between health and wealth[66].

66 Michaud and van Soest (2008) also highlighted the importance of including lagged wealth in order to estimate dynamic interactions between health and wealth consistently. Lagged wealth was not able to be included in the models used in this chapter due to only three data points being available. Inclusion of lagged wealth would result in the loss of one data point resulting in inability to sufficiently model the age-wealth profile over an adequatetime frame

To control for unobserved effects, health was interacted with the year dummies denoting observations from 2006 and 2010 (waves 6 and 10). These interaction terms are included to help control for correlation between health and unobserved determinants of wealth. The models also include the Mundlak augmentation (the average of the time variant explanatory variables) to control for relatively fixed underlying differences between individuals.

The health measure used is the health index constructed in chapter 4. A similar approach was also followed in Michaud and van Soest (2008) and Hum *et al.* (2008). The health measure chosen reduces the possibility of endogeneity of health influencing results. The particular health measure used in the econometric analyses in this chapter is initial health. This is the health index at t=1 (2001). Use of health at a point in time was chosen to isolate the effect of health without changing health status affecting the health measure and confusing the interpretation of the effect of health on wealth[67].

While the use of the health index is preferred, for comparison purposes a specification was estimated which included a variable indicating a long term condition. This measure used responses to the question in HILDA as to whether individuals had 'any long-term health condition, impairment or disability that restricts the individual in everyday activities and which has lasted, or is likely to last, for six months or more.'

The model used is an adaptation of the standard model of age-earnings profiles derived from human capital theory. Earnings (and correspondingly wealth) increase as a function of labour market experience. There is a direct measure of experience in HILDA, however age and employment experience are very highly correlated for both men and women. Age is used as a proxy for experience in the models as well as providing empirical estimates of the effects of health on wealth by age[68]. The

[67] This was necessary in order to estimate the effect of health on age-wealth profiles. Unfortunately the health measure used does not distinguish between transitory and continuous health states however there is a degree of persistence in health therefore the method used will still be informative with regards to estimating the effect of health on wealth.
[68] It must be noted that age is a poorer proxy of experience for women than it is for men however in HILDA the correlation between age and experience for women is 0.84 (compared with 0.95 for men), suggesting that it is not unreasonable to use age as a proxy in the models.

relationship is not a purely linear one over the life cycle. To reflect this, the age-wealth specification uses a quadratic functional form. This age-wealth profile is used to test the cumulative disadvantage hypothesis set out in section 7.2.

Figure 16 presents two stylized scenarios by which the effect of health on wealth may be expected to vary with age. The horizontal line A represents the level of wealth of those who experience good health. Line B represents the cumulative disadvantage hypothesis. Under this hypothesis, poor health will result in a lower rate of growth in wealth relative to healthy persons of the same age. This will result in a different level and shape to the age-wealth profile.

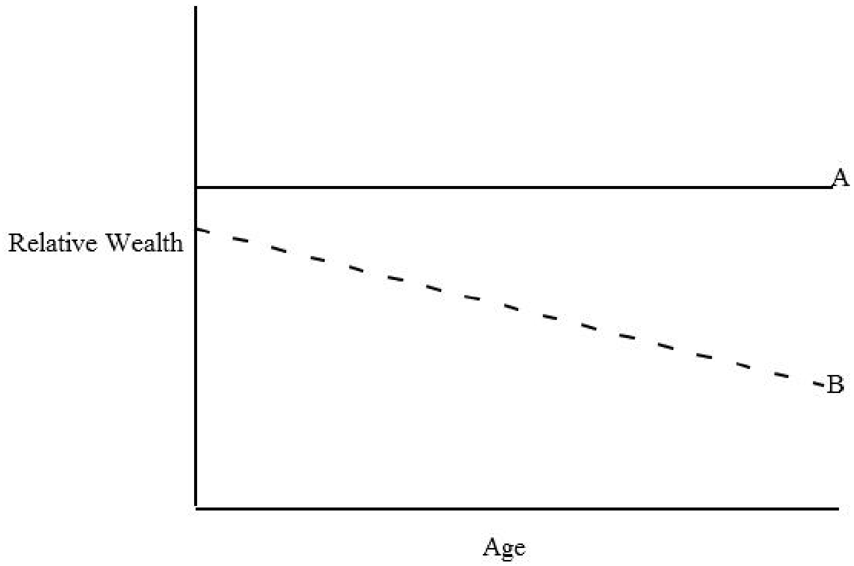

Figure 16: Hypothesised Effects of Poor Health on Age-Wealth Profiles

This chapter examines inflation-adjusted wealth (2010 dollars) collected at three points in time for those aged 25 to 65 in 2002. The dependent variables are log of the value of superannuation for the superannuation model and log of household net worth for the household net worth model. Transforming the dependent variable in each model into the log allows the parameter estimates to be interpreted as the percentage change in wealth for a one unit change in the explanatory variable. Given that wealth data involves large numbers this interpretation is much more straightforward than interpreting changes in wealth in dollars from a change in the explanatory variable. Wealth data are also skewed adding to the motivation for using a log transformation of the dependent variable. The variables containing imputed wealth are used in order to minimise loss of observations from missing values.

The models estimate age-wealth profiles using a random effects model for a continuous outcome. This is specified as:

$$Y_{it} = \beta' X_{it} + \lambda \bar{x_i} + u_i + e_{it} \qquad (1)$$

where log of wealth for individual *i* at time *t* (Y_{it}) is a function of the vector of observed individual characteristics (the explanatory variables given by ***X***), $\bar{x_i}$ are the equivalent of the Mundlak augmentation (the average of the time variant Xs), there is a normally distributed individual random effect (u_i) and an individual time specific error term (e_{it}) which is assumed to have a normal distribution.

The case could be made that a fixed effects model may yield less biased estimates, especially given how few observations of wealth there are per person in HILDA. A random effects model does however provide estimates with a lower sample-to-sample variability, leading to estimates that are closer, on average, to the true value in any particular sample (Clark and Linzer, 2015). Aside from considering the tradeoff between bias and variance, there are explanatory variables of interest in the model which are time invariant by individual. The main one is the choice of health measure, in this case health index score in 2001. The effect of time invariant variables cannot be estimated in a fixed effects model, hence a random effects model was chosen.

Estimation used generalised least squares via the xtreg command in Stata. Chapters 5 and 6 showed that a dynamic specification should be preferred in modelling the effects of health. Unfortunately, with only three data points available inclusion of dynamics poses difficulties, especially given that inclusion of lags removes one wave of observations in the models. Due to these difficulties, a static approach is adopted, with dynamic modelling of the effect of health on wealth in Australia left as an area for future research when more data becomes available.

A quadratic specification of experience (age) is used to estimate the age-wealth profiles. A centred measure of age is included along with a quadratic age term. With the centred age variable, a value of age equal to 0 corresponds to age 25, a value of 1 is age 26 and so on. This specification allows the main effect of the health variable to represent the impact of health on wealth at the intercept (age 25).

Interaction terms between health and age and health and the quadratic age term are used to test how the impact of health on the age-wealth profile varies over time. Different patterns of significant main and interaction effects are examined to determine whether there is support for the cumulative disadvantage hypothesis. Key evidence for the cumulative disadvantage hypothesis would be a significant positive interaction between health and age.

The models in this chapter were estimated for all persons in the desired sample but also separately by gender. In contrast with the previous two chapters, the model specification used in this chapter allowed disaggregation by gender. The nature of the dependent variable and explanatory variables used resulted in a sufficient number of observations to enable models to be separately estimated by gender.

The next section discusses the estimating sample and explanatory variables included in the models of wealth.

7.5 Sample and Explanatory Variables

The sample used for the econometric analyses in this chapter was restricted to those aged between 25 and 60 years in 2002. Persons under 25 years of age in 2002 are excluded as a significant proportion of children will have moved out of the parental home between 2002 and 2006 and are then likely to dominate the low-growth wealth group because of the decline in household wealth that accompanies a move out of home. This source of wealth change is not relevant to the research question in this chapter. Those aged over 60 in 2002 are excluded to minimise those transitioning to retirement.

Table 53 sets out and defines the variables used in the wealth models[69].

Table 53: Variables used in Wealth Models

Variable	Description of Variable
Dependent variables-	
Superannuation	Real individual superannuation in 2010 dollars*
Household net worth	Real household net worth in 2010 dollars*
Explanatory variables	
2006	1 if observation is from 2006, 0 otherwise
2010	1 if observation is from 2010, 0 otherwise
Health index in 2001	Health index score from 2001
Health in 2001*2006	Interaction term between health index score in 2001 and year dummy for 2006
Health in 2001*2010	Interaction term between health index score in 2001 and year dummy for 2010
Age	Age, centred so the value of age=0 corresponds to age 25
Age squared	Square of centred age variable
Health in 2001*age	Interaction term between health index score in 2001 and age
Health in 2001*age squared	Interaction term between health index score in 2001 and age squared
Female	1 if female, 0 otherwise
Has children aged 0-4	1 if has children aged 0-4, 0 otherwise
Has children aged 5-14	1 if has children aged 5-14, 0 otherwise

[69] Summary statistics for many of these variables can be found in Table 2 in Chapter 3. Comparing mean superannuation and mean household wealth in Table 2 by gender along with considering the discussion in section 7.3.2 of descriptive statistics relating to the wealth measures illustrates the value of modelling superannuation as well as household wealth given that mean household wealth differs little by gender in contrast with mean superannuation.

Variable	**Description of Variable**
Has children aged 0-4*female	Interaction term between presence of young children in household and female
Household size^	Number of persons in household
AUSEI06 in 2001	Ranking on Australian Socioeconomic Index in 2001
Self employed	1 if self employed, 0 otherwise
Migrant	1 if migrant, 0 if Australian born
Rural	1 if lives in rural area, 0 otherwise
Married/De Facto	1 if married or has partner, 0 otherwise
Father's occupation	AUSEI06 occupational status scale, father's occupation when respondent was aged 14
Education	Measured by dummy variables reflecting highest educational attainment
Degree or above	1 if has degree or above, 0 otherwise
Advanced diploma/diploma	1 if has advanced diploma or diploma, 0 otherwise
Certificate	1 if has certificate I/II/III or IV, 0 otherwise
Year 12	1 if has year 12, 0 otherwise
Year 11 or below	Reference category, 1 if has year 11 or below

Notes: *Superannuation and Household Net Worth are inflated to the value in the year 2010 by the RBA annual inflation rate over the period (2001-2010) derived from the ABS Consumer Price Index. ^Household size variable is only included in the household net worth model.

After taking account of missing values, the estimation sample for the superannuation model comprises 19,492 person-wave observations for 8,706 individuals and sample for the household net worth model comprises 20,378 person-wave observations for 8,841 individuals[70]. After disaggregating by gender, this reduces to 9,241 observations for men and 10,251 observations for women for the superannuation model and 9,581 observations for men and 10,797 observations for women for the household net worth model. As noted, the number of observations for both wealth

[70] These observations are assumed missing at random.

models are much lower than that for the models in the previous chapters due to wealth data only being collected in three waves of the HILDA survey.

The explanatory variables included in the models in this chapter are those which theory suggests are determinants of earnings and wealth and those which have been used in previous studies of determinants of wealth. These include demographic characteristics such as age, marital status, presence of children, whether the individual was a migrant and educational attainment. Selected labour market factors were also included; specifically whether the individual was self employed and their AUSEI06 occupational ranking in 2001.

Household composition is a major determinant of household net worth. Given that it is a household measure, the number of persons present in the household will affect the level of household net worth. For this reason, a household size variable was included in the household net worth model.

Growth in superannuation balances depends on several factors such as the individual's income, the amount of their personal and employer contributions, the proportion of time employed (hours worked as well as years spent employed) as well as returns on superannuation. Returns on superannuation will be an important factor to account for as this is likely to have affected the 2010 data given the global financial crisis occurred in 2008. In order to reflect this, dummy variables for year 2006 and 2010 were included in the models.

The next section presents results from estimating the models described in section 7.4.

7.6 Results

Table 54 presents estimates from the random effects model of log of wealth using the superannuation measure. Results are presented for all persons but also separately for men and women. A Hausman test was conducted to determine whether results were significantly different between men and women. Results from this test suggested that there was a significant difference.

The main effect of health in 2001 was statistically significant in the results for all persons and for the results by gender. A higher score on the health index in 2001 is associated with higher superannuation. The interaction between health and age is positive and significant for all models. This provides some support for the cumulative disadvantage hypothesis. This suggests that wealth differs by health and that the differential is greater with age. The negative and significant interaction between health in 2001 and the year dummies for 2006 and 2010 suggest that health differences in super narrowed slightly compared to 2002, supporting the cross sectional findings on growth in median superannuation in section 7.3. This supports the inclusion of this interaction term in capturing interactions between health and unobserved determinants of wealth taking place during these years.

Table 54: Estimates (and Standard Errors) for Random Effects Model of Log of Superannuation for non-retirees aged 25-60 in 2002 (Standard Error)

	Persons	Men	Women
2006	1.078*** (0.212)	0.818** (0.329)	1.290*** (0.279)
2010	1.955*** (0.296)	1.934*** (0.443)	1.979*** (0.396)
Health index in 2001	0.018*** (0.006)	0.019** (0.009)	0.018** (0.009)
Health in 2001*2006	-0.008*** (0.003)	-0.007 (0.004)	-0.009** (0.004)
Health in 2001*2010	-0.016*** (0.004)	-0.018*** (0.006)	-0.013** (0.005)
Age	-0.0007 (0.0503)	-0.0024 (0.0740)	-0.0195 (0.0680)
Age squared	-0.0059*** (0.00120)	-0.0072*** (0.00175)	-0.0044*** (0.00162)
Health in 2001*Age	0.0025*** (0.0007)	0.0025*** (0.0010)	0.0028*** (0.0009)
Health in 2001* Age squared	0.00001 (0.00002)	0.00003 (0.00002)	-0.00002 (0.00002)
Female	-1.424***		

	Persons	Men	Women
	(0.0715)		
Has children aged 0-4	-0.120* (0.0659)	-0.0589 (0.0686)	-0.433*** (0.0851)
Has children aged 5-14	-0.353*** (0.0558)	-0.108 (0.0716)	-0.558*** (0.0838)
Has children aged 0-4*Female	-0.256*** (0.0961)		
Degree or above	1.213*** (0.332)	0.773** (0.319)	1.411*** (0.498)
Advanced Diploma/Diploma	0.837*** (0.313)	0.599* (0.324)	0.997* (0.509)
Certificate	0.891*** (0.226)	0.800*** (0.286)	0.888*** (0.303)
Year 12	0.630** (0.296)	0.504 (0.373)	0.734* (0.402)
AUSEI06 in 2001	0.0309*** (0.0019)	0.0192*** (0.0024)	0.0416*** (0.0029)
Self employed	-0.768*** (0.100)	-0.857*** (0.129)	-0.774*** (0.158)
Migrant	-1.014*** (0.0919)	-0.897*** (0.119)	-1.070*** (0.137)
Rural	-0.197** (0.0848)	-0.198* (0.112)	-0.202 (0.125)
Married/De Facto	0.195** (0.0832)	0.0442 (0.101)	0.293** (0.129)
Father’s occupation	0.0002 (0.0015)	-0.0024 (0.0019)	0.0034 (0.0022)
Time averaged characteristics			
Has children aged 0-4	-0.223* (0.132)	-0.512*** (0.162)	-0.118 (0.200)
Has children aged 5-14	-0.494*** (0.109)	-0.141 (0.143)	-0.809*** (0.156)
Degree or above	-0.259 (0.360)	-0.167 (0.370)	-0.463 (0.536)
Advanced Diploma/Diploma	0.171	0.0850	0.121

	Persons	**Men**	**Women**
	(0.341)	(0.373)	(0.546)
Certificate	-0.0060	-0.124	-0.0683
	(0.251)	(0.317)	(0.354)
Year 12	0.298	0.378	0.229
	(0.319)	(0.405)	(0.436)
Married/De Facto	0.417***	1.081***	-0.152
	(0.129)	(0.173)	(0.185)
Constant	5.060***	5.338***	3.481***
	(0.509)	(0.737)	(0.688)
Sample	19,492	9,241	10,251
Individuals	8,706	4,171	4,535
R squared within	0.066	0.052	0.080
R squared between	0.286	0.301	0.265
R squared total	0.275	0.286	0.259
Rho	0.665	0.647	0.667

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 3 waves of HILDA.

Rho is the share of the estimated variance of the overall error accounted for by the individual effect. A large value of rho supports the use of a panel data model. In Table 54, Rho is large for all models (greater than 0.6). This indicates that there is unobserved heterogeneity and it lends support to the use of a panel data model.

The year dummies are both significant and have a positive effect. Given that the wealth data are in real terms, this suggests that despite the effect of the global financial crisis on superannuation balances, average superannuation was still higher in 2006 and 2010 than in 2002 (the reference category). Women have lower superannuation (denoted by the female variable being negative and highly significant in the first columns of Table 54).

Educational attainment is an important determinant of superannuation as would be expected. Higher education is linked with higher earnings which in turn results in higher superannuation contributions. Having a degree in particular is highly significant and the magnitude of the effect is large suggesting that persons with higher education have much higher superannuation relative to those who did not complete high school (base case is those with year 11 or below).

Higher occupational ranking (given by AUSEI06 in 2001) is also associated with higher superannuation. This can also be attributed to the relationship between occupation, earnings and level of superannuation contributions.

Self employment and being a migrant are both associated with lower superannuation. Being married or in a de facto relationship is also significant for women. Women who are living with a partner have higher superannuation. Presence of children has a negative effect on superannuation for women and this is understandable given that presence of children, particularly young children, is associated with spells out of the workforce for women.

Few of the time averaged variables are significant determinants of wealth. The few which are significant do support inclusion of controls for individual differences, particularly combined which the high value of Rho which suggests these underlying differences are important.

It was noted earlier that the interaction between health and age is significant in Table 54 for both men and women, supporting the cumulative disadvantage hypothesis. The effect of the interaction term is positive suggesting that at older age, higher values of the health index have a greater effect on superannuation (conversely, at higher levels of health index, age has a greater effect on superannuation). The magnitude of the effect of the interaction appears small but this is misleading. For men, a one unit increase in the health index results in an increase in superannuation of 0.25 per cent per year. For women, a one unit increase in the health index results in an increase in superannuation of around 0.28 per cent per year. Over time, these differentials have the potential to become large, particularly when comparing persons in the worst health with those in the best health.

While results using the health index are to be preferred for reasons already stated, the models were also run using the long term condition health measure (see Table A-34 in the Appendix). The health measure was a dummy variable with value 1 if the individual had a long term condition in 2001 and 0 otherwise. The results are broadly similar to those reported in Table 54 in terms of the significant determinants of superannuation. The interaction between long term condition and age is negative and significant, with those with a long term condition having lower superannuation and this differential increasing with age. This suggests that the evidence for the cumulative disadvantage hypothesis is not sensitive to health measure used.

Table 55 presents estimates from the random effects model of wealth using the log of the household net worth measure. Results are again presented for all persons but also separately for men and women. A Hausman test was again conducted to determine whether results were significantly different between men and women. Results from this test suggested that there was a significant gender difference.

The main effect of health in 2001 was a statistically significant and positive determinant of household wealth for women (and the results for all persons) but not for men in Table 55. This suggests that there is a significant household net worth differential associated with health for women. Women who had better health in 2001 have higher household net worth. The interaction between health and age is significant in the model for men but not women. This provides some support for the cumulative disadvantage hypothesis for men but not for women using this measure of wealth. Wealth differs by health for men and the differential is greater with age. The squared interaction term is also significant and negative for men (though the effect is very small) suggesting that the growth of the health related disparity in household net worth slows a little at later ages.

Table 55: Estimates (and Standard Errors) for Random Effects Model of Household Net Worth for Sample aged 25-60 in 2002

	Persons	**Men**	**Women**
2006	0.341* (0.188)	0.320 (0.264)	0.373 (0.263)
2010	0.407* (0.223)	0.187 (0.325)	0.584* (0.308)
Health index in 2001	0.0191***	0.0013	0.0297***

	Persons	Men	Women
	(0.0062)	(0.0093)	(0.0081)
Health in 2001*2006	-0.0021 (0.0025)	-0.0020 (0.0036)	-0.0025 (0.0034)
Health in 2001*2010	-0.0036 (0.0029)	-0.0003 (0.0043)	-0.0064 (0.0040)
Age	0.0394 (0.0437)	-0.108* (0.0615)	0.139** (0.0596)
Age squared	-0.00003 (0.0010)	0.0033** (0.0013)	-0.0024* (0.0014)
Health in 2001*Age	0.0012** (0.0006)	0.0030*** (0.0008)	-0.0001 (0.0008)
Health in 2001* Age squared	-0.00002 (0.00001)	-0.00006*** (0.00002)	0.00001 (0.00002)
Female	-0.0072 (0.0477)		
Has children aged 0-4	-0.108 (0.0742)	-0.0694 (0.0826)	-0.0230 (0.0794)
Has children aged 5-14	-0.0636 (0.0503)	0.0458 (0.0737)	-0.114* (0.0679)
Has children aged 0-4*Female	0.0925 (0.0897)		
Household size	0.188*** (0.0252)	0.228*** (0.0353)	0.162*** (0.0362)
Degree or above	-0.0070 (0.328)	-0.456 (0.483)	0.227 (0.452)
Advanced Diploma/Diploma	0.486* (0.266)	0.0492 (0.364)	0.745* (0.430)
Certificate	0.276 (0.179)	-0.0486 (0.350)	0.416** (0.206)
Year 12	0.667** (0.284)	0.267 (0.446)	0.878** (0.366)
AUSEI06 in 2001	0.0134***	0.0128***	0.0146***

	Persons	Men	Women
	(0.0013)	(0.0019)	(0.0018)
Self employed	0.131**	0.107	0.147*
	(0.0569)	(0.0740)	(0.0883)
Migrant	-0.333***	-0.436***	-0.235***
	(0.0564)	(0.0805)	(0.0787)
Rural	0.287***	0.309***	0.235***
	(0.0545)	(0.0784)	(0.0755)
Married/De Facto	0.515***	0.0471	0.893***
	(0.0953)	(0.136)	(0.132)
Father's occupation	0.0018	0.0015	0.0018
	(0.0011)	(0.0015)	(0.0015)
Time averaged characteristics			
Has children aged 0-4	-0.172	-0.195	-0.126
	(0.107)	(0.152)	(0.150)
Has children aged 5-14	-0.495***	-0.446***	-0.476***
	(0.0820)	(0.115)	(0.115)
Degree or above	0.227	0.627	0.0563
	(0.340)	(0.503)	(0.468)
Advanced Diploma/Diploma	-0.0511	0.263	-0.190
	(0.276)	(0.382)	(0.442)
Certificate	0.0151	0.416	-0.271
	(0.190)	(0.359)	(0.232)
Year 12	-0.372	-0.0284	-0.531
	(0.294)	(0.468)	(0.378)
Married/De Facto	0.751***	0.770***	0.690***
	(0.117)	(0.172)	(0.159)
Constant	6.928***	8.601***	5.809***
	(0.496)	(0.723)	(0.657)
Sample	20,378	9,581	10,797
Individuals	8,841	4,218	4,623
R squared within	0.063	0.061	0.072
R squared between	0.226	0.211	0.251

	Persons	Men	Women
R squared total	0.208	0.191	0.232
Rho	0.550	0.539	0.558

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 3 waves of HILDA.

As was the case with the superannuation models, the results from the household net worth models in Table 55 show a large value of rho. The individual effect accounts for a large share of the estimated variance of the overall error (there is unobserved heterogeneity). This supports the use of a panel data model when modelling determinants of household wealth.

The strength and magnitude of the relationships between the explanatory variables and the dependent variable (household net worth) differs somewhat from the results from the models using the superannuation measure. This reflects two things: firstly, household net worth is less of a measure of cumulative labour market experience than superannuation and secondly, household net worth is a household measure and this weakens the association between many of the explanatory variables (which are individual measures) and the dependent variable.

The female variable is not significant in the first column of Table 55. This indicates that women do not have significantly lower household net worth than men and is a reflection of the wealth measure being a household measure. There were clear gender differences in the superannuation model (an individual measure of wealth). The household measure masks these differences.

The household size variable is a significant determinant of household net worth. The larger the household size, the greater the household net worth. This reflects greater pooled resources, particularly if lone person households are compared with couples. The presence of children variables might be expected to have a negative effect, however these variables are not significant. It is possible that the inclusion of the household size variable captures some of the effect of presence of children and this might explain the presence of children variables not being significant after disaggregating by gender.

Higher AUSEI06 ranking in 2001 is positively associated with higher household net worth. As discussed earlier, both higher education and higher occupational ranking are associated with higher earnings. The household net worth measure is more loosely associated with individual earnings compared with the superannuation measure however it is still logical for factors linked with higher earnings to be significant determinants of household net worth.

Migrants have lower household net worth while those living in a rural area have higher household net worth. The positive association with rural living can be attributed to higher value property ownership (i.e. farms). Being married or in a de facto relationship is associated with higher household net worth in column 1 and 3 of Table 55, reflecting the effect of pooled resources for couples on the household net worth of women.

Most of the time averaged variables are not significant, again suggesting that most of these relatively fixed underlying differences between individuals included in the model are not determining wealth. The high value of rho and a few time-averaged variables which are significant still support their inclusion and suggest that unobserved individual differences are important.

As was the case with the superannuation model results in Table 54, the positive effect on the interaction term between health and age for men in Table 55 suggests that at higher levels of health index ranking, age has a greater effect on household net worth. For men, a one unit increase in the health index results in an increase in household net worth of 0.30 per cent per year. Taking into account the effect of the significant interaction between health and age squared makes the difference even larger at older ages.

A comparison model using long term condition was also run for the household wealth model (see Table A-35 in the Appendix). The results in Table A-35 again show that the strength and magnitude of the effects of the explanatory variables on household wealth differ from the results using the superannuation model. In this comparison model the interaction between long term condition and age is not significant. Comparing this finding and the finding of no significant interaction between health and age for women in Table 55 suggests that the household measure disguises individual effects such as the health effects on wealth along with masking the gender differences already mentioned.

Figure 17 and Figure 18 illustrate the superannuation differential by age between men and women with mean health index score for the lowest health index quintile and those with the mean health index score for the highest health index quintile[71]. Each figure represents a hypothetical scenario in which individuals in the lowest health quintile are compared with individuals in the highest health quintile in order to determine the average effect of health by age on the accumulation of superannuation over time holding other factors constant. The estimates are crude but provide some feel for the magnitude of the health differential in superannuation by age, giving a numerical estimate of the degree of health related cumulative disadvantage.

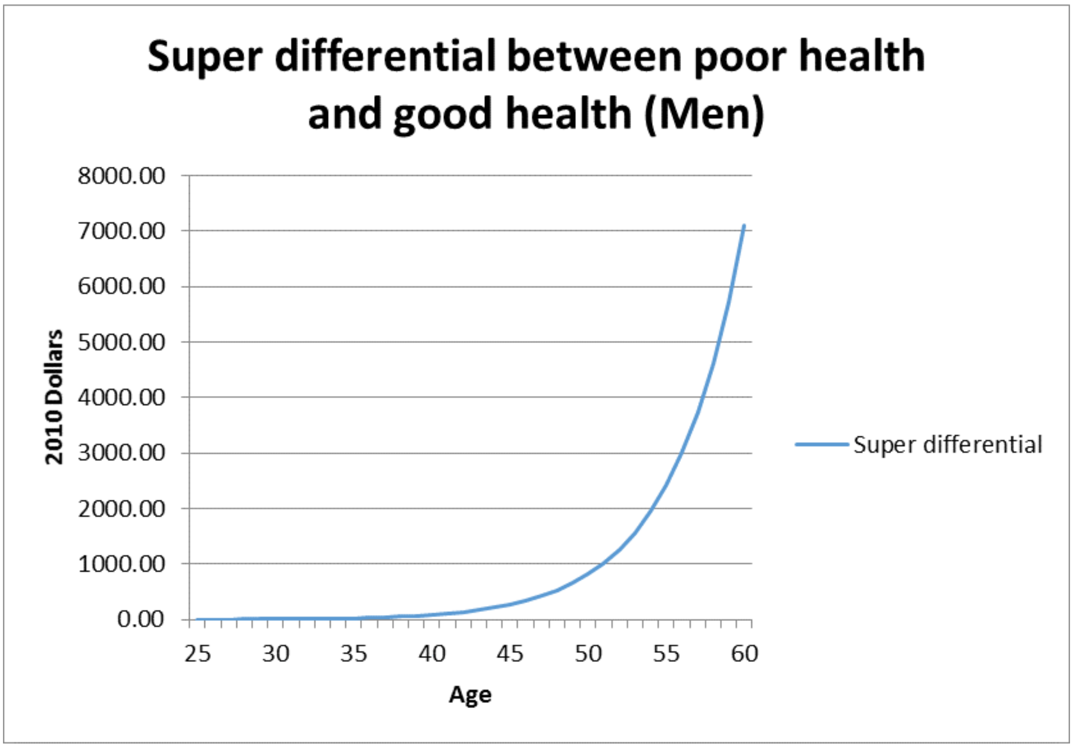

Figure 17: Superannuation Differential between Good Health and Poor Health (Men)

---

[71] Given that household net worth is noted to not be capturing gender differences and has a weaker association with the individual measures such as health, comparable figures are not included for household net worth. Based on the results, the figures using superannuation were judged to be better indicators of magnitude of health differentials in wealth, particularly by gender.

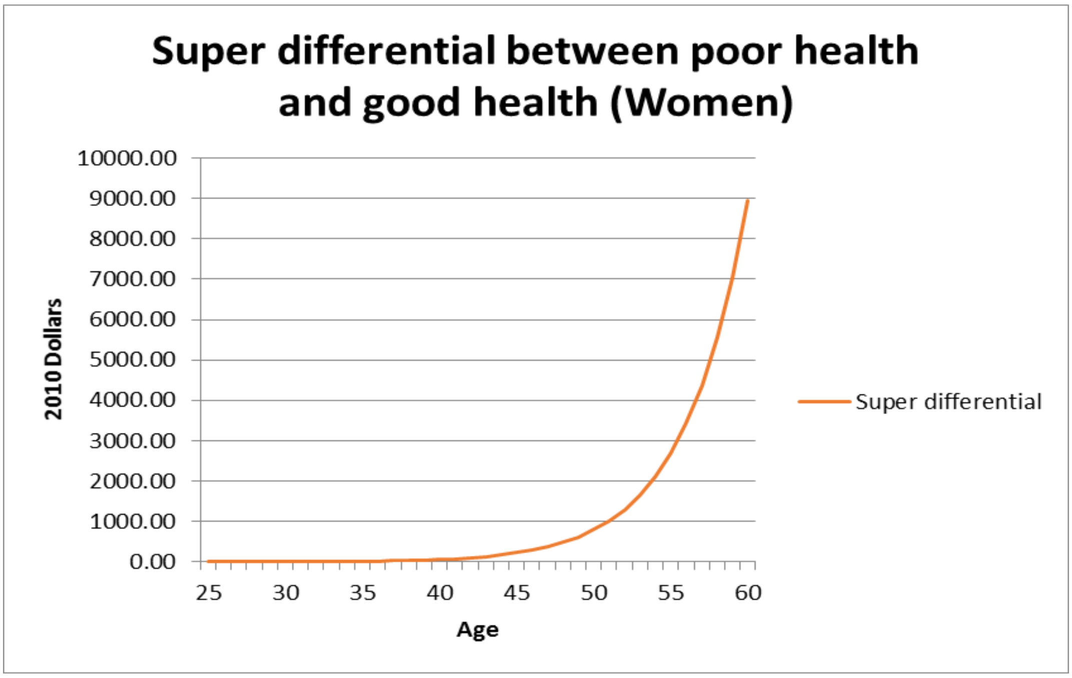

Figure 18: Superannuation Differential between Good Health and Poor Health (Women)

The growth in the health related superannuation differential increases rapidly from around age 40 for men and women. Compared with Table 54, these figures more clearly depict the estimated cumulative disadvantage associated with poor health. The magnitude of the estimated differential is similar for both men and women but the lower average superannuation of women must be kept in mind when viewing these figures. Mean superannuation for men is $121,668 and mean superannuation for women is $66,278 (see Table 2 in chapter 3). The average health differential is just under $7,100 for men and just over $9,150 for women. In light of the mean superannuation figures, the similar health differential in superannuation between those aged 60 who are in good health and those of the same age who are in poor health represents a greater degree of disadvantage for women (about 14% on average) compared with men (about 6% on average). One thing is clear from Figure 17 and Figure 18, persons in better health experience cumulative labour market advantage and this translates into higher growth in superannuation.

The discussion of results in this section has found some evidence to support the cumulative disadvantage hypothesis and has provided a quantitative measure of the degree of this cumulative effect. Results were presented using two measures of wealth aimed at capturing cumulative advantage/disadvantage, an individual measure (superannuation) and a household measure (household net worth). Findings from these results suggest that the superannuation model better captures labour market experience and is thus more able to identify existence and degree of health related cumulative labour market disadvantage.

7.7 Conclusion

There is a range of literature analysing aspects of cumulative disadvantage. The existence and degree of health related cumulative labour market disadvantage is however under-examined in the international literature and in particular does not appear to have been thoroughly researched in the Australian setting. The evidence which does exist focuses on a subset of the population and highlights the need for further investigation using panel data methods.

This chapter aimed to establish evidence on the existence of health related cumulative labour market disadvantage in Australia and to quantitatively measure using panel methods the degree of this cumulative effect. It used measures of wealth which are affected by (and sensitive to) labour market outcomes to capture effects of health related labour market disadvantage over time.

Models were estimated using two measures of wealth: household net worth and individual superannuation. Results suggested that superannuation performed better as an indicator capturing health related labour market disadvantage. While household net worth does represent the resources available to the household and is of interest given that households generally pool their resources, the model found that the association between household health and the explanatory variables included to be much weaker than that in the superannuation model, with most of these being individual measures. This was clearly illustrated when it came to gender. The superannuation model showed clear differences by gender and these differences were masked when using the household measure.

The results in this chapter provided some evidence of the existence of health related cumulative labour market disadvantage. A comparison of estimated wealth differentials between persons in the lowest health index quintile and those in the highest health index quintile indicates health related labour market disadvantage which is increasing over time. A crude estimate of this differential (holding other factors constant to isolate only the effect of health) suggests that a person in the highest health index quintile has on average $9,000 more superannuation at age 60 (in 2010 dollars) than a person who was in the lowest health index quintile. This represents about 6% extra for men and 14% extra for women.

The analysis is unable to distinguish between health conditions having a lasting long term impact and those which are merely transitory. The estimates presented in this chapter can therefore be considered to be conservative given that the effect of health is likely to be much larger amongst person experiencing long term health impairment which can be expected to have a greater deleterious effect on their labour market experience. The disadvantage does increase with age, with the differential widening from age 40.

The evidence of cumulative disadvantage fits within the theory set out in the Grossman model and the previous discussion in the literature of effects of health on wealth using the health production framework. Poor health adversely affects the capacity to accumulate superannuation. This can be attributed to poorer health lowering productivity and wages and adversely affecting the amount of time spent in work. Lower accumulation of human capital for those experiencing poor health (as suggested in chapter 5) also plays a role, with this affecting opportunities for promotion. The resulting lower earnings compared with healthy persons contributes to a differential in wealth which has implications for standards of living in retirement. This adverse impact is substantially moderated for those who live in multi-person households. It appears that the household is paying an important role in moderating the risks of poor health on standard of living.

The analysis in this chapter does suffer from some limitations. Firstly, wealth data was only available at three points in time. This limits the effectiveness of conducting panel data modelling and also limits the degree to which results can be determined as effects over the life course. These three points in time at which wealth data are available only span eight years. This is unfortunate but it is the only data of this kind available and therefore while this limitation must be acknowledged, the results presented here still add a contribution in progressing the analysis of determinants of wealth beyond a simple cross sectional view.

The controls adopted in the models allow better determination of causality though fully accounting for endogeneity is difficult, particularly given that a static approach was adopted. The degree to which causal health effects can be identified is therefore limited. Changes in wealth in the models cannot be exactly attributed to health and this must be taken into account in interpreting findings. The results in this chapter, as with the previous chapters, can be taken as suggestive of causal effects, keeping in mind the caveats already mentioned.

Cohort is important when analysing superannuation, particularly given the evolution of the level of contributions over time. The modelling in this chapter controlled for age, however more detailed investigation of cohort effects is a subject for future research when further data is available. Data covering a longer period of time would also allow for more complex panel data analysis and further investigation of the effect of age of onset of poor health. While onset of most chronic conditions occurs amongst those in older age groups, it is not isolated solely to older people and the estimates in this chapter indicate that early age of onset has the potential to result in widening disadvantage for those experiencing poor health.

Wealth is one indicator of cumulative disadvantage, labour force history is another as established in chapter 3. This chapter focused on analysing wealth as an indicator of cumulative income and a direct observation of outcomes of working life. Analysing the effects of health on labour supply over the life cycle is another way in which the degree of cumulative disadvantage might be determined. While there is some research in this area for the US and Canada, study of the effect of health on years worked for Australia is an area for future research to add to the evidence on cumulative disadvantage provided in this thesis.

Despite the acknowledged limitations, the analysis in this chapter adds to the limited literature on health related cumulative labour market advantage and provides the first evidence in the Australian context. This disadvantage has negative implications with regards to retirement income, suggesting that people experiencing poor health during working age receive lower lifetime earnings and accumulate lower wealth as a result, adversely affecting the resources available to them in retirement.

8. Discussion and Conclusions

8.1 Introduction

Poor health is a substantial issue for the people of working age in Australia. While it is not straightforward to measure population health, the National Health Survey finds that 12 per cent of those of working age report having only poor or fair health, as distinct from good, very good or excellent health. About 15 per cent report that they have a health condition that limits their ability to work: about half of those with a work-limiting condition also report being in poor health.

Poor health is strongly associated with labour force status. In Australia three quarters of people of working age who report very good or excellent health are employed compared with only 36 per cent of people in fair or poor health[72]. While this association is more pronounced with age, the pattern holds for both men and women and for all age groups. Health matters beyond the effect it has on keeping people out of work. It also matters for those who are employed given that over a third of people suffering from poor health are employed. This raises questions as to the disadvantage experienced not just in terms of poor health affecting participation over the life course but also ways in which labour market disadvantage might manifest for those in poor health who are employed.

The ageing of the population and workforce in Australia and many other countries will increase the prevalence of poor health among the working age population. This makes it increasingly important for researchers and policy makers to understand the effects of poor health on labour market outcomes and disadvantage arising from this over the life course. This thesis has enhanced this understanding by providing an econometric analysis of the effects of poor health on some under-examined labour market outcomes together with indicators of accumulating disadvantage in Australia. There is a strong relationship between employment and income therefore the thesis analysed the effect of poor health on measures associated with lifetime earnings.

[72] Calculations obtained using the 2008 National Health Survey CURF.

This chapter pulls together the main elements of the preceding chapters in order to outline the findings, relate them to previous research and to highlight the contributions of the thesis. Section 8.2 discusses the major findings. An evaluation of the work undertaken and identification of limitations is presented in section 8.3. The chapter concludes in section 8.4 with a discussion of policy implications and future research directions.

8.2 Discussion of Findings

This thesis set out to address the following specific questions:

1. Are those in poor health more likely to be in part time or casual employment?
2. What level of occupation are those in poor health employed in and what effect does a change in health (for better or worse) have on level of occupation?
3. Is health related labour market disadvantage cumulative and if so, to what degree?

This section discusses the thesis content in two parts. The first part (Chapters 2-4) covers the background literature, existing data, justification for the research and methodological considerations. The second part discusses the empirical findings (Chapters 5-7) in relation to the research questions.

8.2.1 Part I: Background, Justification and Groundwork

A review of the relevant economic theory suggests that the Grossman model (Grossman, 1972) continues to inform current research. The basic theoretical relationships between health, labour market activity, earnings and wealth employed in this framework continued to form the theoretical basis for empirical work. Health is a form of human capital and in the absence of sickness or injury, individuals have more time available to spend in work, they earn more and accumulate greater wealth. The model has been critiqued but the basic relationships with regards to the theoretical effects of health on labour market outcomes continue to make theoretical and intuitive sense.

Previous research into the effects of health on labour market outcomes has established evidence of negative effects of poor health but it has mostly concentrated on select outcomes. These include the effect of health on labour force participation, the probability of gaining (and retaining) employment, wages, earnings and hours worked and the retirement decision. While the evidence provided from these studies adds considerably to the knowledge on the effects of health on labour market outcomes, evidence is lacking on the degree to which the combined impact of health on the range of labour market outcomes results in cumulative disadvantage over the life course, particularly for Australia. Previous research has focused mainly on establishing causal evidence of the effect of poor health at a point in time rather than considering effects over longer timeframes.

The review of the literature also identified other concerns. It found that until recently, empirical work has focused on a subset of the population, namely older workers. Samples have also often been confined to men. There is evidence of health affecting labour market outcomes of younger workers (García-Gómez *et al.* 2010) and this reinforces the need to consider how the whole working age population might be affected rather than only a subset. The measure of health used was also an issue highlighted in the review, with a need to capture the effects of health beyond pure physical measures and to account for bias from measurement error, self reports and to establish causality.

A final area in which previous research has been limited is in methods used to analyse relationships between health and labour market outcomes. Longitudinal data are required in order to establish causal relationships and take account of methodological issues. The need to control for endogeneity, selection into employment and unobserved heterogeneity has been identified in recent literature. The main reason for the limited research incorporating both suitable methods and establishing causal evidence on cumulative effects can likely be attributed to unavailability of suitable data. Investment in representative large panel surveys has increased in recent times, including in the last decade or two for Australia. The development of the longitudinal HILDA survey and the addition each year to these data are enabling more reliable econometric estimation of causal effects.

To illustrate whether under-examined labour market outcomes and indicators of accumulating disadvantage were associated with health for the working age population, the profile in chapter 3 presented descriptive statistics. The profile drew on data from the ABS's National Health Survey and General Social Survey as well as the HILDA Survey. These cross sectional statistics, while unable to establish causal effects, provided prima facie evidence of links between health and the outcomes of interest in this thesis, justifying further investigation into answering the research questions set out at the beginning of this section. In brief, they identified cross sectional relationships between health and form of employment (men and women in part time and casual employment report poorer health) as well as health and occupation (men and women in manual occupations report poorer health). They also provided some cross sectional evidence displaying the relationships between poor health and labour market outcomes and accumulating disadvantage.

Chapter 4 set out concerns with health measures in more detail and formally developed the health index used to measure general health in this thesis. This method uses a number of indicators of health as well as health measures (mental and physical) in its construction. The review in chapter 2 found that this method is expected to better capture the dimensions of good health along with accounting for sources of bias and measurement error present in self reports of health. An empirical example (the employment participation model) was then used to illustrate the methodological issues highlighted in chapter 2. This formally identified the importance of using panel data methods and accounting for methodological issues such as unobserved heterogeneity, dynamics and initial conditions in order to obtain reliable results. Failing to account for these issues leads to biased results. Relying on biased findings risks incorrect conclusions as to the size of the problem and its significance.

These first chapters laid the groundwork for the econometric analysis in the later chapters. They set out the existing knowledge, justified and established where this thesis fits within the research area and confirmed that there is a basis for the research undertaken in this thesis. The second part of the thesis comprises the empirical contribution, using the panel data methods and the constructed health index established as necessary in order to ensure the most robust and reliable results.

8.2.2 Part II: Empirical findings

Chapters 5 through 7 provided the analysis and evidence to answer the research questions set out in the previous section. Australian longitudinal data were used to analyse the effect of health on under-examined labour market outcomes and to provide evidence on cumulative disadvantage through measures capturing earnings over the life cycle. The use of panel data methods, a data set that represents the entire cohort of working age, and incorporation of variables to capture expected gender differences gave a more complete and reliable picture of the degree of disadvantage arising from poor health.

Health and form of employment

Chapter 5 evaluated the extent to which health affects individuals' choices of forms of employment in Australia. It specifically tested the hypothesis that persons of working age who are in poorer health are more likely to be employed on part time or casual terms, or not employed at all. The focus was on a sample of persons in Australia aged 15 to 64 excluding full time students. The results from dynamic, multilevel multinomial logit models suggested that there is a significantly higher probability of part time or casual employment amongst those persons in poorer health who are employed. Although the estimated effects of poor health are significant, they are small. It was also found, as in previous research, that poor health substantially increases the likelihood of non-employment. Diagnostics showed that the models used perform well in explaining variation in the outcome variables and addressing relevant econometric issues.

The finding of a significant effect of poorer health on increasing the likelihood of part time and casual employment may suggest that flexibility in hours of work and employment arrangements allow accommodation of health impairments. The findings with regard to part time work are supported by the effect of health on hours of work previously found (Currie and Madrian 1999; Pelkowski and Berger 2004; Cai *et al.* 2014). The finding of an increased likelihood of casual employment further contributes to the literature, as does the analysis of part time employment (as opposed to a continuous measure of hours of work) given the implications of these forms of employment in terms of occupation segregation and fewer training opportunities (Arumpalam & Booth, 1998; Draca & Green, 2004; Prowse, 2005; O'Dorchai *et al.*, 2007).

There are gender differences with respect to the relationship between health and form of employment. While it was not possible to separately model the relationships by gender due to lower observation numbers with disaggregation, the results in chapter 5 indicated that health has a significant effect for women, with employed women who are in poor health more likely to be in part time or casual employment, but this effect is not as large as that for men. Health also has a smaller effect on the likelihood of non-employment for women. For women, health is a lesser determinant of form of employment than it is for men.

In order to more accurately quantify the effects of health on form of employment, average predicted probabilities were evaluated and compared by computing probabilities by health index quintile and gender via counterfactuals which simulate the effect of differing levels of health on form of employment. For employed men, being in the lowest health index quintile increases the probability of part time employment (relative to full time employment) by 2.8 per cent compared with those in the highest health index quintile. The smaller effect for women is highlighted in these estimates with being in the lowest health index quintile only increasing the probability of part time employment by 1 per cent. The impact of poor health is thus statistically significant, but small.

The figures for casual employment are very similar to those for part time employment. The probability of casual employment (relative to permanent employment) increases by 2.8 per cent for employed men in the lowest health index quintile compared with those in the best health. The comparable figure for women is an increase in the probability of casual employment of 1.1 per cent amongst those in the poorest health. These estimates for both part time and casual employment illustrate the previous observation that health is a lesser determinant of form of employment for women

The results from the form of employment models also found other factors were associated with form of employment. Greater employment experience (years spent in employment) significantly increases the likelihood of full time and permanent employment as does higher education. Partner wage and non labour income lower the likelihood of full time employment. Having an employed partner increases the likelihood of full time and permanent employment. This may be explained by both the respondent and their partner facing the same local labour market and also partner characteristics. Living in a rural area increases the likelihood of casual employment amongst those who are employed.

These findings support the suggestion by De Lange *et al.* (2004; 2005) and Dalgard *et al.* (2009) that health has a causal relationship on job characteristics such as job demands and job control. De Lange *et al.* (2005) suggested there was good reason to pursue research on the causal relationship between health and form of employment and the findings in chapter 5 confirm this. Given that part time and casual employment both have negative implications for lifetime earnings via occupational segregation, effects on human capital formation and career progression, the results from chapter 5 suggest that the effect of health on form of employment can add to disadvantage already experienced by persons in poor health.

It must be noted that the availability of these forms of employment is likely to make it possible for some people in poorer health to hold down a job, which they could not do if the only option was fulltime permanent work. Nevertheless the effect of poor health on form of employment, whether it results in individuals choosing part time or casual work or selecting out of employment, still puts them at a disadvantage in comparison with healthier individuals who do not face such constraints on their form of employment.

Health and occupation

Chapter 6 analysed the occupation that those persons of working age who are in poor health work in and the effect of changes in health (for better or worse) on occupation. This analysis helps us to understand how people adapt to health limitations and what types of jobs make this harder or easier. As with chapter 5, the focus was on Australians aged 15 to 64 excluding full time students.

The results suggest that after controlling for selection into employment, health (and changes in health) does not have a significant effect on occupation. The diagnostics suggest that the models used perform well in explaining variation in the outcome variables and addressing relevant econometric issues.

Two measures of occupation were used. One was a categorical manual/non-manual measure modelled by dynamic, multinomial multilevel logit models which also included non-employment as an outcome. The second was a continuous measure of occupational status modelled by dynamic multilevel linear regression for those who reported an occupation. This was designed to capture two aspects of occupation highlighted in the literature as linked with health, physical job demands and status. Use of the continuous occupational status measure also addressed the lower number of transitions between the broadly defined manual and non-manual occupations. Use of the rank of occupational status captures more movement in occupation, though people may move occupations within status levels. Different health measures were also used, with the results using the health index compared to analysis which used measures of health shock and health improvement. The findings with regard to no significant effect of health on occupation are robust to both measures of occupation as well as all health measures analysed.

Both the theory and the literature emphasise the effect of health on employment. The theory with regards to the effect of health on occupation is less clear. There is a theoretical argument that persons experiencing poor health have lower levels of human capital via education and labour market experience and this results in employment in lower status, lower skilled and lower paid jobs. However this does not necessarily take into account how individuals might adapt to onset of poor health through other choices. It was theorised that persons in poor health might seek occupations with lower physical demands (i.e. non-manual occupations) in order to accommodate their impaired health however failure to find such employment was expected to result in withdrawal from employment[73].

Literature on the causal effect of health on occupation, with the exception of the job change literature, is lacking. Given the theory makes no firm argument as to the effect of health on occupation, the issue then becomes an empirical one—does poor health in fact affect the level of occupation that is attained? The aim of the analyses in chapter 6 was thus to provide empirical evidence of the direction of the effect of health on occupation. Both the theory and previous empirical findings support the conclusion that poor health reduces the probability of being employed. It is perhaps not surprising then that the results of the analyses in chapter 6 find no significant effect of health on occupation after controlling for selection into employment.

The results reinforce the findings that health selection into employment plays a large role, with persons in poor health less likely to be employed. While poor health had no significant effect on occupational level, it did still play a role in reducing employment in the models. As with the results in chapter 5 and in previous research, poor health was found to result in an increased likelihood of non-employment in the multinomial logit model using the categorical measure of occupation. The model of occupational status controlled for selection in a different manner but still found evidence of selection into employment. This supports the previous results and findings from the literature (see for example Bound *et al.* 1999; Korpi 2001; Cai and Kalb 2006; Schuring *et al.* 2007; Cai 2010; García-Gómez *et al.* 2010; Zucchelli *et al.* 2010, Virtanen *et al.* 2013).

While the findings do not suggest a significant causal effect of health on occupation leading to negative implications for lifetime earnings, the findings with regards to health selection into employment are relevant to this story. Prolonged poor health which results in prolonged time without employment widens the gap in lifetime earnings between those experiencing poor health and those who are in good health and hence are more continually employed.

[73] The relationship between poor mental health and physical job demands may not be so clear cut given that physical job demands may not act as a barrier to the same extent as for a person in poor physical health.

Results also found that higher education is associated with higher level of occupation. Women are also employed in higher levels of occupation on average than men. Women are more likely to be employed in non-manual occupations and this is also reflected in the model of occupational status. Being married or in a de facto relationship is also positively associated with level of occupation. People in higher status occupations are more likely to get married. Higher childhood SES is linked with higher occupational status. The inclusion of job characteristics in the model of occupational status found that these are also significant determinants, with hours worked, job tenure and union membership positively associated with higher occupational ranking and employment in the private sector having a negative effect on occupational status.

Occupational level models were also estimated in order to explicitly examine the degree to which job change is used as a way to adapt to health impairment. Surprisingly, persons experiencing an adverse health shock are not more likely to change occupational level once selection into employment is accounted for. These findings are consistent with persons experiencing poor health being more likely to leave employment than to change occupation. People who experience impaired health and who are not accommodated in their current job have been found in other research to select into less physically demanding jobs (Daly & Bound, 1996; Krause *et al.* 2001). These previous studies focus on samples of people who have experienced health impairment. They do not control for selection out of employment or compare the likelihood of job change with that for persons in better health. The findings in chapter 6 emphasise how important it is to account for this. People with impaired health may change occupational level but they are not significantly more likely to change occupational level compared with persons who do not experience a health shock after taking into account selection out of employment.

It must be acknowledged that people may change jobs within an occupation and this is not captured in the models. Nonetheless, they support the conclusion that withdrawal from the workforce is a more powerful source of harm from poor health than is reduced occupational status. This has implications for lifetime earnings in that loss of income will widen the gap between those who cannot find employment accommodating their health and those healthy individuals who continue working and do not face such barriers.

Cumulative disadvantage

Chapter 7 examined whether health related labour market disadvantage is cumulative and the degree of any cumulative effect for Australia. It used measures of wealth which are affected by (and sensitive to) labour market outcomes to test the hypothesis that there is a cumulative effect and that those experiencing poor health earlier in their working life will experience greater cumulative disadvantage. The analyses found evidence of the existence of health related cumulative disadvantage in Australia. Two measures of wealth were used, superannuation (an individual measure) and household net worth.

The study compared estimated wealth differentials between persons in the lowest health index quintile and those in the highest health index quintile. Results indicated that there is health related labour market disadvantage which increases with age. A crude estimate of the magnitude of this effect suggests that a person in the highest health index quintile has on average just under $9,000 more superannuation at age 60 (in 2010 dollars) than a person who was in the lowest health index quintile. This disadvantage does increase with age, with the differential increasing rapidly from age 40. There were statistically significant gender differences in the superannuation model. The gender differences manifest in women experiencing a higher degree of cumulative disadvantage associated with health in comparison with men. Chirikos (1993) noted that poor health compounds even further the well-known labour market disadvantages of women and this finding reflects that.

Results using household net worth found that the association between household wealth and the explanatory variables was weaker than that found in the superannuation model. This can be attributed to the explanatory variables being individual measures. This weaker association is reflected in the estimated effects of health, with the household net worth model finding evidence of cumulative disadvantage for men but not women.

The household wealth measure masks gender differences arising from health, with there being no significant gender difference in the model. This suggested that the results from the superannuation model are to be preferred both because gender differences are more clearly established and because superannuation is more closely related to labour market experience.

Results also found that higher educational attainment and higher occupational ranking are linked with higher superannuation as might be expected. Self employment and being a migrant are associated with lower superannuation as is the presence of children. The effect of children is greater for women than men but significant for both. Being married or in a de facto relationship is linked with higher superannuation, perhaps reflecting the relationships between partnering and employment outcomes as suggested in the results from chapters 5 and 6.

The main findings of chapter 7 were to establish that there is health related cumulative labour market disadvantage in Australia and to offer a first quantitative measure of this disadvantage using panel data methods. This finding is consistent with the array of findings reported in chapter 2 suggesting that cumulative disadvantage is likely (e.g. Korpi, 2001; Hum *et al.* 2008; Smith, 2009; Haas *et al.* 2011; Lundborg *et al.* 2014). The models of wealth in chapter 7 do control for unobserved heterogeneity by using three waves of panel data. A broader sample is used than that in much of the previous literature on the effect of health on measures of wealth. The finding of poor health adversely affecting wealth is consistent with the causal effect of health on wealth found by Michaud and van Soest (2008) and Smith (2009) but the finding is in this case extended to a wider age range and uses a wealth measure more closely related to labour market disadvantage.

The model may not be as robust as those used in chapters 5 and 6 given that there were added limitations in the data used. Wealth data were only available in three waves of HILDA (spanning eight years) and this limited the effectiveness of conducting panel data modelling and also the degree to which results are able to capture effects over the life course. While this limitation must be acknowledged, the estimates in chapter 7 have still advanced the analysis of determinants of wealth in Australia beyond the previous cross sectional view. The importance of this was emphasised by Hum *et al*. (2008) albeit for lifecycle labour supply rather than wealth where they argued the cross sectional estimates overstate the degree of disadvantage.

These estimates (as well as those in chapters 5 and 6) also do not distinguish between transitory poor health and those conditions having a lasting impact. This suggests that the results may provide conservative estimates of the effects of chronic ill-health. What is clear is that the analyses in this thesis do provide empirical evidence of adverse effects of poor health on labour market outcomes and that this disadvantage results in cumulative disadvantage. The wealth effects with age are of concern given they have implications for standards of living later in life for those suffering health related disadvantage.

In summary, the findings in this thesis suggest that there is evidence of cumulative effects of labour market disadvantage over the life course in Australia that is caused by experiencing chronic or episodic poor health. These arise from selection out of employment by those in poor health, illustrated in the findings from chapters 5 and 6. This finding supports the relationship found in the literature. The analysis in this thesis has provided a robust quantitative estimate of the size of the impact of poor health on the probability of being employed. It is substantial and is the main cause of economic loss arising from poor health.

Aside from selection out of employment there is also some effect of health on labour market outcomes among those who are employed. The literature has found effects of health on wages, earnings and hours worked. The analysis in chapter 5 found that health also has an effect on form of employment and this has implications for career progression and life time earnings. Chapter 6 indicated that the effects of health on labour market outcomes was more about being employed at all than the occupational level people are employed in. These cumulative effects were found in chapter 7 to manifest themselves in health related differentials in life time earnings as proxied by wealth. These findings with regard to adverse effects of health suggest that interactions between health and labour market outcomes over the life course add to the disadvantage already experienced by individuals with impaired health.

8.3 Evaluation and Limitations

This section evaluates the work undertaken in this thesis and identifies limitations in relation to the analyses. The thesis has made empirical contributions as outlined in the previous section. These empirical contributions provide evidence of cumulative effects of labour market disadvantage arising from poor health. The analysis of cumulative effects for the entire working age population and identifying gender differences addressed some gaps in the previous literature.

The discussion of the empirical contributions is incomplete without some discussion of how the findings fit within existing theory and the methodological approach used. This section begins by briefly setting out the theoretical contributions. It then evaluates the methods used and the methodological contributions of the thesis. The final part of this section discusses the limitations of the analyses which must be acknowledged.

Theoretical contributions

The empirical findings from the thesis support the basic relationships in the Grossman model (Grossman, 1972). Individuals in good health are more likely to work and are more likely to work in full time employment. They also accumulate more wealth as measured by superannuation. This reflects higher earnings for those in better health as also predicted by the model. This allows confidence that the theory is broadly accurate but also that the results are supported by what is expected from established theory.

There is however the suggestion within the findings of the thesis that health may have an effect on the rate of human capital appreciation. This is not incorporated within the Grossman model. The effect of health on form of employment and through keeping people out of work is argued to result in persons experiencing poor health being unable to accumulate human capital (both formally and through on the job training) at the same rate as persons who are in good health and able to be continuously employed in permanent and full time employment.

The Grossman model takes into account time use (and time lost from sickness), health, wages and earnings but human capital appreciation resulting from good health will have further effects via wages and earnings. LaPorte (2014) argued that many critiques of the Grossman model can be treated as simplifying assumptions and perhaps this is also the case with respect to the exclusion of human capital appreciation from the model. Nevertheless the identification of this relationship in the thesis is a theoretical contribution.

Methodological contributions

Methods used were discussed in part in section 8.2.2. This section discusses in further detail the methods used and the findings in relation to using these econometric methods to account for known issues and the impact accounting for these has on the reliability of results. It will also further evaluate the analysis undertaken in the thesis by identifying ways in which it addresses the gap in the literature it set out to address and to acknowledge limitations of the analysis undertaken.

The analysis undertaken in this thesis has provided evidence of relationships between poor health and labour market outcomes in an area where evidence had previously been lacking-namely looking at effects over time rather than at a single point in time in order to ascertain cumulative effects over the life course. Efforts were made to ensure the analysis undertaken was as rigorous as possible. The econometrics took into account a number of modelling issues in order to avoid results being biased and to increase the reliability of findings. There were also certain robustness checks performed in order to test the sensitivity of results.

The analyses studied the working age population and both men and women. Previous research focused heavily on older workers and was often confined to analysis of men. The results in chapter 4 through 7 suggest there is a significant effect of health on labour market outcomes for the working age population. This supports the finding highlighted by García-Gómez *et al.* (2010) that health has an effect on younger workers. When analysing cumulative disadvantage it is particularly important to capture the effect on younger persons as well as those who are older in order to determine the degree of disadvantage over the whole of working age and into retirement. Confining analysis to an older sample misses the full effect of health and understates the health related disadvantage experienced.

Gender differences were expected given the different patterns of labour force participation for men and women and results from the analyses did find differences. Health was a lesser determinant of employment and had a smaller effect on form of employment for women than men. This is most likely explained by the fact that women are more likely than men to be out of the labour force or working part-time for reasons that are unrelated to their health (mainly, raising children). There were also gender differences in the effect of health on wealth (measured by superannuation), with poor health resulting in greater cumulative labour market disadvantage for women than men. Again, failure to consider both men and women presents an incomplete picture of the relationships between health and labour market outcomes and the differences in the magnitude of these relationships.

Methodological issues identified as being relevant to modelling the causal relationships of interest in this thesis included state dependence, unobserved heterogeneity, the role of initial conditions, selection into employment and choice of health measure. Each of these were considered in econometric modelling undertaken in this thesis both to identify sources of bias in modelling relationships between health and labour market outcomes over the life course and to control for these biases.

The methodological contributions of the analyses of chapters 5 and 6 are broadly similar even if they do aim to answer different research questions. Both analyse the effect of health for under-examined labour market outcomes in the Australian setting. The models do add to the empirical evidence on disadvantage experienced by those in poor health compared to their healthier counterparts. Aside from quantifying these relationships and identifying health related labour market disadvantage, the results in these chapters make contributions in supporting previous empirical studies with regard to methods.

The econometric studies presented in chapters 5 and 6 illustrated the importance of controlling for state dependence, selection into employment and initial conditions in particular. In both of these chapters the dependent variable(s) were labour market outcomes so that outcomes were only observed for individuals who were employed. Methods were used to address selection into employment and these controls for selection found that health based selection into employment is a source of bias which needs to be accounted for. Failure to control for selection into employment results in overestimates of the effect of health on form of employment. It also results in larger estimates of the effect of health on level of occupation although these still fail to meet conventional levels of significance. This supports previous research which finds that failing to account for selection can overstate relationships (Heckman, 1979).

The inclusion of dynamics in the analyses in chapters 5 and 6 showed that past labour supply behaviour is an important determinant of current labour supply behaviour for the outcomes analysed in this thesis. This suggests that there is state dependence which must be accounted for in order to determine causal relationships between health and labour market outcomes. Including controls for state dependence improved the fit of the models of form of employment and level of occupation and provided more reliable estimates of the magnitude of the effect of explanatory variables.

Similarly, the controls for the initial conditions problem used in chapters 5 and 6 indicated that initial conditions do play an important role and cannot be ignored in analysing relationships between health and labour markets outcomes. The estimator is biased in a model which fails to account for the initial conditions problem (Wooldridge, 2005). The inclusion of the controls for initial conditions further improved the fit of the model as well as adding to confidence that results are reliable and do not overestimate the relationships of interest.

In all three econometric studies (chapters 5 through 7) unobserved heterogeneity was identified as being of particular importance. This highlights the shortcomings in relation to past research using cross sectional data. Panel data methods are required in order to identify causal effects and to control for unobserved individual differences in modelling interactions between health and labour market outcomes.

Research has emphasised the need to account for unobserved heterogeneity (Cai and Kalb 2006; Hyslop, 1999; Cai 2010) and the econometric studies conducted in this thesis lend strong support to this claim.

Results which do not control for unobserved heterogeneity are biased and the direction and magnitude of the bias depends upon the correlation between the explanatory variables and the omitted information. Both pooled models with no control for unobserved heterogeneity and panel models accounting for unobserved heterogeneity were run in order to determine the best model fit. In the models in chapters 5 and 6, results which do not control for unobserved heterogeneity overestimate the effects of state dependence and underestimate the effects of higher education. The estimates of the magnitude of the effect of health are a little larger after accounting for unobserved heterogeneity although not significantly so. The estimates of the magnitude of the effect of health in the wealth model are a little smaller in the panel model. Aside from differences in the magnitude of estimates, the diagnostics in all analyses conducted clearly indicate there is unobserved heterogeneity and as such this must be accounted for when modelling the outcomes analysed in this thesis.

Following the recent literature on concerns with using subjective measures of health, this thesis sought to control for measurement error and sources of bias in the health measure by constructing an index of health via estimating a latent variable model. This model specified self assessed health as a function of more objective measures of health and demographic characteristics. Until recently research focused primarily on physical health and self reports. The construction of the index used indicators of both physical and mental health and can therefore be considered not only to address measurement error and bias but also better capture the multidimensional nature of good health. This method has been extensively used in empirical literature on health and labour market outcomes over the last decade (see for example Au *et al.* 2005, Disney *et al.* 2006, Zucchelli *et al.* 2007, Hagan *et al.* 2009, García-Gómez *et al.* 2010). The constructed index of health was then used in each of the econometric studies appearing in this thesis.

Aside from taking steps to address the methodological issues outlined above, certain robustness checks were undertaken to test reliability of results. For each econometric study undertaken, comparison specifications were estimated to test the sensitivity of the results. Models were estimated using different and equally suitable estimation procedures and results using these alternative procedures found that estimates were not sensitive to the estimation procedure used. Checks were also undertaken to ensure findings were not sensitive to variable inclusion. Results were found to be robust to all checks performed.

Controlling for the methodological issues set out in this section offers more reliable and robust results, particularly after running comparison models to determine how sensitive the results are. These methods give greater confidence that the findings are reliable and represent the relationships the thesis set out to estimate for the population of interest. All of these conclusions with regards to methodological issues add to the mounting evidence that panel data and panel methods are to be preferred. Causal relationships cannot be estimated with any degree of certainty without addressing these biases if they are present in data.

Limitations

Despite the efforts undertaken to ensure that the modelling was rigorous, a number of limitations must be acknowledged. Firstly, the research in this thesis does not distinguish between long term poor health and episodic (transitory) poor health. There is a certain amount of persistence in health status, however the modelling in this thesis does not explicitly capture the degree of persistence of individual health. While this is an important concern, it does not negate the findings in this thesis. It simply means that the results found must be interpreted in light of assumptions made within the econometric studies conducted.

In the case of chapters 5 and 6, the results presented are the effect of health at one specific point in time (year t). As such if poor health is long term rather than transitory, the results in these chapters can be considered to be conservative. The same can be said of the econometric estimates provided in chapter 7. These estimate the average effect of health status on measures of wealth at time t and could also be considered as conservative. On the other hand, the results in the figures presented towards the end of the chapter comparing wealth differentials over working age assume continuous poor health compared with continuous good health. This assumption must be explicitly considered when taking account of the magnitude of the estimates. Given that the estimates provided in chapter 7 add to the limited literature on health related cumulative labour market advantage and provides the first evidence in the Australian context it is still an important contribution.

The models in chapters 5 and 6 were not run separately for gender due to lower observation numbers for categorical variables with disaggregation. This limited the extent to which gender differences could be identified. Control variables were included for gender as well as interaction terms between gender and health and other relevant variables. This allowed identification of some differences between men and women, in particular for effects of health which was the focus of this thesis.

The empirical studies in this thesis are also restricted in terms of only being able to make use of the data available and this is particularly pertinent in the context of determining cumulative effects. HILDA is growing as a panel survey however it is still a relatively short panel in comparison with international data such as the US Panel Survey of Income Dynamics (spanning 1968-2011), German Socio-Economic Panel (28 waves currently spanning 1984-2011) and the British Household Panel Survey (18 waves spanning 1991-2009). As HILDA matures further, it will be possible to more effectively analyse cumulative effects over the life course, particularly with respect to the wealth data analysed in chapter 7 which to date is only available in three waves of data.

One common problem with longitudinal survey data is attrition. HILDA was fairly representative in wave 1. While non-response was not random, the size of discrepancies are not considered large (Watson and Wooden, 2002b). If there is non-random attrition this would bias the findings presented in this thesis. This might be a particular concern if persons experiencing health impairments are more likely to attrite from the sample however this is not known to be the case. This problem is not new and is not isolated to the studies undertaken in this thesis. Attrition rates have fallen over time in HILDA, particularly in later waves and HILDA has also been found to compare well with international household panel studies (Watson and Wooden, 2006). The findings in this thesis assume that values are missing at random and that attrition does not bias the results nevertheless the limitation associated with this assumption must be acknowledged.

It was acknowledged in the previous section that limitations in the wealth data reduced the effectiveness of the panel data modelling. It is also likely that the evolution of superannuation in Australia in terms of level and eligibility for contributions is important. These are both factors which might be better addressed when more data becomes available. These are considerations for future research.

When considering aspects of disadvantage (and cumulative disadvantage), those who are in the worst health are compared with those in the best health. The outcome used to measure disadvantage was a measure of incoming funds broadly captured via wealth data. On average, however, people with health impairments may possibly have different expenses leading to a need to consider outgoing expenses as well as incoming funds in order to determine the true extent of disadvantage (and cumulative disadvantage), that is, measures of poverty. This is particularly important given that persons with health impairments have less income on average but also have greater expenses. While this is acknowledged as an important consideration in analysing disadvantage and cumulative disadvantage, an analysis of outgoing expenses as well as incoming funds was beyond the scope of this thesis and is suggested as a topic for future research.

8.4 Policy Implications and Future Research

The results from this thesis have generated findings which have potential implications for government policy and future research. The results from estimating the effect of health on measures of wealth, capturing disadvantage over the life course, show that health related labour market disadvantage has an increasing effect over time. This culminates in the greatest disadvantage in terms of wealth and lifetime earnings occurring between those nearing retirement who have experienced continuous poor health compared with those of the same age who have experienced continuous good health.

These wealth and lifetime earnings differentials have broader implications in terms of perpetuating the cycle of disadvantage for those already at a disadvantage by leading to further poverty, social exclusion and a poorer standard of living in retirement compared with persons who do not experience poor health. In terms of policy implications, the cumulative disadvantage found operates mostly through the effect of health on the likelihood of employment. It should be noted that however that the government funded old age pension is available at the same level in Australia (subject to the means test) regardless of prior employment history.

While this thesis found that there is some effect of health on labour market outcomes for those who are employed, there is a greater effect on the likelihood of employment. Persons in poor health are much less likely to be employed and this may have important implications for the emphasis of policy efforts to address the negative employment related outcomes of poor health. This finding is not new but many previous studies focused only on a subset of the population, namely older workers. This thesis found that younger people respond to poor health in a similar way and suggests that governments need to also keep younger workers in the ‘policy frame’ when considering the impact of health on employment.

The level of compulsory superannuation contributions made by employers will increase to 10 per cent from July 2021 and will increase by 0.5 per cent a year until reaching 12 per cent in July 2025. This increase in compulsory employer contributions will increase the average amount of income Australians will have upon retiring but it is linked to employment participation. However, for persons with impaired health this is not likely to assist in reducing the level of disadvantage. These measures will increase wealth and income later in life for those who are able to remain in employment. Policies aimed at increasing the number of people in poor health who are working and which make it easier for those in poor health to remain employed will have a greater effect on reducing disadvantage and improving living standards.

The findings from this thesis can also provide directions for future research. As discussed in the previous section, the HILDA survey is relatively young in comparison with other leading household panel surveys. This thesis makes use of the first ten waves of HILDA but funding for HILDA has been guaranteed for at least sixteen waves. Future research could make use of the longer panel as HILDA matures. This would have advantages in terms of further implementing the types of dynamic panel data models estimated in this thesis and in better capturing disadvantage over time.

A longer panel will be particularly useful in future analyses of the wealth data analysed in chapter 7. As further data become available more complex modelling techniques could be adopted in analysing the wealth data. While the research presented in this thesis provides a starting point in an area in which there is limited evidence, a greater number of data points in future will also aid in more effectively investigating the degree to which health affects wealth and cumulative disadvantage arising from poor health.

It was acknowledged in the previous section that in order to capture the full extent of disadvantage in financial terms, both incoming funds and outgoing expenses should be considered in order to measure levels of poverty. This is particularly relevant for persons with health impairments who have higher expenses. An investigation encompassing both incoming funds and outgoing expenses in analysing cumulative disadvantage was beyond the scope of this thesis but is an important area of concern for future research, particularly with the emergence of better data in this area.

Future research could also seek to replicate the findings in this thesis for other countries. The findings presented in this thesis use representative data for Australia however it would be useful to know whether these findings extend beyond the specific characteristics of the Australian labour market and the characteristics of the Australian population itself. This would be particularly informative with regards to analysing the cumulative effects of health related labour market disadvantage. There is a scarcity of evidence in this area. Given the implications of ageing and its consequences for the health of working age population, and concerns for the standard of living of the growing proportion of retirees, pinpointing evidence on causes of health related disadvantage will be vital for informing policy.

Appendix

Appendix A

Table A-1: Labour Force Status in 2009 compared with Labour Force Status in 2010 if Reported Fair/Poor Health in 2009, 25 to 64 year olds, Per cent

	Labour Force Status in 2010			
Labour Force Status in 2009	*Employed*	*Unemployed*	*Not in the labour force*	Total
	%	%	%	%
Employed	90.9	27.5	3.9	36.2
Unemployed	1.8	37.5	1.0	2.2
Not in the labour force	7.3	35.0	95.1	61.6
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Table A-2: Labour Force Status in 2009 compared with Labour Force Status in 2010 if Reported Good Health or Better in 2009, 25 to 64 year olds, Per cent

	Labour Force Status in 2010			
Labour Force Status in 2009	*Employed*	*Unemployed*	*Not in the labour force*	Total
	%	%	%	%
Employed	95.0	55.3	12.5	70.4
Unemployed	1.5	24.7	1.5	1.9
Not in the labour force	3.6	20.0	86.0	27.6
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Table A-3: ABS Definitions of Forms of Employment

Form of Employment	Definition
Part time	Part-time workers are those workers who usually work less than 35 hours per week in all jobs
Full time	Full-time workers are those workers who usually work 35 hours or more per week in their main job
Permanent	Permanent employees are those employees who are entitled to either paid sick leave, paid holiday leave, or both and are not employed on a fixed term contract or casual basis.
Casual	Casual employees are those employees who do not have a written agreement on the minimum number of days that will be worked. They are usually paid a higher rate of pay to compensate for lack of permanency and leave entitlements. Casual employees are those who are entitled to either paid holiday leave or sick leave but not both or who have no leave entitlements and who consider their jobs to be casual. Casuals may be full-time or part-time depending upon the hours they have agreed to work.

Sources: Australian Bureau of Statistics (2006) Labour Statistics: Concepts Sources and Methods, August 2006, Catalogue No. 6102.0.55.001. Australian Bureau of Statistics (2011) Forms of Employment, Australia, November 2010, Catalogue No. 6359.0.

Table A-4: Whether Took Part in any Work Related Training in the Last 12 Months by Health, 25 to 64 Year Olds

	Very good/Excellent	Good	Fair/Poor	Total
	%	%	%	%
Yes	33.2	29.8	26.5	31.1
No	66.8	70.2	73.5	68.9
Total	100.0	100.0	100.0	100.0

Source: HILDA Release 10

Note: Population weighted results

Table A-5: 1-Digit ANZSCO Occupation by Self Assessed Health, Men aged 25 to 64 years, 2007-08 Per cent

Occupation (main job)	**Excellent or Very good**	**Good**	**Fair or Poor**	**Total**
	%	%	%	%
Managers	61.1	29.3	9.5	100.0
Professionals	66.0	25.8	8.2	100.0
Technicians and Trades Workers	58.6	30.3	11.1	100.0
Community and Personal Service Workers	62.0	26.2	11.8	100.0
Clerical and Administrative Workers	64.7	26.4	8.9	100.0
Sales Workers	52.5	31.8	15.7	100.0
Machinery Operators and Drivers	47.3	40.3	12.4	100.0
Labourers	55.7	36.4	7.9	100.0
Total	59.3	30.6	10.1	100.0

Source: 2007-08 National Health Survey CURF data

Note: Population weighted results. Percentages may not add up to 100 due to rounding

Table A-6: 1-Digit ANZSCO Occupation by Self Assessed Health, Women aged 25 to 64 years, 2007-08 Per cent

Occupation (main job)	Excellent or Very good	Good	Fair or Poor	Total
	%	%	%	%
Managers	67.9	25.0	7.1	100.0
Professionals	71.1	22.8	6.2	100.0
Technicians and Trades Workers	56.1	36.7	7.1	100.0
Community and Personal Service Workers	65.2	26.7	8.1	100.0
Clerical and Administrative Workers	67.6	23.9	8.5	100.0
Sales Workers	66.5	23.8	9.7	100.0
Machinery Operators and Drivers	43.0	42.0	15.0	100.0
Labourers	48.4	38.3	13.2	100.0
Total	65.7	26.1	8.2	100.0

Source: 2007-08 National Health Survey CURF data

Note: Population weighted results. Percentages may not add up to 100 due to rounding

Table A-7: Non-manual/Manual Occupation by Self Assessed Health, 25 to 64 year old Men, 2007-08, Per cent

	Excellent or Very good	Good	Fair or Poor	Total
	%	%	%	%
Non-manual	62.7	27.7	9.6	100.0
Manual	54.8	34.4	10.7	100.0
Total	59.3	30.6	10.1	100.0

Source: 2007-08 National Health Survey CURF data

Note: Population weighted results. Percentages may not add up to 100 due to rounding

Table A-8: Non-manual/Manual Occupation by Self Assessed Health, 25 to 64 year old Women,2007-08, Per cent

	Excellent or Very good	Good	Fair or Poor	Total
	%	%	%	%
Non-manual	68.2	24.1	7.7	100.0
Manual	50.5	38.2	11.3	100.0
Total	65.7	26.1	8.2	100.0

Source: 2007-08 National Health Survey CURF data

Note: Population weighted results. Percentages may not add up to 100 due to rounding

Table A-9: Estimates (and Standard Errors) for Dynamic marginal effects probit models of probability of employment at year *t*, Men aged 15 to 64

	Pooled	Initial conditions exogenous	Wooldridge
Employed at t-1	0.385*** (0.0124)	0.220*** (0.0190)	0.161*** (0.0173)
Employed at t=1			0.0467*** (0.0075)
Post GFC	0.0053 (0.0038)	0.0001 (0.0037)	-0.0004 (0.0034)
Lagged health index	0.0012*** (0.0002)	0.0008*** (0.0001)	0.0008*** (0.0001)
Initial health	0.0006*** (0.0002)	0.0007*** (0.0001)	0.0006*** (0.0001)
Has children aged 0-4	-0.0048 (0.0056)	-0.0014 (0.0062)	-0.0005 (0.0055)
Has children aged 5-14	0.0129*** (0.0040)	0.0010 (0.0055)	0.0008 (0.0050)
Married/De Facto	-0.0124*** (0.0042)	-0.0212*** (0.0052)	-0.0199*** (0.0047)
Partner is employed	0.0523*** (0.0049)	0.0334*** (0.0056)	0.0319*** (0.0053)
Weekly non labour	-0.0009***	-0.0005***	-0.0005***

	Pooled	Initial conditions exogenous	Wooldridge
income ($100's)	(0.0001)	(0.0001)	(0.0001)
Partner wage	-0.00004 (0.0001)	0.00003 (0.0001)	0.00003 (0.0001)
Rural	-0.0049 (0.0045)	-0.0056 (0.0040)	-0.0046 (0.0038)
Migrant	-0.0032 (0.0038)	-0.0048 (0.0036)	-0.0040 (0.0034)
Experience	0.0036*** (0.0006)	0.0029*** (0.0009)	0.0026*** (0.0008)
Experience squared	-0.0001*** (0.00001)	-0.0001*** (0.00001)	-0.0001*** (0.00001)
Economic inactivity	-0.0179*** (0.0008)	-0.0124*** (0.0013)	-0.0115*** (0.0012)
Economic inactivity squared	0.0004*** (0.00003)	0.0004*** (0.00003)	0.0003*** (0.00003)
Unemployment rate	-0.0036*** (0.0008)	-0.0017** (0.0007)	-0.0017*** (0.0006)
Degree or above	0.0129*** (0.0043)	0.0364*** (0.0123)	0.0378*** (0.0105)
Advanced Diploma/Diploma	-0.0032 (0.0058)	0.0285*** (0.0085)	0.0261*** (0.0072)
Certificate	0.0042 (0.0040)	0.0198* (0.0114)	0.0217** (0.010)
Year 12	-0.0014 (0.0055)	0.0105 (0.0129)	0.0136 (0.0103)
Time averaged characteristics			
Experience		-0.0004 (0.0008)	-0.0005 (0.0007)
Economic inactivity		-0.0038*** (0.0011)	-0.0023** (0.0011)
Unemployment rate		-0.0043*** (0.0012)	-0.0029** (0.0011)
Has children aged 0-4		-0.0040 (0.0094)	-0.0045 (0.0088)

Appendix

	Pooled	**Initial conditions exogenous**	**Wooldridge**
Has children aged 5-14		0.0155** (0.0075)	0.0146** (0.0070)
Married/De facto		0.0141* (0.0085)	0.0150* (0.0079)
Partner is employed		0.0174** (0.0076)	0.0127* (0.0071)
Weekly non labour income ($100's)		-0.0006** (0.0002)	-0.0005** (0.0002)
Partner wage		-0.0001 (0.0002)	-0.0001 (0.0001)
Degree or above		-0.0374* (0.0213)	-0.0457** (0.0197)
Advanced Diploma/Diploma		-0.0504** (0.0230)	-0.0476** (0.0211)
Certificate		-0.0195 (0.0145)	-0.0231* (0.0133)
Year 12		-0.0113 (0.0173)	-0.0153 (0.0159)
Constant	-0.743*** (0.122)	-0.285*** (0.199)	-0.489*** (0.2131)
Rho		0.252*** (0.0262)	0.305*** (0.0264)
Sample	26,382	26,382	26,382
Individuals	4,896	4,896	4,896
Pseudo R^2	0.5457	0.5542	0.5576
Log Likelihood	-4752.111	-4663.29	-4627.90
BIC	9728.191	9693.076	9632.475

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students. 3) Data are marginal effects for probit model. 4) Rho is the proportion of the total variance contributed by the panel-level variance component.

Table A-10: Estimates (and Standard Errors) for Dynamic marginal effects probit models of probability of employment at year *t*, Women aged 15 to 64

	Pooled	**Initial conditions exogenous**	**Wooldridge**
Employed at t-1	0.566*** (0.0073)	0.442*** (0.0129)	0.368*** (0.0134)
Employed at t=1			0.185*** (0.0138)
Post GFC	-0.0013 (0.0076)	-0.0108 (0.0095)	-0.0124 (0.0095)
Lagged health index	0.0022*** (0.0003)	0.0022*** (0.0003)	0.0022*** (0.0003)
Initial health	0.0012*** (0.0003)	0.0018*** (0.0004)	0.0014*** (0.0004)
Has children aged 0-4	-0.258*** (0.0106)	-0.258*** (0.0175)	-0.285*** (0.0179)
Has children aged 5-14	0.0132* (0.0069)	-0.0120 (0.0121)	-0.0119 (0.0120)
Married/De Facto	-0.135*** (0.0088)	-0.127*** (0.0155)	-0.127*** (0.0152)
Partner is employed	0.173*** (0.0115)	0.147*** (0.0171)	0.154*** (0.0172)
Weekly non labour income ($100's)	-0.0019*** (0.0004)	-0.0019*** (0.0005)	-0.0021*** (0.0005)
Partner wage	-0.0007*** (0.0001)	-0.0003** (0.0001)	-0.0003** (0.0001)
Rural	-0.0013 (0.0087)	-0.0023 (0.0109)	-0.0077 (0.0113)
Migrant	-0.0232*** (0.0078)	-0.0336*** (0.0104)	-0.0233** (0.0107)
Experience	0.0140*** (0.0010)	0.0162*** (0.0024)	0.0147*** (0.0024)
Experience squared	-0.0004*** (0.00002)	-0.0005*** (0.00003)	-0.0004*** (0.00003)

	Pooled	Initial conditions exogenous	Wooldridge
Economic inactivity	-0.0186*** (0.0011)	-0.0118*** (0.0024)	-0.0104*** (0.0024)
Economic inactivity squared	0.0002*** (0.00003)	0.0003*** (0.00004)	0.0003*** (0.00004)
Unemployment rate	-0.0023 (0.0019)	-0.0039* (0.0022)	-0.0045** (0.0022)
Degree or above	0.055*** (0.0080)	0.145*** (0.0393)	0.165*** (0.0365)
Advanced Diploma/Diploma	0.0276*** (0.0103)	0.111*** (0.0368)	0.119*** (0.0333)
Certificate	0.0327*** (0.0085)	0.107*** (0.0195)	0.110*** (0.0185)
Year 12	0.00468 (0.0094)	0.0338 (0.0374)	0.0485 (0.0350)
Time averaged characteristics			
Experience		0.0029 (0.0021)	0.0017 (0.0021)
Economic inactivity		-0.0135*** (0.0022)	-0.011*** (0.0022)
Unemployment rate		0.0010 (0.0044)	0.0061 (0.0045)
Has children aged 0-4		-0.118*** (0.0207)	-0.0923*** (0.0211)
Has children aged 5-14		0.0487*** (0.0165)	0.0835*** (0.0169)
Married/De facto		-0.0526** (0.0266)	-0.0456* (0.0270)
Partner is employed		0.121*** (0.0246)	0.0882*** (0.0251)
Weekly non labour income ($100's)		-0.0008	-0.0007

	Pooled	Initial conditions exogenous	Wooldridge
		(0.0010)	(0.0010)
Partner wage		-0.0014***	-0.0013***
		(0.0003)	(0.0003)
Degree or above		-0.0919*	-0.132**
		(0.0544)	(0.0543)
Advanced Diploma/Diploma		-0.104*	-0.126**
		(0.0625)	(0.0626)
Certificate		-0.0922***	-0.104***
		(0.0308)	(0.0308)
Year 12		-0.0228	-0.0425
		(0.0435)	(0.0433)
Constant	-1.063***	-0.9707***	-1.242***
	(0.0870)	(0.1607)	(0.1728)
Rho		0.255***	0.302***
		(0.0189)	(0.0183)
Sample	29,280	29,280	29,280
Individuals	5,241	5,241	5,241
Pseudo R^2	0.4977	0.5079	0.5148
Log Likelihood	-8801.246	-8622.461	-8501.528
BIC	17828.75	17615.17	17383.59

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students. 3) Data are marginal effects for probit model. 4) Rho is the proportion of the total variance contributed by the panel-level variance component.

Table A-11: ANZSCO major groups and skill level

Major group	Predominant Skill level
Managers	I/II
Professionals	I
Technicians and Trades Workers	II/III

Community and Personal Service Workers	II/III/IV/V
Clerical and Administrative Workers	II/III/IV/V
Sales Workers	II/III/IV/V
Machinery Operators and Drivers	IV
Labourers	IV/V

Source: ABS ANZSCO-Australian and New Zealand Standard Classification of Occupations, 2006, Cat. No. 1220.0

Table A-12: Occupation Worked by Form of Employment, Men, 2010 (Per cent)

Occupation	**Full-time**	**Part-time**	**Permanent**	**Casual**
Managers	93.7	6.3	53.0	3.1
Professionals	86.9	13.1	70.4	6.9
Technicians and Trades Workers	90.8	9.2	62.4	11.3
Community and Personal Service Workers	64.0	36.0	59.7	32.6
Clerical and Administrative Workers	86.7	13.3	77.5	11.6
Sales Workers	61.8	38.2	53.4	32.2
Machinery Operators and Drivers	86.7	13.3	63.7	22.8
Labourers	66.9	33.1	47.0	36.1
Total (%)	83.3	16.7	60.8	16.2
Total (000's)	5157.4	1035.0	3766.1	1005.4

Source: ABS Labour Market Statistics, Cat No. 6105.0, July 2012

Table A-13: Occupation Worked by Form of Employment, Women, 2010 (Per cent)

Occupation	Full-time	Part-time	Permanent	Casual
Managers	74.7	25.3	58.1	6.3
Professionals	63.9	36.1	78.1	10.7
Technicians and Trades Workers	59.7	40.3	53.8	23.8
Community and Personal Service Workers	38.6	61.4	55.6	37.0
Clerical and Administrative Workers	58.8	41.2	71.9	15.4
Sales Workers	32.4	67.6	42.5	51.2
Machinery Operators and Drivers	69.3	30.7	65.0	27.2
Labourers	37.2	62.8	43.1	44.7
Total (%)	53.5	46.5	62.7	24.2
Total (000's)	2746.2	2384.6	3217.6	1240.2

Source: ABS Labour Market Statistics, Cat No. 6105.0, July 2012

Table A-14: AQF skill level and typical education and experience

Predominant Skill level	Education and experience
I	Bachelor degree or higher, or at Least 5 years relevant experience
II	Diploma/advanced diploma, or at least 3 years relevant experience
III	AQF Certificate III or IV, or at Least 3 years relevant experience

IV	AQF Certificate II or III, or at least 1 years relevant experience
V	Compulsory schooling or AQF Certificate I

Note: AQF is the abbreviated form of the Australian Qualifications Framework

Source: ABS ANZSCO-Australian and New Zealand Standard Classification of Occupations, 2006, Cat. No. 1220.0

Table A-15: Multinomial Logit Parameter Estimates (and Standard Errors) for Outcomes of not-employed and Part-time Relative to Full-time Employment, Models estimated using MCMC

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Part-time**	**Not employed**	**Part-time**
Not employed at t-1	3.554*** (0.0660)	2.359*** (0.0654)	2.808*** (0.0726)	1.850*** (0.0657)
Part-time at t-1	1.790*** (0.0684)	3.083*** (0.0577)	1.276*** (0.0662)	2.461*** (0.0479)
Not employed at t=1			2.105*** (0.117)	1.475*** (0.0937)
Part-time at t=1			1.219*** (0.0922)	1.783*** (0.0697)
Post GFC	0.0117 (0.0553)	0.0618 (0.0445)	0.0747 (0.0611)	0.0846 (0.0526)
Lagged health index	-0.0323*** (0.0019)	-0.0154*** (0.0017)	-0.0354*** (0.0033)	-0.0182*** (0.0028)
Initial health	-0.0167*** (0.0019)	-0.00102 (0.0014)	-0.0151*** (0.0028)	-0.00176 (0.0021)
Female	-0.606*** (0.151)	0.481** (0.199)	-0.607*** (0.191)	0.172 (0.166)
Lagged health index*female	0.0177*** (0.0021)	0.0106*** (0.0025)	0.0176*** (0.0028)	0.0130*** (0.0020)
Has children aged 0-4	-0.162	-0.0142	-0.277**	0.0720

Appendix

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Part-time**	**Not employed**	**Part-time**
	(0.121)	(0.102)	(0.141)	(0.115)
Has children aged 5-14	0.0133 (0.0619)	0.342*** (0.0468)	0.327*** (0.0929)	0.431*** (0.0707)
Has children aged 0-4*Female	3.244*** (0.145)	1.810*** (0.127)	3.530*** (0.161)	1.984*** (0.135)
Married/De Facto	0.837*** (0.0888)	0.0360 (0.0743)	0.859*** (0.112)	-0.174* (0.102)
Partner is employed	-1.307*** (0.0803)	-0.123* (0.0696)	-1.202*** (0.0889)	-0.152 (0.102)
Weekly non labour income ($100’s)	0.0285*** (0.0028)	0.0176*** (0.0027)	0.0213*** (0.0032)	0.0125*** (0.0031)
Partner wage	0.0090*** (0.0013)	0.0065*** (0.0012)	0.0062*** (0.0016)	0.0051*** (0.0015)
Experience	-0.142*** (0.0058)	-0.050*** (0.0069)	-0.094*** (0.0093)	-0.042*** (0.0069)
Experience squared	0.0038*** (0.0001)	0.0016*** (0.0002)	0.0036*** (0.0002)	0.0016*** (0.0001)
Economic inactivity	0.3147*** (0.0118)	0.1622*** (0.0119)	0.2114*** (0.0157)	0.1362*** (0.0231)
Economic inactivity squared	-0.0052*** (0.0003)	-0.0031*** (0.0004)	-0.0050*** (0.0004)	-0.0030*** (0.0004)
Unemployment rate	0.0687*** (0.0121)	0.0588*** (0.00976)	0.0709*** (0.0123)	0.0502*** (0.0115)
Degree or above	-0.695*** (0.0782)	-0.406*** (0.0645)	-2.825*** (0.345)	-2.174*** (0.224)
Advanced Diploma/Diploma	-0.303*** (0.0970)	-0.222*** (0.0827)	-1.679*** (0.430)	-0.917*** (0.243)
Certificate	-0.374*** (0.0753)	-0.175*** (0.0671)	-1.290*** (0.193)	-0.454*** (0.160)

Appendix

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Part-time**	**Not employed**	**Part-time**
Year 12	-0.0498 (0.0850)	-0.0539 (0.0723)	-0.723** (0.281)	-0.547*** (0.194)
Time averaged characteristics				
Experience			-0.0306*** (0.0097)	0.0017 (0.0100)
Economic inactivity			0.0965*** (0.0174)	0.0227 (0.0220)
Unemployment rate			-0.0315 (0.0257)	0.00582 (0.0230)
Has children aged 0-4			0.608*** (0.166)	0.172 (0.141)
Has children aged 5-14			-1.033*** (0.137)	-0.468*** (0.108)
Married/De facto			0.121 (0.132)	0.360** (0.145)
Partner is employed			-0.396*** (0.115)	0.0345 (0.136)
Weekly non labour income ($100's)			0.0510*** (0.0084)	0.0331*** (0.0071)
Partner wage			0.0125*** (0.0029)	0.0040 (0.0025)
Degree or above			2.243*** (0.348)	1.907*** (0.217)
Advanced Diploma/Diploma			1.398*** (0.452)	0.704*** (0.251)
Certificate			0.996*** (0.198)	0.251 (0.167)
Year 12			0.627** (0.289)	0.451** (0.194)
Constant	-0.557*** (0.175)	-2.826*** (0.125)	-1.280*** (0.294)	-3.369*** (0.225)

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	Part-time	Not employed	Part-time
Between individual variance	1.549***	1.173***	2.558***	1.701***
	(0.148)	(0.110)	(0.209)	(0.093)
Covariance	0.828***		1.429***	
	(0.118)		(0.127)	
Sample	51,941		51,941	
Individuals	9,696		9,696	
DIC	48039.06		46054.01	

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students. 4) Covariance is the covariance of the random effect terms between the not employed and part-time states. 5) DIC is the deviance information criterion and is the only model comparison criterion reported by MLwiN.

Table A-16: Average Predicted Probability of Form of Employment by Age

	Not Employed	Part-time	Full-time
15-24	0.178	0.216	0.606
25-34	0.171	0.178	0.651
35-44	0.169	0.231	0.599
45-54	0.184	0.219	0.597
55-64	0.446	0.198	0.356

Table A-17: Average Predicted Probability of Form of Employment by Health Index Quintile and Gender

	Not Employed	Part-time	Full-time
Men			
lowest health quintile	0.324	0.106	0.571
2	0.106	0.089	0.805
3	0.076	0.081	0.843
4	0.059	0.077	0.864
highest health quintile	0.053	0.079	0.868
Women			

lowest health quintile	0.507	0.242	0.251
2	0.322	0.323	0.355
3	0.265	0.343	0.393
4	0.230	0.343	0.428
highest health quintile	0.186	0.325	0.489

Table A-18: Average Predicted Probability of Form of Employment by Physical Functioning Quintile and Gender

	Not Employed	Part-time	Full-time
Men			
lowest health quintile	0.415	0.105	0.480
2	0.157	0.103	0.740
3	0.092	0.086	0.823
highest health quintile	0.065	0.076	0.859
Women			
lowest health quintile	0.502	0.239	0.259
2	0.321	0.321	0.358
3	0.238	0.349	0.413
highest health quintile	0.211	0.327	0.462

Table A-19: Average Predicted Probability of Form of Employment by Mental Health Quintile and Gender

	Not Employed	Part-time	Full-time
Men			
lowest health quintile	0.255	0.095	0.650
2	0.141	0.090	0.769
3	0.110	0.084	0.806
4	0.098	0.086	0.817
highest health quintile	0.120	0.090	0.790
Women			
lowest health quintile	0.404	0.280	0.317

2	0.293	0.322	0.385
3	0.257	0.331	0.412
4	0.247	0.330	0.423
highest health quintile	0.278	0.312	0.410

Table A-20: Average Predicted Probability of Form of Employment by Type of Long Term Condition

	Not Employed	**Part-time**	**Full-time**
Physical condition	0.344	0.191	0.466
Mental condition	0.400	0.219	0.382
Physical and Mental conditions	0.664	0.146	0.189
Other condition type not determined	0.313	0.203	0.484

Table A-21: Average Predicted Probability of Form of Employment by Type of Long Term Condition and by Gender

	Not Employed	**Part-time**	**Full-time**
Men			
Physical condition	0.268	0.113	0.619
Mental condition	0.349	0.129	0.521
Physical and Mental conditions	0.683	0.094	0.222
Other condition type not determined	0.206	0.102	0.692
Women			
Physical condition	0.420	0.268	0.312
Mental condition	0.438	0.286	0.276
Physical and Mental conditions	0.649	0.186	0.164
Other condition type not determined	0.394	0.279	0.328

Table A-22: Average Predicted Probability of Form of Employment by Type of Long Term Condition and by Gender

	Not Employed	Part-time	Full-time
Men			
health condition limits type of work	0.462	0.120	0.418
health condition has no impact	0.136	0.093	0.771
No long term health condition	0.081	0.082	0.837
Women			
health condition limits type of work	0.536	0.231	0.233
health condition has no impact	0.320	0.301	0.378
No long term health condition	0.247	0.332	0.421

Table A-23: Average Predicted Probability of Form of Employment by Duration of Long Term Condition

	Not Employed	Part-time	Full-time
A year or less	0.279	0.210	0.511
2 to 5 years	0.395	0.183	0.423
6 to 10 years	0.488	0.182	0.330
11 to 20 years	0.511	0.174	0.315
More than 20 years	0.515	0.160	0.325

Table A-24: Multinomial Logit Parameter Estimates (and Standard Errors) for Outcomes of not-employed and Casual Relative to Permanent Employment, Models estimated using MCMC

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	Casual	Not employed	Casual
Not employed at t-1	3.311*** (0.0705)	2.200*** (0.0712)	2.763*** (0.0686)	1.852*** (0.0778)

Appendix

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Casual**	**Not employed**	**Casual**
Casual at t-1	1.281*** (0.0721)	2.629*** (0.0599)	1.014*** (0.0755)	2.225*** (0.0601)
Not employed at t=1			2.050*** (0.124)	1.427*** (0.114)
Casual at t=1			0.929*** (0.105)	1.525*** (0.0870)
Post GFC	-0.143** (0.0569)	-0.248*** (0.0548)	-0.0189 (0.0623)	-0.147** (0.0688)
Lagged health index	-0.0384*** (0.0037)	-0.0208*** (0.0030)	-0.0367*** (0.0025)	-0.0201*** (0.0027)
Initial health	-0.0227*** (0.0029)	-0.0053* (0.003)	-0.0178*** (0.0018)	-0.0042 (0.0027)
Female	-1.336*** (0.303)	-0.533** (0.267)	-0.867*** (0.230)	-0.484*** (0.155)
Lagged health index*female	0.0229*** (0.0042)	0.0127*** (0.0037)	0.0165*** (0.0030)	0.0116*** (0.0022)
Has children aged 0-4	-0.283** (0.123)	-0.293** (0.119)	-0.469*** (0.157)	-0.317** (0.137)
Has children aged 5-14	-0.0836 (0.0718)	0.121* (0.0666)	0.167* (0.0974)	0.145 (0.0911)
Has children aged 0-4*Female	2.702*** (0.148)	0.968*** (0.151)	2.886*** (0.174)	1.052*** (0.156)
Married/De Facto	0.852*** (0.0802)	0.0335 (0.0867)	1.038*** (0.136)	0.0253 (0.121)
Partner is employed	-1.106*** (0.0672)	-0.229*** (0.0740)	-1.072*** (0.110)	-0.203* (0.107)
Rural	0.442*** (0.0767)	0.400*** (0.0772)	0.465*** (0.0830)	0.391*** (0.0779)
Migrant	0.297*** (0.0662)	0.0781 (0.0690)	0.238*** (0.0802)	0.0363 (0.0792)
Experience	-0.1848***	-0.1248***	-0.1524***	-0.1440***

Appendix

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Casual**	**Not employed**	**Casual**
	(0.0108)	(0.0104)	(0.0132)	(0.0204)
Experience squared	0.0046***	0.0026***	0.0042***	0.0021***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Economic inactivity	0.3163***	0.1580***	0.1988***	0.1329***
	(0.0091)	(0.0091)	(0.0245)	(0.0201)
Economic inactivity squared	-0.0053***	-0.0035***	-0.0051***	-0.0029***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Unemployment rate	0.0711***	0.0566***	0.0633***	0.0477***
	(0.0114)	(0.001)	(0.0144)	(0.0161)
Degree or above	-0.608***	-0.808***	-1.674***	-1.099***
	(0.0896)	(0.0855)	(0.314)	(0.294)
Advanced Diploma/Diploma	-0.265**	-0.442***	-1.136***	-0.00274
	(0.107)	(0.108)	(0.379)	(0.388)
Certificate	-0.407***	-0.249***	-1.108***	-0.0456
	(0.0794)	(0.0728)	(0.179)	(0.174)
Year 12	-0.159*	-0.291***	-0.369**	-0.0533
	(0.0863)	(0.0882)	(0.168)	(0.201)
Time averaged characteristics				
Experience			0.0001	0.0536***
			(0.0094)	(0.0158)
Economic inactivity			0.1085***	0.0023
			(0.0174)	(0.0165)
Unemployment rate			-0.0191	-0.0119
			(0.0357)	(0.0253)
Has children aged 0-4			0.720***	0.211
			(0.185)	(0.166)
Has children aged 5-14			-0.882***	-0.280**
			(0.138)	(0.137)
Married/De facto			-0.133	0.0935
			(0.190)	(0.199)
Partner is employed			-0.0600	-0.0566

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Casual**	**Not employed**	**Casual**
			(0.176)	(0.182)
Degree or above			1.273*** (0.323)	0.448 (0.302)
Advanced Diploma/Diploma			1.029** (0.400)	-0.343 (0.416)
Certificate			0.858*** (0.210)	-0.155 (0.190)
Year 12			0.185 (0.190)	-0.264 (0.208)
Constant	1.283*** (0.234)	-0.423*** (0.148)	-0.159 (0.447)	-1.346*** (0.190)
Between individual variance	2.289*** (0.189)	2.236*** (0.159)	3.160*** (0.227)	2.625*** (0.158)
Covariance	1.615***		2.025***	
	(0.153)		(0.173)	
Sample	43,651		43,651	
Individuals	8,951		8,951	
DIC	39288.66		37970.21	

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students and the self-employed. 4) Covariance is the covariance of the random effect terms between the not employed and part-time states. 5) DIC is the deviance information criterion and is the only model comparison criterion reported by MLwiN.

Table A-25: Average Predicted Probability of Form of Employment by Age

	Not Employed	Casual	Permanent
15-24	0.203	0.256	0.541
25-34	0.203	0.128	0.669
35-44	0.206	0.125	0.669
45-54	0.228	0.120	0.652
55-64	0.531	0.106	0.364

Table A-26: Average Predicted Probability of Form of Employment by Health Index Quintile and Gender

	Not Employed	Casual	Permanent
Men			
lowest health quintile	0.395	0.104	0.500
2	0.138	0.107	0.755
3	0.100	0.098	0.802
4	0.076	0.096	0.828
highest health quintile	0.068	0.113	0.819
Women			
lowest health quintile	0.565	0.130	0.305
2	0.372	0.162	0.465
3	0.311	0.169	0.520
4	0.268	0.155	0.577
highest health quintile	0.219	0.151	0.630

Table A-27: Average Predicted Probability of Form of Employment by Physical Functioning Quintile and Gender

	Not Employed	Casual	Permanent
Men			
lowest health quintile	0.491	0.097	0.412
2	0.201	0.105	0.695
3	0.122	0.095	0.783
highest health quintile	0.085	0.109	0.806
Women			
lowest health quintile	0.562	0.124	0.314
2	0.372	0.154	0.474

3	0.281	0.158	0.561
highest health quintile	0.247	0.163	0.590

Table A-28: Average Predicted Probability of Form of Employment by Mental Health Quintile and Gender

	Not Employed	**Casual**	**Permanent**
Men			
lowest health quintile	0.312	0.113	0.576
2	0.181	0.110	0.709
3	0.142	0.100	0.758
4	0.124	0.096	0.780
highest health quintile	0.153	0.099	0.748
Women			
lowest health quintile	0.457	0.151	0.392
2	0.342	0.158	0.500
3	0.302	0.154	0.544
4	0.289	0.154	0.557
highest health quintile	0.321	0.146	0.533

Table A-29: Average Predicted Probability of Form of Employment by Type of Long Term Condition

	Not Employed	**Casual**	**Permanent**
Physical condition	0.409	0.120	0.471
Mental condition	0.440	0.146	0.414
Physical and Mental conditions	0.716	0.095	0.189
Other condition type not determined	0.373	0.124	0.503

Table A-30: Average Predicted Probability of Form of Employment by Type of Long Term Condition and by Gender

	Not Employed	Casual	Permanent
Men			
health condition limits type of work	0.547	0.103	0.350
health condition has no impact	0.176	0.100	0.723
No long term health condition	0.106	0.106	0.788
Women			
health condition limits type of work	0.593	0.121	0.285
health condition has no impact	0.371	0.149	0.480
No long term health condition	0.289	0.161	0.550

Table A-31: Multinomial Logit Parameter Estimates (and Standard Errors) for Outcomes of "Not employed" and Manual Relative to Non-Manual Employment, Models estimated using MCMC

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Manual**	**Not employed**	**Manual**
Not employed at t-1	3.189*** (0.066)	2.365*** (0.088)	2.592*** (0.072)	1.460*** (0.103)
Manual at t-1	2.136*** (0.089)	4.566*** (0.070)	1.329*** (0.101)	2.431*** (0.098)
Not employed at t=1			1.725*** (0.086)	1.904*** (0.148)
Manual at t=1			1.432*** (0.133)	4.180*** (0.187)
Post GFC	-0.010	-0.005	-0.059	-0.124

Appendix

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Manual**	**Not employed**	**Manual**
	(0.107)	(0.090)	(0.103)	(0.116)
Female	-1.686***	-1.245***	-1.429***	-1.344***
	(0.189)	(0.243)	(0.313)	(0.501)
Post GFC*Female	0.224*	0.0852	0.243*	0.258*
	(0.127)	(0.140)	(0.130)	(0.155)
Lagged health index	-0.029***	-0.004	-0.030***	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Initial health	-0.019***	0.005	-0.015***	0.005
	(0.002)	(0.004)	(0.003)	(0.005)
Lagged health index*female	0.023***	-0.002	0.020***	-0.005
	(0.002)	(0.003)	(0.004)	(0.007)
Has children aged 0-4	-0.482***	0.020	-0.368**	0.044
	(0.168)	(0.123)	(0.167)	(0.142)
Has children aged 5-14	-0.025	-0.170	-0.043	-0.244*
	(0.098)	(0.117)	(0.105)	(0.125)
Has children aged 0-4*Female	2.220***	0.131	2.301***	0.184
	(0.169)	(0.171)	(0.176)	(0.216)
Married/De Facto	0.889***	0.095	0.907***	0.171
	(0.129)	(0.168)	(0.136)	(0.175)
Partner is employed	-1.079***	-0.166	-1.172***	-0.290**
	(0.104)	(0.129)	(0.107)	(0.115)
Weekly non labour income ($100’s)	0.012***	-0.001	0.013***	-0.002
	(0.003)	(0.004)	(0.003)	(0.004)
Partner wage	0.0004	-0.001	0.001	-0.0003

Appendix

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	Manual	Not employed	Manual
	(0.001)	(0.003)	(0.001)	(0.003)
Rural	0.263***	0.604***	0.256***	0.566***
	(0.0835)	(0.076)	(0.086)	(0.097)
Migrant	0.665**	-0.319	0.387	-0.432
	(0.327)	(0.489)	(0.296)	(0.431)
Migrant*Lagged health index	-0.006	0.003	-0.002	0.002
	(0.005)	(0.007)	(0.004)	(0.006)
Migrant*Lagged health index*female	0.0002	0.006***	-0.001	0.008**
	(0.002)	(0.002)	(0.002)	(0.003)
Father's occupation	-0.004***	-0.008***	-0.004***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.002)
Experience	-0.115***	-0.065***	-0.086***	-0.082***
	(0.014)	(0.010)	(0.015)	(0.012)
Experience squared	0.003***	0.001***	0.003***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Economic inactivity	0.167***	-0.0003	0.158***	0.016
	(0.015)	(0.023)	(0.022)	(0.028)
Economic inactivity squared	-0.004***	0.0004	-0.004***	-0.0002
	(0.0003)	(0.0004)	(0.0004)	(0.0005)
Unemployment rate	0.042***	0.009	0.065***	0.021
	(0.015)	(0.017)	(0.019)	(0.021)
Degree or above	-1.598***	-1.857***	-2.461***	-2.024***
	(0.385)	(0.357)	(0.327)	(0.647)
Advanced Diploma/Diploma	-1.313***	-1.736***	-1.888***	-2.008***

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	Manual	Not employed	Manual
	(0.381)	(0.421)	(0.393)	(0.489)
Certificate	-1.227***	-0.991***	-1.424***	-0.947***
	(0.264)	(0.262)	(0.250)	(0.274)
Year 12	-0.394	-0.542*	-0.782***	-0.396
	(0.277)	(0.304)	(0.278)	(0.418)
Time averaged characteristics				
Experience	0.002	0.015	-0.015	0.031
	(0.015)	(0.013)	(0.012)	(0.022)
Economic inactivity	0.103***	0.010	0.093***	0.021
	(0.013)	(0.020)	(0.018)	(0.026)
Unemployment rate	0.044**	-0.046	-0.009	-0.033
	(0.022)	(0.033)	(0.028)	(0.045)
Has children aged 0-4	0.771***	0.00203	0.666***	0.109
	(0.155)	(0.162)	(0.174)	(0.204)
Has children aged 5-14	-0.526***	0.062	-0.779***	-0.007
	(0.133)	(0.148)	(0.153)	(0.188)
Married/De facto	-0.121	0.053	-0.033	0.087
	(0.166)	(0.195)	(0.182)	(0.224)
Partner is employed	-0.483***	0.095	-0.396**	0.167
	(0.180)	(0.167)	(0.187)	(0.201)
Weekly non labour income ($100’s)	0.003	-0.032***	0.003	-0.034**
	(0.005)	(0.010)	(0.006)	(0.014)
Partner wage	0.008***	-0.015***	0.008***	-0.019***
	(0.003)	(0.004)	(0.003)	(0.004)
Degree or above	0.699*	-0.269	1.588***	-0.402
	(0.387)	(0.373)	(0.333)	(0.674)

	Multilevel MCMC (1)		Multilevel MCMC (2)	
	Not employed	**Manual**	**Not employed**	**Manual**
Advanced Diploma/Diploma	0.872** (0.400)	0.481 (0.441)	1.423*** (0.401)	0.599 (0.520)
Certificate	0.969*** (0.283)	0.840*** (0.276)	1.152*** (0.283)	0.838*** (0.297)
Year 12	0.178 (0.288)	-0.124 (0.320)	0.554* (0.301)	-0.294 (0.450)
Constant	0.346 (0.222)	-0.742*** (0.260)	-0.242 (0.284)	-2.129*** (0.268)
Between individual variance	1.250** (0.123)	0.509*** (0.094)	2.065*** (0.157)	3.856*** (0.330)
Covariance	0.198*** (0.095)		1.485*** (0.159)	
Sample	38,774		38,774	
Individuals	7,735		7,735	
DIC	28678.86		26132.05	

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students. 4) Covariance is the covariance of the random effect terms between the not employed and manual employment states. 5) DIC is the deviance information criterion and is the only model comparison criterion reported by MLwiN.

Table A-32: Multinomial Logit Parameter Estimates (and Standard Errors) for Outcomes of "Not employed" and Manual Relative to Non-Manual Employment, Comparison Specifications Including Different Health Measures Estimated using gllamm

	Health shock		Health improvement	
	Not employed	*Manual*	*Not employed*	*Manual*
Not employed at t-1	2.625*** (0.090)	1.223*** (0.108)	2.606*** (0.089)	1.216*** (0.107)
Manual at t-1	0.924***	2.963***	0.911***	2.954***

Appendix

	Health shock		Health improvement	
	Not employed	*Manual*	*Not employed*	*Manual*
	(0.113)	(0.117)	(0.112)	(0.116)
Not employed at t=1	1.846***	1.868***	1.853***	1.885***
	(0.117)	(0.140)	(0.117)	(0.140)
Manual at t=1	2.115***	3.131***	2.128***	3.146***
	(0.149)	(0.145)	(0.149)	(0.145)
Post GFC	0.052	-0.080	0.034	-0.077
	(0.098)	(0.096)	(0.098)	(0.096)
Female	-0.211**	-1.208***	-0.272***	-1.161***
	(0.087)	(0.096)	(0.087)	(0.098)
Post GFC*Female	0.092	0.234*	0.120	0.240*
	(0.116)	(0.131)	(0.117)	(0.132)
Health shock	0.658***	-0.201		
	(0.129)	(0.144)		
Health improvement			-0.212	0.0962
			(0.131)	(0.117)
Initial health	-0.023***	-0.003	-0.025***	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Health shock*female	-0.212	0.507**		
	(0.171)	(0.211)		
Health improvement*female			0.236	-0.046
			(0.165)	(0.179)
Has children aged 0-4	-0.453***	-0.104	-0.439***	-0.098
	(0.161)	(0.135)	(0.161)	(0.135)
Has children aged 5-14	-0.036	-0.273**	-0.046	-0.271**
	(0.105)	(0.112)	(0.105)	(0.112)
Has children aged 0-4*Female	2.336***	0.639***	2.333***	0.628***
	(0.171)	(0.190)	(0.171)	(0.190)
Married/De Facto	0.961***	0.292*	0.951***	0.293*
	(0.164)	(0.169)	(0.164)	(0.169)
Partner is employed	-1.147***	-0.387***	-1.140***	-0.383***

Appendix

	Health shock		Health improvement	
	Not employed	*Manual*	*Not employed*	*Manual*
	(0.130)	(0.146)	(0.130)	(0.145)
Weekly non labour income ($100's)	0.013***	-0.001	0.013***	-0.0003
	(0.003)	(0.004)	(0.003)	(0.004)
Partner wage	0.001	0.001	0.001	0.0003
	(0.002)	(0.003)	(0.002)	(0.003)
Rural	0.291***	0.569***	0.292***	0.564***
	(0.090)	(0.096)	(0.090)	(0.096)
Migrant	0.153*	0.011	0.127	-0.017
	(0.082)	(0.097)	(0.082)	(0.098)
Migrant*health shock	-0.075	-0.004		
	(0.247)	(0.268)		
Migrant*health improvement			0.370	0.010
			(0.252)	(0.252)
Migrant*health shock*female	0.253	0.0301		
	(0.324)	(0.416)		
Migrant*health improvement*female			-0.172	0.338
			(0.326)	(0.368)
Father's occupation	-0.005***	-0.009***	-0.005***	-0.009***
	(0.001)	(0.002)	(0.001)	(0.001)
Experience	-0.077***	-0.086***	-0.075***	-0.083***
	(0.018)	(0.020)	(0.018)	(0.020)
Experience squared	0.003***	0.001***	0.003***	0.001***
	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Economic inactivity	0.163***	0.051**	0.163***	0.050**
	(0.020)	(0.023)	(0.020)	(0.023)
Economic inactivity squared	-0.003***	-0.0002	-0.003***	-0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Unemployment rate	0.041**	0.013	0.042**	0.015

	Health shock		Health improvement	
	Not employed	*Manual*	*Not employed*	*Manual*
	(0.018)	(0.018)	(0.017)	(0.018)
Degree or above	-2.463***	-2.068***	-2.483***	-2.101***
	(0.474)	(0.470)	(0.471)	(0.469)
Advanced Diploma/Diploma	-1.600***	-1.905***	-1.628***	-1.911***
	(0.538)	(0.501)	(0.538)	(0.500)
Certificate	-1.248***	-0.929***	-1.253***	-0.934***
	(0.295)	(0.318)	(0.294)	(0.318)
Year 12	-0.507	-0.320	-0.518	-0.308
	(0.389)	(0.382)	(0.390)	(0.380)
Time averaged characteristics				
Experience	-0.012	0.030*	-0.016	0.029*
	(0.015)	(0.016)	(0.015)	(0.016)
Economic inactivity	0.076***	0.014	0.076***	0.015
	(0.018)	(0.021)	(0.018)	(0.021)
Unemployment rate	-0.007	-0.031	-0.009	-0.033
	(0.033)	(0.036)	(0.033)	(0.036)
Has children aged 0-4	0.737***	0.367*	0.722***	0.367*
	(0.187)	(0.195)	(0.187)	(0.195)
Has children aged 5-14	-0.733***	-0.071	-0.723***	-0.074
	(0.147)	(0.158)	(0.147)	(0.158)
Married/De facto	-0.115	0.064	-0.105	0.046
	(0.207)	(0.222)	(0.208)	(0.222)
Partner is employed	-0.302	0.0105	-0.318*	0.0199
	(0.187)	(0.222)	(0.187)	(0.222)
Weekly non labour income ($100’s)	0.001	-0.031**	0.001	-0.032**
	(0.008)	(0.013)	(0.008)	(0.013)
Partner wage	0.007**	-0.013**	0.007**	-0.013**
	(0.003)	(0.005)	(0.003)	(0.005)
Degree or above	1.436***	0.131	1.470***	0.153
	(0.488)	(0.501)	(0.484)	(0.500)

	Health shock		Health improvement	
	Not employed	*Manual*	*Not employed*	*Manual*
Advanced Diploma/Diploma	0.970*	0.735	0.997*	0.731
	(0.551)	(0.515)	(0.552)	(0.514)
Certificate	1.033***	0.842**	1.045***	0.841**
	(0.313)	(0.335)	(0.313)	(0.335)
Year 12	0.238	-0.261	0.264	-0.285
	(0.408)	(0.405)	(0.410)	(0.403)
Constant	-1.555***	-1.580***	-1.256***	-1.640***
	(0.350)	(0.412)	(0.349)	(0.412)
Between individual variance	2.180***		2.205***	
	(0.176)		(0.177)	
Sample	39,446		39,446	
Individuals	7,600		7,600	
Pseudo R squared	0.6321		0.6310	
BIC	29415.59		29493.63	

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students

Table A-33: Estimates (and Standard Errors) of Determinants of Occupational Status (Dependent Variable AUSEI06 score 0-100)-Multilevel Linear Regression, Comparison Specifications Including Different Health Measures

	Health shock		Health improvement	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
AUSEI06 at t-1	0.328***	0.328***	0.329***	0.328***
	(0.008)	(0.009)	(0.008)	(0.009)
AUSEI06 at t=1	0.335***	0.337***	0.335***	0.337***
	(0.009)	(0.010)	(0.009)	(0.010)
Post GFC	0.693***	0.677***	0.693***	0.678***
	(0.228)	(0.239)	(0.228)	(0.239)

	Health shock		Health improvement	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
Female	1.732*** (0.257)	1.842*** (0.267)	1.661*** (0.258)	1.782*** (0.268)
Post GFC*Female	-0.577** (0.259)	-0.527* (0.269)	-0.572** (0.259)	-0.524* (0.269)
Health shock	0.219 (0.317)	0.204 (0.329)		
Health improvement			-0.260 (0.293)	-0.235 (0.312)
Initial health	-0.006 (0.009)	-0.026** (0.011)	-0.006 (0.009)	-0.026** (0.011)
Health shock*female	-0.249 (0.435)	-0.268 (0.453)		
Health improvement*female			0.626 (0.389)	0.584 (0.410)
Has children aged 0-4	0.197 (0.285)	-0.071 (0.306)	0.195 (0.285)	-0.077 (0.306)
Has children aged 5-14	0.075 (0.209)	0.098 (0.216)	0.073 (0.208)	0.096 (0.216)
Has children aged 0-4*Female	-0.263 (0.381)	0.951 (0.593)	-0.269 (0.381)	0.947 (0.592)
Married/De Facto	0.776** (0.371)	1.165*** (0.421)	0.773** (0.371)	1.161*** (0.421)
Partner is employed	-0.003 (0.282)	-0.492 (0.348)	-0.004 (0.282)	-0.489 (0.348)
Weekly non labour income ($100's)	0.007 (0.007)	0.014 (0.009)	0.007 (0.007)	0.014 (0.009)
Partner wage	0.004 (0.004)	0.005 (0.004)	0.004 (0.004)	0.005 (0.004)

Appendix

	Health shock		Health improvement	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
Rural	-0.675** (0.265)	-0.698** (0.274)	-0.677** (0.265)	-0.701** (0.274)
Migrant	-0.802*** (0.264)	-0.610** (0.270)	-0.687*** (0.264)	-0.552** (0.271)
Migrant*health shock	-0.137 (0.686)	-0.558 (0.703)		
Migrant*health improvement			0.194 (0.645)	0.341 (0.656)
Migrant*health shock*female	0.453 (0.941)	0.680 (0.957)		
Migrant*health improvement*female			-1.538* (0.847)	-1.564* (0.869)
Father's occupation	0.035*** (0.005)	0.034*** (0.005)	0.035*** (0.005)	0.034*** (0.005)
Experience	0.075 (0.052)	0.018 (0.058)	0.075 (0.052)	0.018 (0.058)
Experience squared	-0.001 (0.0008)	0.0006 (0.001)	-0.001 (0.0008)	0.0006 (0.001)
Economic inactivity	-0.251* (0.148)	-0.119 (0.157)	-0.250* (0.148)	-0.118 (0.157)
Economic inactivity squared	0.002 (0.002)	0.0001 (0.003)	0.002 (0.002)	0.0001 (0.003)
Unemployment rate	-0.179*** (0.048)	-0.168*** (0.050)	-0.179*** (0.048)	-0.168*** (0.050)
Hours worked	0.069*** (0.007)	0.067*** (0.007)	0.069*** (0.007)	0.067*** (0.007)
Job tenure	0.057*** (0.012)	0.051*** (0.013)	0.057*** (0.012)	0.051*** (0.013)

Appendix

	Health shock		Health improvement	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
Union member	0.167 (0.187)	0.177 (0.193)	0.166 (0.187)	0.175 (0.193)
Private sector	-3.418*** (0.250)	-3.382*** (0.257)	-3.417*** (0.250)	-3.380*** (0.257)
Degree or above	13.44*** (1.613)	13.36*** (1.766)	13.45*** (1.613)	13.39*** (1.766)
Advanced Diploma/Diploma	5.452*** (1.367)	5.423*** (1.443)	5.446*** (1.365)	5.420*** (1.441)
Certificate	1.100 (0.746)	0.821 (0.802)	1.095 (0.745)	0.819 (0.802)
Year 12	-0.829 (1.168)	-0.767 (1.222)	-0.849 (1.167)	-0.786 (1.220)
Time averaged characteristics				
Experience	-0.068* (0.040)	-0.070* (0.041)	-0.068* (0.040)	-0.069* (0.041)
Economic inactivity	0.110 (0.148)	0.111 (0.151)	0.112 (0.147)	0.112 (0.150)
Unemployment rate	0.336*** (0.107)	0.340*** (0.110)	0.339*** (0.107)	0.343*** (0.110)
Has children aged 0-4	-0.589 (0.474)	-0.268 (0.499)	-0.575 (0.474)	-0.254 (0.499)
Has children aged 5-14	-0.156 (0.358)	-0.293 (0.380)	-0.152 (0.358)	-0.289 (0.380)
Married/De facto	-0.250 (0.602)	-0.329 (0.607)	-0.258 (0.601)	-0.335 (0.607)
Partner is employed	-0.885 (0.566)	-0.949 (0.577)	-0.886 (0.565)	-0.950* (0.576)
Partner wage	0.030*** (0.010)	0.031*** (0.010)	0.030*** (0.010)	0.031*** (0.010)
Degree or above	-2.844*	-2.994	-2.865*	-3.025*

	Health shock		Health improvement	
	Without control for selection	*With control for selection*	*Without control for selection*	*With control for selection*
	(1.679)	(1.821)	(1.679)	(1.821)
Advanced Diploma/Diploma	0.260	0.281	0.257	0.273
	(1.435)	(1.505)	(1.433)	(1.503)
Certificate	0.350	0.541	0.351	0.539
	(0.809)	(0.855)	(0.809)	(0.854)
Year 12	4.132***	4.060***	4.154***	4.081***
	(1.228)	(1.281)	(1.227)	(1.280)
Constant	10.66***	10.30***	10.71***	10.31***
	(1.275)	(1.343)	(1.269)	(1.335)
Generalised residual		0.921***		0.920***
		(0.346)		(0.346)
Between individual variance	48.504***	48.323***	48.462***	48.280***
	(2.937)	(3.044)	(2.934)	(3.041)
Residual variance	100.232***	99.750***	100.226***	99.748***
	(2.263)	(2.356)	(2.261)	(2.355)
Sample	38,995	36,269	38,995	36,269
Individuals	7,627	7,501	7,627	7,501
BIC	299602.0	278701.6	299595.6	278696.8

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 10 waves of HILDA. 3) Excludes full-time students

Table A-34: Estimates (and Standard Errors) for Random Effects Model of Log of Superannuation for non-retirees aged 25-60 in 2002: Comparison Specification using Long Term Condition in 2001

	Persons	Men	Women
2006	0.489***	0.319***	0.664***
	(0.0370)	(0.0498)	(0.0541)
2010	0.821***	0.598***	1.068***
	(0.0469)	(0.0607)	(0.0700)

	Persons	Men	Women
Long term condition in 2001	-0.326	-0.472*	-0.274
	(0.198)	(0.270)	(0.292)
Long term condition in 2001*2006	0.240***	0.314**	0.172
	(0.0932)	(0.132)	(0.132)
Long term condition in 2001*2010	0.392***	0.474***	0.305*
	(0.127)	(0.179)	(0.180)
Age	0.194***	0.189***	0.192***
	(0.0097)	(0.0136)	(0.0138)
Age squared	-0.0056***	-0.0050***	-0.0062***
	(0.0003)	(0.0004)	(0.0004)
Long term condition in 2001*Age	-0.0890***	-0.0749**	-0.103***
	(0.0222)	(0.0313)	(0.0315)
Long term condition in 2001* Age squared	-0.0001	-0.0010	0.0010
	(0.0006)	(0.0008)	(0.0008)
Female	-1.436***		
	(0.0685)		
Has children aged 0-4	-0.117*	-0.0720	-0.356***
	(0.0641)	(0.0663)	(0.0803)
Has children aged 5-14	-0.355***	-0.117*	-0.545***
	(0.0535)	(0.0682)	(0.0804)
Has children aged 0-4*Female	-0.206**		
	(0.0922)		
Degree or above	1.386***	0.846***	1.597***
	(0.306)	(0.292)	(0.455)
Advanced Diploma/Diploma	0.869***	0.630**	0.931*
	(0.294)	(0.297)	(0.475)
Certificate	1.115***	0.817***	1.208***
	(0.210)	(0.248)	(0.284)
Year 12	0.775***	0.713**	0.812**
	(0.286)	(0.330)	(0.398)
AUSEI06 in 2001	0.0351***	0.0233***	0.0461***

Appendix

	Persons	Men	Women
	(0.0018)	(0.0023)	(0.0027)
Self employed	-0.732***	-0.788***	-0.741***
	(0.0940)	(0.119)	(0.152)
Migrant	-1.037***	-0.936***	-1.081***
	(0.0858)	(0.113)	(0.127)
Rural	-0.144*	-0.127	-0.165
	(0.0803)	(0.106)	(0.119)
Married/De Facto	0.156**	0.0112	0.257**
	(0.0786)	(0.100)	(0.118)
Father's occupation	0.0005	-0.0034*	0.0048**
	(0.0014)	(0.0019)	(0.0021)
Time averaged characteristics			
Has children aged 0-4	-0.328***	-0.500***	-0.314
	(0.126)	(0.156)	(0.191)
Has children aged 5-14	-0.415***	-0.0276	-0.761***
	(0.103)	(0.138)	(0.147)
Degree or above	-0.0930	0.270	-0.391
	(0.332)	(0.337)	(0.491)
Advanced Diploma/Diploma	0.380	0.374	0.368
	(0.321)	(0.348)	(0.509)
Certificate	-0.0997	-0.00406	-0.238
	(0.234)	(0.279)	(0.333)
Year 12	0.330	0.330	0.336
	(0.307)	(0.362)	(0.428)
Married/De Facto	0.674***	1.208***	0.174
	(0.122)	(0.170)	(0.172)
Constant	5.863***	6.296***	4.291***
	(0.142)	(0.181)	(0.205)
Sample	22,395	10,688	11,707
Individuals	10,204	4,950	5,254
R squared within	0.066	0.054	0.078
R squared between	0.272	0.263	0.264
R squared total	0.266	0.258	0.257
Rho	0.679	0.672	0.677

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 3 waves of HILDA.

Table A-35: Estimates (and Standard Errors) for Random Effects Model of Household Net Worth for Sample aged 25-60 in 2002: Comparison Specification using Long Term Condition in 2001

	Persons	Men	Women
2006	0.208*** (0.0326)	0.180*** (0.0472)	0.226*** (0.0450)
2010	0.169*** (0.0388)	0.164*** (0.0558)	0.160*** (0.0542)
Long term condition in 2001	-0.674*** (0.228)	-0.354 (0.294)	-0.986*** (0.342)
Long term condition*2006	0.0091 (0.0853)	0.100 (0.119)	-0.0769 (0.121)
Long term condition*2010	0.109 (0.101)	0.167 (0.134)	0.0483 (0.151)
Age	0.123*** (0.0079)	0.122*** (0.0119)	0.122*** (0.0104)
Age squared	-0.0015*** (0.0002)	-0.0014*** (0.0003)	-0.0014*** (0.0002)
Long term condition in 2001*Age	-0.0108 (0.0208)	-0.0483* (0.0268)	0.0253 (0.0313)
Long term condition in 2001* Age squared	0.00002 (0.0005)	0.0007 (0.0006)	-0.0006 (0.0007)
Female	0.0096 (0.0468)		
Has children aged 0-4	-0.102 (0.0704)	-0.0551 (0.0775)	-0.0419 (0.0772)
Has children aged 5-14	-0.0536 (0.0482)	0.0696 (0.0687)	-0.121* (0.0663)
Has children aged 0-4*Female	0.0711 (0.0863)		
Household size	0.188***	0.213***	0.177***

	Persons	Men	Women
	(0.0242)	(0.0347)	(0.0339)
Degree or above	0.0913	-0.343	0.331
	(0.300)	(0.451)	(0.404)
Advanced Diploma/Diploma	0.506**	0.0955	0.771**
	(0.248)	(0.352)	(0.379)
Certificate	0.246	-0.0115	0.357*
	(0.165)	(0.314)	(0.191)
Year 12	0.662**	0.239	0.889***
	(0.259)	(0.418)	(0.332)
AUSEI06 in 2001	0.0160***	0.0147***	0.0177***
	(0.0013)	(0.0018)	(0.0018)
Self employed	0.150***	0.138*	0.150
	(0.0577)	(0.0725)	(0.0935)
Migrant	-0.368***	-0.456***	-0.283***
	(0.0541)	(0.0781)	(0.0754)
Rural	0.307***	0.332***	0.251***
	(0.0527)	(0.0756)	(0.0731)
Married/De Facto	0.577***	0.138	0.937***
	(0.0912)	(0.132)	(0.126)
Father's occupation	0.0021**	0.0014	0.0026*
	(0.0010)	(0.0014)	(0.0015)
Time averaged characteristics			
Has children aged 0-4	-0.223**	-0.176	-0.221
	(0.104)	(0.143)	(0.147)
Has children aged 5-14	-0.476***	-0.398***	-0.465***
	(0.0773)	(0.109)	(0.108)
Degree or above	0.314	0.738	0.112
	(0.312)	(0.469)	(0.421)
Advanced Diploma/Diploma	0.0879	0.453	-0.120
	(0.259)	(0.369)	(0.393)
Certificate	0.128	0.451	-0.0847
	(0.176)	(0.325)	(0.216)
Year 12	-0.215	0.162	-0.400
	(0.271)	(0.439)	(0.345)
Married/De Facto	0.857***	0.792***	0.864***

	Persons	Men	Women
	(0.112)	(0.166)	(0.152)
Constant	8.067***	8.422***	7.703***
	(0.121)	(0.164)	(0.170)
Sample	23,383	11,074	12,309
Individuals	10,370	5,012	5,358
R squared within	0.062	0.057	0.073
R squared between	0.209	0.195	0.233
R squared total	0.196	0.182	0.217
Rho	0.569	0.564	0.571

Notes: 1) ***Statistically significant at 1% level. **Statistically significant at 5% level. *Statistically significant at 10% level. 2) Sample is number of observations spread over the 3 waves of HILDA.

References

Aittomaki, A., Martikainen, P., Laaksonen, M., Lahelma, E. & Rahkonen, O. (2010). ‘The Associations of Household Wealth and Income with Self-Rated Health- A Study on Economic Advantage in Middle-aged Finnish Men and Women’, *Social Science & Medicine*, Vol. 71, pp. 1018-1026.

Almeida-Santos, P. & Mumford, K. (2004). ‘Employee Training in Australia: Evidence from AWIRS’. *The Economic Record*, Vol. 80 (S1), pp. S53-S64.

Altonji, J., Smith, A., & Vidangos, I. (2013). ‘Modeling Earnings Dynamics’. *Econometrica*, Vol. 81 (4), pp. 1395-1454.

Anderson, K. & Burkhauser, R. (1985). ‘The Retirement-Health Nexus: A New Measure of an Old Puzzle’. *Journal of Human Resources*, Vol. 20 (3), pp. 315-330.

Artazcoz, L., Benach, J., Borrell, C., & Cortes, I. (2005). 'Social Inequalities in the Impact of Flexible Employment on Different Domains of Psychosocial Health'. *Journal of Epidemiology and Community Health*, Vol. 59 (9), pp. 761-767.

Arulampalam, W. & Booth, A. (1998), ‘Training and Labour Market Flexibility: Is There a Trade-off?’, *British Journal of Industrial Relations*, Vol. 36 (4), pp. 521-536.

Arulampalam, W., Gregg, P. & Gregory, M. (2001). ‘Unemployment Scarring’. *Economic Journal*, Vol. 111 (475), pp. 577-584.

Arulampalam, W. & Stewart, M. (2009), ‘Simplified implementation of the Heckman estimator of the dynamic probit model and a comparison with alternative estimators’. *Oxford Bulletin of Economics and Statistics*, Vol. 71 (5), pp. 659-681.

Au, D., Crossley, T. & Schellhorn, M. (2005), ‘The Effect of Health Changes and Long Term Health on the Work Activity of Older Canadians’. *Health Economics*, Vol. 14 (10), pp. 999-1018.

Australian Bureau of Statistics (2002a). *Australian Social Trends*, 2002, Catalogue No. 4102.0.

Australian Bureau of Statistics (2002b), *2001 National Health Survey: Summary of Results*, Catalogue number 4364.0.

Australian Bureau of Statistics (2003). *Population Projections, Australia, 2002-2101*, Catalogue No. 3222.0.

Australian Bureau of Statistics (2006a), *Australian and New Zealand Standard Classification of Occupations, First Edition, 2006*, Catalogue No. 1220.0.

Australian Bureau of Statistics (2006b). *Australian Social Trends*, 2006, Catalogue No. 4102.0.

Australian Bureau of Statistics (2006c), *2004-05 National Health Survey: Summary of Results*, Catalogue No. 4364.0.

Australian Bureau of Statistics (2008a), *Australian and New Zealand Standard Industrial Classification (ANZSIC), 2006 (Revision 1.0)*, Catalogue No. 1292.0.

Australian Bureau of Statistics (2008b). *National Health Survey (2007-08)*, Basic CURF, CD-ROM. Findings based on use of ABS CURF data.

Australian Bureau of Statistics (2009a), *Employment Arrangements, Retirement and Superannuation*, Catalogue number 6361.0.

Australian Bureau of Statistics (2009b), *National Health Survey: Summary of Results*, Catalogue number 4364.0.

Australian Bureau of Statistics (2009c), *National Health Survey: Users Guide-Electronic*, Catalogue number 4363.0.55.001.

Australian Bureau of Statistics (2010a), *Consumer Price Index, Australia*, Catalogue No. 6401.0.

Australian Bureau of Statistics (2010b). *General Social Survey (2010)*, Basic CURF, CD-ROM. Findings based on use of ABS CURF data.

Australian Bureau of Statistics (2011a). *Forms of Employment, Australia*, November 2010, Catalogue No. 6359.0.

Australian Bureau of Statistics (2011b), *General Social Survey: User Guide*, Catalogue number 4159.0.55.002.

Australian Bureau of Statistics (2012). *Australian Labour Market Statistics*, July 2012, Catalogue No. 6105.0.

Australian Taxation Office (2015), accessed 6th August 2015, < https://www.ato.gov.au/Rates/Key-superannuation-rates-and-thresholds/>

References

Australian Treasury (2001). *Towards Higher Retirement Incomes for Australians: A History of the Australian Retirement Income System since Federation*, Economic Roundup, centenary edition, Commonwealth Government, Canberra.

Baldwin, M. & Marcus, S. (2014). 'The Impact of Mental and Substance-Use Disorders on Employment Transitions'. *Health Economics*, Vol. 23 (3), pp. 332-344.

Bassanini, A., Booth, A., Brunello, G., De Paola, M & Leuven, E. (2005). *Workplace Training in Europe*, IZA Discussion Paper No. 1640.

Beam Dowd, J. & Zajacova, A. (2007). 'Does the Predictive Power of Self-rated Health for Subsequent Mortality Risk Vary by Socioeconomic Status in the US?' *International Journal of Epidemiology*, Vol. 36 (6), pp. 1214-1221.

Becker, G. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. Chicago: University of Chicago Press.

Becker, G. (2007). 'Health as Human Capital: Synthesis and Extensions'. *Oxford Economic Papers*, Vol. 59 (3), pp. 379-410.

Bell, D. & Heitmueller, A. (2009). 'The Disability Discrimination Act in the UK: Helping or Hindering Employment Among the Disabled'. *Journal of Health Economics*, Vol. 28 (2), pp. 465-480.

Benach, J. & Muntaner, C. (2007). 'Precarious Employment and Health: Developing a Research Agenda'. *Journal of Epidemiology and Community Health*, Vol. 61 (4), pp. 276-277.

Benavides, F., Benach, J., Diez-Roux, A. & Roman, C. (2000). 'How do Types of Employment Relate to Health Indicators? Findings from the Second European Survey on Working Conditions'. *Journal of Epidemiology and Community Health*, Vol. 54 (7), pp. 494-501.

Böckerman, P. & Ilmakunnas, P. (2009). 'Unemployment and Self-Assessed Health: Evidence from Panel Data'. *Health Economics*, Vol. 18 (2), 161-179.

Bound, J. (1991). 'Self-Reported versus Objective Measures of Health in Retirement Models'. *Journal of Human Resources*, Vol. 26 (1), pp. 106-138.

Bound, J. & Burkhauser, R. (1999). 'Economic Analysis on Transfer Programs Targeted on People with Disabilities'. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics* (Vol. 3C): Elsevier Science B.V.

Bound, J., Schoenbaum, M., Stinebrickner, T., & Waidman, T. (1999). 'The Dynamic Effects of Health on the Labor Force Transitions of Older Workers'. *Labour Economics*, Vol. 6 (2), pp. 179-202.

Bound, J., Stinebrickner, T. & Waidmann, T. (2010). 'Health, Economic Resources and the Work Decisions of Older Men'. *Journal of Econometrics*, Vol. 156 (1), pp. 106-129.

Brault, M., Meuleman, B. & Bracke, P. (2012). 'Depressive Symptoms in the Belgian Population: Disentangling Age and Cohort Effects'. *Social Psychiatry and Psychiatric Epidemiology*, Vol. 47 (6), pp. 603-615.

Buddelmeyer, H. & Cai, L. (2009). *Interrelated Dynamics of Health and Poverty in Australia*, IZA Discussion Paper No. 4602.

Burchardt, T. (2003) *Being and Becoming: Social Exclusion and the Onset of Disability*, CASE Report 21, ESRC Centre for Analysis of Social Exclusion, London School of Economics.

Burkhauser, R., Butler, J. & Kim, Y. (1995). 'The Importance of Employer Accommodation on the Job Duration of Workers with Disabilities: A Hazard Model Approach', *Labour Economics*, Vol. 2 (2), pp. 109-130.

Cai, L., & Kalb, G. (2006). 'Health Status and Labour Force Participation: Evidence From Australia'. *Health Economics*, Vol. 15 (3), pp. 241-261.

Cai, L., & Kalb, G. (2007) 'Health Status and Labour Force Status of Older Working-Age Australian Men', *Australian Journal of Labour Economics* Vol. 10 (4), pp. 227-252.

Cai, L. (2009a). "Be Wealthy to Stay Healthy: An Analysis of Older Australians using the HILDA Survey", *Journal of Sociology*, Vol. 45, pp. 55-70.

Cai, L. (2009b). 'Effects of Health on Wages of Australian Men', *Economic Record*, Vol. 85 (270), pp. 290-306.

Cai, L. (2010), 'The Relationship between Health and Labour Force Participation: Evidence from a Panel Data Simultaneous Equation Model'. *Labour Economics*, Vol. 17 (1), pp. 77-90.

Cai, L., Mavromaras, K. & Oguzoglu, U. (2014). 'The Effect of Health Status and Health Shocks on Hours Worked'. *Health Economics*, Vol. 23 (5), pp. 516-528.

Campolieti, M. (2004). 'The Correlates of Accommodations for Permanently Disabled Workers', *Industrial Relations*, Vol. 43 (3), pp. 546-572.

Cappellari, L., & Jenkins, S. (2008), ‘Estimating low pay transition probabilities accounting for endogenous selection mechanisms’, *Journal of the Royal Statistical Society, Series C (Applied Statistics)*,Vol. 57 (2), pp. 165–186.

Chalmers, J. & Hill, T. (2007). ‘Marginalising Women in the Labour Market: ‘Wage Scarring’ Effects of Part-time Work’, *Australian Bulletin of Labour*, Vol. 33 (2), pp. 180-201.

Chamberlain, G. (1984), ‘Panel data’, in Zvi Griliches and Michael Intrilligator (Eds), Handbook of Econometrics, North-Holland: Amsterdam.

Chandola, T., Ferrie, J., Sacker, A., & Marmot, M. (2007). 'Social Inequalities in Self Reported Health in Early Old Age: Follow-up of Prospective Cohort Study'. *British Medical Journal*, Vol. 334, pp. 990-996.

Chang, F. (1996). ‘Uncertainty and Investment in Health’, *Journal of Health Economics*, Vol. 15 (3), pp. 369-376.

Chatterji P., Alegria, M, Lu, M,, Takeuchi, D. (2007). ‘Psychiatric Disorders and Labor Market Outcomes: Evidence from the National Latino and Asian American Study’. *Health Economics*, Vol. 16 (10), pp. 1069–1090.

Chatterji, P., Alegria, M. & Takeuchi, D. (2011). ‘Psychiatric Disorders and Labor Market Outcomes: Evidence from the National Comorbidity Survey-Replication’. *Journal of Health Economics*, Vol. 30 (5), pp. 858-868.

Chau, N. & Khlat, M. (2009). ‘Strong Association of Physical Job Demands with Functional Limitations among Active People: A Population-based Study in North-Eastern France’, *International Archives of Occupational and Environmental Health*, Vol. 82 (7), pp. 857-866.

Cheng, Y., Kawachi, I., Coakley, E., Schwartz, J., & Colditz, G. (2000). 'Association Between Psychosocial Work Characteristics and Health Functioning in American Women: Prospective Study'. *British Medical Journal*, Vol. 320, pp. 1432-1436.

Chirikos, T. (1993). 'The Relationship between Health and Labor Market Status'. *Annual Review of Public Health*, Vol. 14, pp. 293-312.

Chirikos, T. & Nestel, G. (1985). ‘Further Evidence on the Economic Effects of Poor Health’. *Review of Economics and Statistics*, Vol. 67 (1), pp. 61-69.

Christensen, B. & Kallestrup-Lamb, M. (2012). ‘The Impact of Health Changes on Labor Supply: Evidence from Merged Data on Individual Objective Medical

Diagnosis Codes and Early Retirement Behavior’. *Health Economics*, Vol. 21 (Suppl. 1), pp. 56-100.

Clare, R. (2012). *Equity and Superannuation-The Real Issues*, Association of Superannuation Funds of Australia Research and Resource Centre.

Clark, T. & Linzer, D. (2015). ‘Should I Use Fixed or Random Effects’, *Political Science Research and Methods*, Vol. 3 (2), pp. 399-408.

Cohiden, C., Imbernon, E. & Goldberg, M. (2009). ‘Prevalence of Common Mental Disorders and Their Work Consequences in France, According to Occupational Category’, *American Journal of Industrial Medicine*, Vol. 52 (2), pp. 141-152.

Connolly, S., O’Reilly, D. & Rosato, M. (2010). “House Value as an Indicator of Cumulative Wealth is Strongly Related to Morbidity and Mortality Risk in Older People: A Census-based Cross-sectional and Longitudinal Study”, *International Journal of Epidemiology*, Vol. 39, pp. 383-391.

Cropper, M. (1977). ‘Health, Investment in Health, and Occupational Choice’, *Journal of Political Economy,* Vol. 85 (6), pp. 1273-1294.

Currie, J., & Madrian, B. (1999). 'Health, Health Insurance and the Labor Market'. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics* (Vol. 3C): Elsevier Science B.V.

Dalgard, O., SØrensen, T., Sandanger, I., Nygård, J., Svensson, E. & Reas, D. (2009). ‘Job Demands, Job Control, and Mental Health in an 11-Year Follow-up Study: Normal and Reversed Relationships’. *Work and Stress*, Vol. 23 (3), pp.

Daly, M., & Bound, J. (1996). Worker Adaptation and Employer Accommodation Following the Onset of a Health Impairment. *Journals of Gerontology*, Vol. 51B, pp. S53-S60.

Davis, K. (2012). *Superannuation over the Past Decade: Individual Experiences*, Report by the Australian Centre for Financial Studies for the Australian Institute of Superannuation Trustees, March 2012.

De Lange, A., Taris, T., Kompier, M., Houtman, I., & Bongers, P. (2004). 'The Relationships Between Work Characteristics and Mental Health: Examining Normal, Reversed and Reciprocal Relationships in a 4-Wave Study'. *Work and Stress,* Vol. 18 (2), pp. 149-166.

De Lange, A., Taris, T., Kompier, M., Houtman, I. & Bongers, P. (2005). ‘Different Mechanisms to Explain the Reversed Effects of Mental Health on Work Characteristics’. *Scandinavian Journal of Work, Environment and Health*, Vol. 31 (1), pp. 3-14.

De Raeve, L., Kant, I., Jansen, N., Vasse, R. & van den Brandt, P. (2009). ‘Changes in Mental Health as a Predictor of Changes in Working Time Arrangements and Occupational Mobility: Results from a Prospective Cohort Study’, *Journal of Psychosomatic Research*, Vol. 66 (2), pp. 137-145.

De Witte, H. (1999). ‘Job Insecurity and Psychological Well-being: Review of the Literature and Exploration of Some Unresolved Issues’. *European Journal of Work and Organizational Psychology*, Vol. 8 (2), pp. 155-177.

Deaton, A., & Paxson, C. (1998). 'Aging and Inequality in Income and Health'. *American Economic Review*, Vol. 88 (2), pp. 248-253.

Dewilde, C. (2012). ‘Lifecourse Determinants and Incomes in Retirement: Belgium and the United Kingdom Compared’, *Ageing and Society*, Vol. 32 (4), pp. 587-615.

Disney, R., Emmerson, C., & Wakefield, M. (2006). 'Ill Health and Retirement in Britain: A Panel Data-Based Analysis'. *Journal of Health Economics,* Vol. 25 (4), pp. 621-649.

Dooley, D., Fielding, J. & Levi, L. (1996). ‘Health and Unemployment’, *Annual Review of Public Health*, Vol. 17, pp. 449-465.

Draca, M. & Green, C. (2004). ‘The Incidence and Intensity of Employer Funded Training: Australian Evidence on the Impact of Flexible Work’. *Scottish Journal of Political Economy*, Vol. 51 (5), pp. 609-625.

Dwyer, D. & Mitchell, O. (1999). ‘Health Problems as Determinants of Retirement: Are Self Rated Measures Endogenous?’ *Journal of Health Economics*, Vol. 18 (2), pp. 173-193.

Ehrlich, I. & Chuma, H. (1990). ‘A Model of the Demand for Longevity and the Value of Life Extensions’, *Journal of Political Economy*, Vol. 98 (4), pp. 761-782.

Erbsland, M., Ried, W. & Ulrich, V. (1995), ‘Health, Health Care , and the Environment. Econometric Evidence from German Micro Data’, *Health Economics*, Vol. 4 (3), pp. 169-182.

Erikson, R., Goldthorpe, J., & Portocarero, L. (1979). 'Intergenerational class mobility in three Western European societies: England, France and Sweden', *British Journal of Sociology*, Vol. 30 (4), pp. 415-451.

Erikson, R & Goldthorpe, J. (1993). *The Constant Flux: A Study of Class Mobility in Industrial Societies*. Oxford: Clarendon Press.

Ettner S., Frank, R., Kessler, R. (1997). 'The Impact of Psychiatric Disorders on Labor Market Outcomes'. *Industrial and Labor Relations Review*, Vol. 51 (1), pp. 64–81.

Ferrie, J. (1999). 'Health Consequences of Job Insecurity'. In *Labour Market Changes and Job Insecurity: A Challenge for Social Welfare and Health Promotion*: World Health Organisation.

Ferrie, J., Shipley, M., Davey Smith, G., Stansfeld, S. & Marmot, M. (2002). 'Change in Health Inequalities among British Civil Servants: the Whitehall II Study', *Journal of Epidemiology and Community Health*, Vol. 56 (12), pp. 922-926.

Fitzgerald, E. (2007) Disability and Poverty. In Cousins, M., *Welfare Policy and Poverty*, Chapter 8, Institute of Public Administration, Dublin.

Fletcher, J. & Sindelar, J. (2009). *Estimating Causal Effects of Early Occupational Choice on Later Health: Evidence using the PSID*, Working Paper 15256, National Bureau of Economic Research.

Forrier, A. & Sels, L. (2003). 'Temporary Employment and Employability: Training Opportunities and Efforts of Temporary and Permanent Employees in Belgium', *Work, Employment and Society*, Vol. 17 (4), pp. 641-666.

Francesconi, M. (2001). 'Determinants and Consequences of Promotions in Britain', *Oxford Bulletin of Economics and Statistics*, Vol. 63 (3), pp. 279-310.

Francesconi, M. & Gosling, A. (2005). 'Career Paths of Part-time Workers', Equal Opportunities Commission Working Paper no.19, Manchester.

Frijters, P., Johnston, D. & Shields, M. (2014). 'The Effect of Mental Health on Employment: Evidence from Australian Panel Data'. *Health Economics,* Vol. 23 (9), pp. 1058-1071.

Galama, T. & Kapteyn, A. (2011) 'Grossman's Health Threshold'. *Journal of Health Economics*, Vol. 30 (5), pp. 1044-1056.

Galama, T., Kapteyn, A., Fonseca, R., & Michaud, P. (2013) ‘A Health Production Model with Endogenous Retirement’. *Health Economics*, Vol. 22 (8), pp. 883-902.

Gan, L. & Gong, G. (2007). *Estimating Interdependence between Health and Education in a Dynamic Model*, Working Paper 12830, National Bureau of Economic Research.

Ganzeboom, H., & Treiman, D. (1996). ‘Internationally comparable measures of occupational status for the 1988 International Standard Classification of Occupations’. *Social Science Research*, Vol. 25 (3), pp. 201-239.

Ganzeboom, H. & Treiman, D. (2003). ‘Three internationally standardized measures for comparative research on occupational status’ in Hoffmeyer-Zlotnik, J. and Wolf, C. (eds) *Advances in Cross-national Comparison. A European working book for demographic and socio-economic variables*.

García-Gómez, P., Jones, A. & Rice, N. (2010). ‘Health Effects on Labour Market Exits and Entries’. *Labour Economics*, Vol. 17 (1), pp. 62-76.

Goldthorpe, J. (1980). *Social Mobility and Class Structure in Modern Britain*, Oxford: Clarendon. Press.

Grossman, M. (1972). 'On the Concept of Health Capital and the Demand for Health'. *Journal of Political Economy*, Vol. 80 (2), pp. 223-255.

Grossman, M. (2000). ‘The Human Capital Model’. In A. Culyer & J. Newhouse (Eds), *Handbook of Health Economics* (Vol. 1). Elsevier Science B. V.

Gruber, J. & Madrian, B. (2002). *Health Insurance, Labor Supply and Job Mobility: A Critical Review of the Literature*, National Bureau of Economic Research, Working Paper 8817.

Gueorguieva, R., Sindelar, J., Falba, T., Fletcher, J., Keenan, P., Wu, R. & Gallo, W. (2009). ‘The Impact of Occupation on Self-Rated Health: Cross-Sectional and Longitudinal Evidence from the Health and Retirement Survey’, *Journals of Gerontology*, Vol. 64B (1), pp. 118-124.

Haas, S. (2008). ‘Trajectories of Functional Health: The ‘Long arm’ of Childhood Health and Socioeconomic Factors’, *Social Science & Medicine*, Vol. 66 (4), pp. 849-861.

Haas, S., Glymour, M. & Berkman, L. (2011). ‘Childhood Health and Labor Market Inequality over the Life Course’, *Journal of Health and Social Behavior*, Vol. 52 (3), pp. 298-313.

Hagan, R., Jones, A. & Rice, N. (2009). 'Health and Retirement in Europe'. *International Journal of Environmental Research and Public Health*, Vol. 6 (10), pp. 2676-2695.

Hajat, A., Kaufman, J., Rose, K., Siddiqi, A. & Thomas, J. (2010). "Long-Term Effects of Wealth on Mortality and Self-rated Health Status", *American Journal of Epidemiology*, Vol. 173, pp. 192-200.

Halleröd, B. & Gustaffson, J. (2011). 'A Longitudinal Analysis of the Relationship between Changes in Socio-Economic Status and Changes in Health', *Social Science and Medicine*, Vol. 72 (1), pp. 116-123.

Harley, B. & Whitehouse, G. (2001). 'Women in Part-Time Work: A Comparative Study of Australia and the United Kingdom', *Labour and Industry*, Vol. 12 (2), pp. 33-59.

Harrison, E. & Rose, D. (2006). *The European Socio-economic Classification (ESeC) User Guide*, Institute for Social and Economic Research, University of Essex.

Haynes, M., Western, M., Yu, L. & Spellak, M. (2008). *Employment Transitions of Australian Women: Analysing Nominal Data from a Panel Survey*, Paper prepared for the 103rd Annual Meeting of the American Sociological Association, 1-4 August 2008, Boston, USA.

Headey, B., Marks, G. & Wooden, M. (2005). "Household Wealth in Australia: Its Components, Distribution and Correlates", *Journal of Sociology*, Vol. 41, pp. 47-68.

Headey, B. & Warren, D. (2008), *Families, Incomes and Jobs, Volume 5: A Statistical Report on Waves 1 to 5 of the Household, Income and Labour Dynamics in Australia Survey*, Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Headey, B., Warren, D. & Wooden, M. (2008). *The Structure and Distribution of Household Wealth in Australia: Cohort Differences and Retirement Issues*, Social Policy Research Paper No. 33.

Headey, B. & Wooden, M. (2004). "The Effects of Wealth and Income on Subjective Well-Being and Ill-Being", *Economic Record*, Vol. 80, pp. S24-S33.

Heckman, J. (1979). 'Sample Selection Bias as a Specification Error', *Econometrica*, Vol. 47 (1), pp. 153-161.

Heckman, J. (1981), ‘The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process’, in Charles F. Manski and Daniel McFadden (eds), *Structural Analysis of Discrete Data with Econometric Applications,* MIT Press, Cambridge, MA.

Henkens, K. & van Dalen, H. (2003). ‘Early Retirement Systems and Behaviour in an International Perspective’. In G. Adams & T. Beehr (Eds), *Retirement, Reasons, Processes and Results* (pp. 242-263). New York: Springer.

Hum, D., Simpson, W. & Fissuh, E. (2008). *The Impact of Health on Labour Supply over the Life Cycle*, Paper Presented to the Oxford Business and Economics Conference, Oxford, June 23, 2008.

Hyde, M., Jakub, H., Melchior, M., Van Oort, F. & Weyers, S. (2006). ‘Comparison of the Effects of Low Childhood Socioeconomic Position and Low Adulthood Socioeconomic Position on Self Rated Health in Four European Studies’, *Journal of Epidemiology and Community Health*, Vol. 60 (10), pp. 882-886.

Hyslop, D. (1999). 'State Dependence, Serial Correlation and Heterogeneity in Intertemporal Labor Force Participation of Married Women', *Econometrica,* Vol. 67 (6), pp. 1255-1294.

Jackson, N., Walter, M., Felmingham, B., & Spinaze, A. (2006). 'Will Older Workers Change Their Retirement Plans in Line With Government Thinking? A Review of Recent Literature on Retirement Intentions'. *Australian Bulletin of Labour*, Vol. 32 (4), pp. 315-344.

Jenkins, S. & Cappellari, L. (2008), *The Dynamics of Social Assistance Receipt: Measurement and Modelling Issues, with an Application to Britain,* ISER Working Paper Series No. 2008-34.

Jiménez-Martin, S., Labeaga, J. & Vilaplana Prieto, C. (2006). ‘A Sequential Model of Older Workers’ Labor Force Transitions after a Health Shock’. *Health Economics,* Vol. 15 (9), pp. 1033-1054.

Jin, R., Shah, C., Svoboda, T. (1995). ‘The Impact of Unemployment on Health: A Review of the Evidence’, *Canadian Medical Association Journal,* Vol. 153 (5), pp. 529-540.

Johnson, R. & Schoeni, R. (2011). ‘The Influence of Early-Life Events on Human Capital, Health Status, and Labour Market Outcomes over the Life Course’, *B.E. Journal of Economic Analysis and Policy,* Vol. 11 (3), pp. 1-55.

Jones, A., Rice, N. & Roberts, J. (2010). ‘Sick of Work or Too Sick to Work? Evidence on Self-Reported Health Shocks and Early Retirement from the BHPS’. *Economic Modelling,* Vol. 27 (4), pp. 866-880.

Jorm, A. (2000). ‘Does Old Age Reduce the Risk of Anxiety and Depression? A Review of Epidemiological Studies Across the Adult Life Span’. *Psychological Medicine,* Vol. 30 (1), pp. 11-22.

Jorm, A., Windsor, T., Dear, K., Anstey, K., Christensen, H. & Rodgers, B. (2005). ‘Age Group Differences in Psychological Distress: The Role of Psychological Risk Factors that Vary with Age’, *Psychological Medicine*, Vol. 35 (9), pp. 1253-1263.

Juster, F., Smith, J. & Stafford, F. (1999). “The Measurement and Structure of Household Wealth”, *Labour Economics*, Vol.

Kapteyn, A., Smith, J. & van Soest, A. (2009). *Work Disability, Work, and Justification Bias in Europe and the U.S.*, NBER Working Paper No. 15245.

Keegan, M. (2011). “Mandatory Superannuation and Self-Sufficiency in Retirement: An Application of the APPSIM Dynamic Microsimulation Model”, *Social Science Computer Review,* Vol. 29, pp. 67-84.

Kerkhofs, M. & Lindeboom, M. (1995). ‘Subjective Health Measures and State Dependent Reporting Errors’. *Health Economics,* Vol. 4 (3), pp. 221-235.

van Kippersluis, H., Van Ourti, T., O’Donnell, O. & van Doorslaer, E. (2009). ‘Health and Income across the Life cycle and Generations in Europe’, *Journal of Health Economics*, Vol. 28 (4), pp. 818-830.

Korpi, T. (2001). 'Accumulating Disadvantage: Longitudinal Analyses of Unemployment and Physical Health in Representative Samples of the Swedish Population'. *European Sociological Review,* Vol. 17 (3), pp. 255-273.

Krause, N., Dasinger, L., & Neuhauser, F. (1998). ‘Modified Work and Return to Work: A Review of the Literature’, *Journal of Occupational Rehabilitation,* Vol. 8 (2), pp. 113-139.

Krause, N., Frank, J., Dasinger, L., Sullivan, T., & Sinclair, S. (2001). ‘Determinants of Duration of Disability and Return-to-Work After Work-Related Injury and Illness: Challenges for Future Research’, *American Journal of Industrial Medicine,* Vol. 40 (4), pp. 464-484.

LaPorte, A. (2014) *Should the Grossman Model Retain its Iconic Status in Health Economics?* Working Paper No: 2014-04, Canadian Centre for Health Economics.

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

Lazear, E. (1986). 'Retirement from the Labor Force'. In O. Ashenfelter & R. Layard (Eds.), *Handbook of Labor Economics* (Vol. I): Elsevier Science BV.

Liljas, B. (1998). ‘The Demand for Health with Uncertainty and Insurance’, *Journal of Health Economics*, Vol. 17 (2), pp. 153-170.

Lindeboom, M. (2006). ‘Health and Work of Older Workers’. In A. Jones & E. Elgar (Eds.). *Elgar Companion to Health Economics*. Cheltenham, UK.

Luijkx, R. & Wolbers, M. (2009). ‘The Effects of Non-Employment in Early Work-Life on Subsequent Employment Chances of Individuals in the Netherlands’, *European Sociological Review*, Vol. 25 (6), pp. 647-660.

Lumsdaine, R., & Mitchell, O. (1999). 'New Developments in the Economic Analysis of Retirement'. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics* (Vol. 3C): Elsevier Science B.V.

Lundborg, P., Nilsson, A. & Rooth, D. (2014). ‘Adolescent Health and Adult Labor Market Outcomes’, *Journal of Health Economics*, Vol. 37, pp. 25-40.

McMillan, J., Beavis, A. & Jones, F. (2009). ‘The AUSEI06: A new socioeconomic index for Australia’, *Journal of Sociology*, Vol. 45 (2), pp. 123-149.

McMillan (2010). *Occupation-based Conceptualisations of Socioeconomic Status*, Paper Presented to the Socioeconomic Status and Australian Higher Education Students Symposium, UTS Sydney, April 2010.

Mackenbach, J., Meerding, W., & Kunst, A. (2010). ‘Economic Costs of Health Inequalities in the European Union’, *Journal of Epidemiology and Community Health*, Vol. 65 (5), pp. 412-419.

Manor, O., Matthews, S. & Power, C. (2003). ‘Health Selection: The Role of Inter- and Intra-generational Mobility on Social Inequalities in Health’. *Social Science & Medicine*, Vol. 57 (11), pp. 2217-2227.

Marmot, M. (2004). *Status Syndrome-How Your Social Standing Directly Affects Your Health and Life Expectancy*. London: Bloomsbury & Henry Holt New York.

Marmot, M. & Wilkinson, R. (2005) *Social Determinants of Health*, 2nd Edition, Oxford University Press.

Mathers, C. & Schofield, D. (1998). ‘The Health Consequences of Unemployment: The Evidence’. *Medical Journal of Australia*, Vol. 168 (4), pp. 178-182.

van de Mheen, H., Stronks, K. & Mackenbach, J. (1998). ‘A Lifecourse Perspective on Socioeconomic Inequalities in Health: The Influence of Childhood Socio-economic Conditions and Selection Processes’. *Sociology of Health & Illness*, Vol. 20 (5), pp. 754-777.

Michaud, P. & van Soest, A. (2008). ‘Health and Wealth of Elderly Couples: Causality Tests using Dynamic Panel Data Models’, *Journal of Health Economics*, Vol. 27 (5), pp. 1312-1325.

Mundlak, Y. (1978), ‘On the pooling of time series and cross section data’, Econometrica, Vol. 46 (1), pp. 69–85.

Mushkin, S. (1962). 'Health as an Investment'. *Journal of Political Economy*, Vol. 70 (5), pp. 129-157.

Myck, M. & Paull, G. (2001). *The Role of Employment Experience in Explaining the Gender Wage Gap*, Institute for Fiscal Studies Discussion Paper W01/18.

OECD (2010), *Health at a Glance: Europe 2010*, OECD Publishing. http://dx.doi.org/10.1787/health_glance-2010-en

O’Dorchai, S., Plasman, R. & Rycx, F. (2007). ‘The Part-time Wage Penalty in European Countries: How Large is it for Men?’, *International Journal of Manpower*, Vol. 28 (7), pp. 571-603.

Oguzoglu, U. (2010). ‘Dynamics of Work Limitation and Work in Australia’. *Health Economics*, Vol. 19 (6), pp. 656-669.

Olsen, W. & Walby, S. (2004). *Modelling Gender Pay Gaps*, Equal Opportunities Commission Working Paper No. 17, Manchester.

Orme, C. (1997). ‘The initial conditions problem and two-step estimation in discrete panel data models’, Discussion Paper No. 9633, School of Social Sciences, University of Manchester. Revised version, June 2001, retitled as: ‘Two-Step inference in dynamic non-linear panel data models’, http://personalpages.manchester.ac.uk/staff/chris.orme/documents/Research%20Papers/initcondlast.pdf

Pagán, R. (2009). ‘Part-time Work among Older Workers with Disabilities in Europe’. *Public Health*, Vol. 123 (5), pp. 378-383.

Parr, N., Ferris, S. & Mahuteau, S. (2007). “The Impact of Children on Australian Women’s and Men’s Superannuation”, *Economic and Labour Relations Review,* Vol. 18, pp. 3-26.

Pelkowski, J., & Berger, M. (2003). 'The Onset of Health Problems and the Propensity of Workers to Change Employers and Occupations'. *Growth and Change,* Vol. 34 (3), pp. 276-298.

Pelkowski, J., & Berger, M. (2004). 'The Impact of Health on Employment, Wages and Hours Worked over the Life Cycle'. *Quarterly Review of Economics and Finance,* Vol. 44 (1), pp. 102-121.

Podor, M. & Halliday, T. (2012). ‘Health Status and the Allocation of Time’. *Health Economics*, Vol. 21 (5), pp. 514-527.

Polidano, C. & Vu, H. (2015). ‘Differential Labour Market Impacts from Disability Onset’. *Health Economics*, Vol. 24 (3), 302-317.

Prowse, V. (2005). *How Damaging is Part-Time Employment to a Woman’s Occupational Prospects?,* IZA Discussion Paper No. 1648.

Rabe-Hesketh, S., Skrondal, A. & Pickles, A. (2005) ‘Maximum Likelihood Estimation of Limited and Discrete Dependent Variable Models with Nested Random Effects’. *Journal of Econometrics*, Vol. 128 (2), pp. 301-323.

Richardson, S. & Law, V. (2009). ‘Changing Forms of Employment and Their Implications for the Development of Skills’. *Australian Bulletin of Labour,* Vol. 35 (3), pp. 355-392.

Richardson, S., Lester, L. & Zhang, G. (2012). ‘Are Casual and Contract Terms of Employment Hazardous for Mental Health in Australia?’ *Journal of Industrial Relations*, Vol. 54 (5), pp. 557-578.

Rodriguez, E. (2002). 'Marginal Employment and Health in Britain and Germany: Does Unstable Employment Predict Health?' *Social Science and Medicine,* Vol. 55 (6), pp. 963-979.

Rodríguez G. & Goldman N. (2001) ‘Improved estimation procedures for multilevel models with binary response: a case-study’. *Journal of the Royal Statistical Society*, Series A, 164 (2), 339-355

Rose, D. (2005). *Socio-economic Classifications: Classes and Scales, Measurement and Theories.* Paper presented at the First Conference of the European Survey Research Association, Pompeu Fabra University, Barcelona, July 18-22, 2005.

Rose, D., Pevalin, D. & O'Reilly, K. (2005). *The National Statistics Socio-economic Classification: Origins, Development and Use*, London: Palgrave McMillan for Office for National Statistics and Economic and Social Research Council.

Rose, D. & Harrison, E. (eds) (2009). *Social Class in Europe: An Introduction to the European Socio-economic Classification*, London: Routledge.

Ross, C., & Wu, C. (1996). 'Education, Age, and the Cumulative Advantage in Health'. *Journal of Health and Social Behavior*, Vol. 37 (1), pp. 104-120.

Rothman, G. & Tellis, D. (2008). *Projecting the Distributions of Superannuation Flows and Assets*, Retirement & Intergenerational Modelling & Analysis Unit, Department of the Treasury.

Russo, G. & Hassink, W. (2005). *The Part-time Wage Penalty: A Career Perspective*, IZA Discussion Paper No. 1468.

Sacker, A., Clarke, P., Wiggins, R., & Bartley, M. (2005). 'Social Dynamics of Health Inequalities: A Growth Curve Analysis of Aging and Self Assessed Health in the British Household Panel Survey 1991-2001'. *Journal of Epidemiology and Community Health*, Vol. 59 (6), pp. 495-501.

Schmitz, H. (2011). 'Why are the Unemployed in Worse Health? The Causal Effect of Unemployment on Health'. *Labour Economics.* Vol. 18 (1), pp. 71-78.

Schuring, M., Burdorf, L., Kunst, A., & Mackenbach, J. (2007). 'The Effects of Ill Health on Entering and Maintaining Paid Employment: Evidence in European Countries'. *Journal of Epidemiology and Community Health*, Vol. 61 (7), pp. 597-604.

Scott, K., Von Korff, M., Alonso, J., Angermeyer, M., Bromet, E., Bruffaerts, R., de Girolamo, G., de Graaf, R., Fernandez, A., Gureje, O., He, Y., Kessler, R., Kovess, V., Levinson, D., Medina-Mora, M., Mneimneh, Z., Oakley Browne, M., Posada-Villa, J., Tachimori, H., & Williams, D. (2008). 'Age Patterns in the Prevalence of DSM-IV Depressive/Anxiety Disorders with and without Physical Co-Morbidity'. *Psychological Medicine*, Vol. 38 (11), pp. 1659-1669.

Sickles, R. & Taubman, P. (1986). 'An Analysis of the Health and Retirement Status of the Elderly'. *Econometrica*, Vol. 54 (6), pp. 1339-1356.

Sindelar, J., Fletcher, J., Falba, T., Keenan, P. & Gallo, W. (2007). *Impact of First Occupation on Health at Older Ages*, Working Paper 13715, National Bureau of Economic Research.

Singh-Manoux, A., Ferrie, J., Chandola, T., & Marmot, M. (2004). 'Socioeconomic Trajectories Across the Life Course and Health Outcomes in Midlife: Evidence for the Accumulation Hypothesis?' *International Journal of Epidemiology*, Vol. 33 (5), pp. 1072-1079.

Singh-Manoux, A., Dugravot, A., Shipley, M., Ferrie, J. Martikainen, P., Goldberg, M. & Zins, M. (2007). 'The Association between Self-rated Health and Mortality in Different Socioeconomic Groups in the GAZEL Cohort Study'. *International Journal of Epidemiology*, Vol. 36 (6), pp. 1222-1228.

Smith, J. (1999). 'Healthy bodies and thick wallets: The dual relation between health and economic status'. *Journal of Economic Perspectives*, Vol. 13 (2), pp.145-166.

Smith, J. (2009). 'The Impact of Childhood health on Adult Labor Market Outcomes', *Review of Economics and Statistics*, Vol. 91 (3), pp. 478-489.

Stansfeld, S. & Candy, B. (2006). 'Psychosocial Work Environment and Mental Health-A Meta-Analytic Review', *Scandinavian Journal of Work Environment and Health*, Vol. 32 (6), pp. 443-462.

Steele, F. (2008). *Module 5: Introduction to Multilevel Modelling Concepts*, LEMMA VLE, University of Bristol, Centre for Multilevel Modelling. Accessed at /cmm/lemma.

Stern, S. (1989). 'Measuring the Effect of Disability on Labor Force Participation'. *Journal of Human Resources*, Vol. 24 (3), pp. 361-395.

Stordal, E., Mykleton, A. & Dahl, A. (2003). 'The Association between Age and Depression in the General Population: A Multivariate Examination'. *Acta Psychiatrica Scandinavica*, Vol. 107 (2), pp. 132-141.

Toivanen, S. (2011). 'Exploring the Interplay between Work Stress and Socioeconomic Position in Relation to Common Health Complaints: The Role of Interaction', *American Journal of Industrial Medicine*, Vol. 54 (10), pp. 780-790.

Turrell G., Stanley L., de Looper M. & Oldenburg B. (2006). *Health Inequalities in Australia: Morbidity, health behaviours, risk factors and health service use.* Health Inequalities Monitoring Series No. 2. AIHW Cat. No. PHE 72. Canberra: Queensland University of Technology and the Australian Institute of Health and Welfare

Vella, F. & Verbeek, M. (1999). ‘Two-step Estimation of Panel Data Models with Censored Endogenous Variables and Selection Bias’, *Journal of Econometrics*, Vol. 90 (2), pp. 239-263.

Virtanen, M., Kivimäki, M., Joensuu, M., Virtanen, P., Elovainio, M. & Vahtera, J. (2005). ‘Temporary Employment and Health: A Review’. *International Journal of Epidemiology*, Vol. 34 (3), pp. 610-622.

Virtanen, P., Janlert, U. & Hammarström, A. (2013). ‘Health Status and Health Behaviours as Predictors of the Occurrence of Unemployment and Prolonged Unemployment’. *Public Health*, Vol. 127 (1), pp. 46-52.

Waghorn, G., & Lloyd, C. (2005). 'The Employment of People with a Mental Illness'. *Australian e-Journal for the Advancement of Mental Health*, Vol. 4 (2).

Wagstaff, A. (1986), ‘The Demand for Health: Some New Empirical Evidence’, *Journal of Health Economics*, Vol. 5 (3), pp. 195-233.

Wagstaff, A. (1993), ‘The Demand for Health: An Empirical Reformulation of the Grossman Model’, *Health Economics*, Vol. 2 (2), pp. 189-198.

Ware, J., Snow, K. & Kosinski, M. (2000), *SF-36 Health Survey: Manual and Interpretation Guide*, QualityMetric Inc., Lincoln, Rhode Island.

Watson, N. & Wooden, M. (2002a). *The Household, Income and Labour Dynamics in Australia (HILDA) Survey: Wave 1 Survey Methodology*. HILDA Project Technical Paper Series No. 1/02, Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Watson, N. & Wooden, M. (2002b). *Assessing the Quality of the HILDA Survey Wave 1 Data*. HILDA Project Technical Paper Series No. 4/02, Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Watson, N. & Wooden, M. (2006). *Modelling Longitudinal Survey Response: The Experience of the HILDA Survey*. HILDA Project Discussion Paper Series No. 2/06, Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Webber, D. & Bjelland, M. (2015). ‘The Impact of Work-Limiting Disability on Labor Force Participation’. *Health Economics*, Vol. 24 (3), pp. 333-352.

van der Wel, K. (2011). ‘Long-term Effects of Poor Health on Employment: The Significance of Life Stage and Educational Level’, *Sociology of Health & Illness*, Vol. 33 (7), pp. 1096-1111.

Wilkins, R., Warren, D., Hahn, M. & Houng, B. (2010), *Families, Incomes and Jobs, Volume 5: A Statistical Report on Waves 1 to 7 of the Household, Income and Labour Dynamics in Australia Survey*, Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Wilkins, R., Warren, D., Hahn, M. & Houng, B. (2011), *Families, Incomes and Jobs, Volume 6: A Statistical Report on Waves 1 to 8 of the Household, Income and Labour Dynamics in Australia Survey*, Melbourne Institute of Applied Economic and Social Research, University of Melbourne.

Willson, A., Shuey, K. & Elder, G. (2007). 'Cumulative Advantage Processes as Mechanisms of Inequality in Life Course Health', *American Journal of Sociology*, Vol. 112 (6), pp. 1886-1924.

Wooden, M. & Warren, D. (2004). 'Non-Standard Employment and Job Satisfaction: Evidence from the HILDA Survey'. *Journal of Industrial Relations*, Vol. 46 (3), pp. 275-297.

Wooldridge, J. (2005), 'Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity', *Journal of Applied Econometrics*, Vol. 20 (1), pp. 39–54.

World Health Organisation (1986) *Ottawa Charter for Health Promotion*. Health and Welfare Canada and Canadian Public Health Association.

World Health Organisation (2003) *Social Determinants of Health: the Solid Facts,* 2nd Edition,

World Health Organisation (2007) *Achieving Health Equity: From Root Causes to Fair Outcomes,* Interim Statement, Commission on Social Determinants of Health.

Yamaguchi, S. (2010). 'Career Progression and Comparative Advantage', *Labour Economics,* Vol. 17 (4), pp. 679-689.

Zhang, X., Zhao, X., & Harris, A. (2009). 'Chronic Diseases and Labour Force Participation in Australia', *Journal of Health Economics*, Vol. 28 (1), pp. 91-108.

Zucchelli, E., Harris, A., Jones, A. & Rice, N. (2007). *Health and Retirement among Older Workers*, HEDG Working Paper 07/19, University of York.

Zucchelli, E., Jones, A. & Rice, N. & Harris, A. (2010). 'The Effects of Health Shocks on Labour Market Exits: Evidence from the HILDA Survey'. *Australian Journal of Labour Economics*, Vol. 13 (2), pp. 191-218.

Zucchelli, E., Harris, M. & Zhao, X. (2012). *Ill-Health and Transitions to Part-time Work and Self-Employment among Older Workers*, HEDG Working Paper 12/04, University of York.

Zweifel, P. (2012) ‘The Grossman Model After 40 Years’. *European Journal of Health Economics*, Vol. 13 (6), pp. 677-682.