Trends and access to treatment for mental health in Australia from 1989 to 2004-05

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Trends and Access to Treatment for Mental Health in Australia from 1989 to 2004-05

Doctor of Philosophy

by

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School of Economics
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Abstract

Accounting for 24 per cent of total disability in Australia, mental health disorders result in significant social and economic costs. Health care costs alone amounted to $4.1 billion in 2004-05. Mental health sufferers are more likely to be in low income groups and they often lack the financial, educational and social resources required to seek appropriate treatment. To date, no economic studies in Australia have investigated income and price issues related to the demand for mental health care, nor have any previous studies considered the importance of concession prices associated with the Australian health card for accessing mental health medication.

My first paper establishes the trend in the use of mental health medication in Australia from 1989 to 2004-05, which has previously not been documented. Using decomposition analysis to investigate the contributing factors to the three-fold increase in the use of mental health medication over this period, I show that socio-demographic characteristics account for only a small amount of the growth. An examination of trends in the association of income with mental health risk and with mental health medication use shows a negative income gradient for both.

My second paper examines in greater depth the effect of income on mental health medication use in 2004-05. Selection methods are used to separate the effect of income on medication use from the effect of income on mental health risk. By estimating mental health medication use separately for those with and without the health card, I determine that having the health card improves access to mental health medication use and that a positive income gradient for mental health medication use exists for those without the health card.

My third paper uses a natural experiment approach to determine the price responsiveness of mid-high income seniors for mental health medication following income eligibility increases in 1999 for the Commonwealth Seniors Health Card. The results indicate that after controlling for health status no significant change in mental

health medication use occurred following the policy for this group of mid-high income seniors, confirming the greater importance of the health card for mental health sufferers with low income.

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Chapter 1

Introduction

1.1 Background

Health economics has become an important sub-field within the economics discipline due to the expansion of the health sector in developed countries over past 30 years, and the availability of data sets amenable to economic modelling. The findings of the RAND Health Insurance Experiment conducted between 1974 and 1982, which showed the importance of cost-sharing arrangements on health care utilisation, were important for establishing the relevance of economics in health policy. Most developed economies face rising health care expenditures due in part to the growth of medical innovations as well as the increased health requirements of an ageing population. Given the inherent information problems and other market failures associated with health provision, optimal health policies must balance efficiency with impacts on equity. The aim of my PhD research has been to analyse the interplay of recent policy efforts in the area of mental health in Australia.

Mental health is one of Australia's eight national health priority areas, in addition to asthma, cancer, cardiovascular disease, diabetes, injuries, arthritis and musculoskeletal conditions, and dementia. The latest burden of disease data attributes 13 per cent of Australia's disease burden to mental disorders, with mental disorders being the top contributor to the non-fatal disease burden or disability at 24 per cent (Begg et al, 2007). Mental health disorders cover a broad number of conditions, which are often characterised by degrees of severity. The main conditions covered in the National Health Survey (NHS) include: behavioural and emotional problems, anxiety, depression, mood disorders, personality disorders, psychosis, and alcohol and drug problems.

1.2 Aims and contributions

Ensuring access to treatment is a special challenge in the area of mental health. Mental health sufferers are more likely to be in low income groups and often lack the financial, educational and social resources required to seek appropriate treatment. In Australia, there are several health policies aimed at reducing these barriers. To date, no economic studies in Australia have investigated income and price issues related to the demand for mental health care, nor have any previous studies considered the importance of concession prices associated with the Australian health card for accessing mental health medication.

Conducting empirical research on economic factors that affect access to treatment – income and prices – requires addressing the issue of endogeneity. The two-way relationship between mental health and income requires econometric techniques such as natural experiments, instrumental variables or utilising data from panel surveys. Few panel surveys in Australia include extensive information on mental health. Identifying good instrumental variables and timing of surveys to construct natural experiments are typical challenges in health economics research. Whether due to these reasons or other factors, limited economic studies on mental health exist in Australia, as documented by Williams and Doessel (2008, 2006).

My thesis contributes to the field of health economics and specifically the area of mental health in Australia by providing empirical findings in the following areas. I investigate the trends in mental health risk and related medication use between 1989 and 2004-05 and provide some evidence of the contributing factors to increased mental health medication use for people with mental health risk over the 15 year period. I also provide evidence on the effects of income and price on mental health medication use that shows the importance of the Australian health card for access to mental health medication for low income people with mental health risk.

1.3 Overview of topics covered

My thesis is organised as follows. I begin with an overview chapter on economic issues in mental health which aims to provide a context for the analytical papers that follow. In addition to a summary of economics and mental health issues identified in the literature, the overview chapter provides background on the policy and institutional setting in Australia. The chapter reviews the key economic issues raised in the literature on mental health care in Australia, including concerns about equity as well as efficiency. I also discuss data sources for mental health economic research in Australia with reference to the data and timeframe used in my thesis. The three analytical papers follow.

Chapter 3 reviews trends in mental health in Australia from 1989 to 2004-05. The paper begins with a review of trends in mental health prevalence and treatment from the literature. The chapter provides an overview of mental health data from four National Health Surveys: 1989, 1995, 2001, and 2004-05, and reports on the growth in both mental health risk and mental health medication use over the time period. The chapter includes decomposition analysis of the factors that are associated with the increase in mental health medication use and the increase in mental health risk between 1989 and 2004-05. Trends in the association of income with mental health risk and related medication use are also examined.

Chapter 4 provides a more in-depth examination of the effect of income on mental health medication use in 2004-05. Selection methods are used to separate the effect of income on medication use from the effect of income on mental health risk. I utilise a novel approach to identify the model by excluding personal income in the mental health medication equation, since household purchases like medication depends on household income. The assumption is that personal income does not impact on medication use over and above the effect of household income, whereas personal income is assumed to affect the predilection of mental health risk. Models of mental health medication use are estimated separately for those with and without the health card to determine the importance of having the health card for accessing mental health medication use and possible evidence of a positive income gradient for mental health medication use for those without the health card.

Chapter 5 uses a natural experiment approach to determine the price responsiveness of mid-high income seniors for mental health medication following income eligibility increases in 1999 for the Commonwealth Seniors Health Card. Models are estimated with data for one pre-policy period and two post-policy periods, and two control groups are considered – a pre-pension age group with mid-high income and a pension age group with low income. An alternative specification uses the health card variable and an instrumental variable approach to control for the possible endogeneity of the health card. In this framework, the policy variables act as instruments for health card status.

Chapter 6 summarises the results, concludes and discusses areas for future research.

Chapter 2

Economics and mental health in Australia

2.1 Introduction

This chapter provides background on economic issues related to income and mental health research in Australia. First, I provide an overview of economic issues specific to financing mental health care and highlight some unique issues related to economic research on mental health. Second, I outline key features of Australia's health care system, with special focus on mental health policy issues, technological developments and health system expenditure trends. This is followed with a discussion of economic issues related to financing mental health care in Australia. The chapter also includes a review of Australian data for economic research on mental health. Next, I define the mental health population at risk and the timeframe used in my thesis. Lastly, the conclusion summarises the key issues raised in this chapter which have relevance for the subsequent chapters.

2.2 Background on mental illness

Mental health disorders cover a broad number of conditions, which are often characterised by degrees of severity. The main conditions include: behavioural and emotional problems, anxiety, depression, mood disorders, personality disorders, psychosis, and alcohol and drug problems. An estimated 18 per cent of the adult population in Australia is affected by mental health disorders, with an estimated 2.5 per cent of the adult population experiencing severe or profound psychiatric disability (AIHW, 2006). The latest burden of disease data attributes 13 per cent of Australia's disease burden to mental disorders, with mental disorders being the top contributor to the non-fatal disease burden or disability at 24 per cent (Begg et al, 2007). As a result, mental health disorders account for significant social and economic costs. Costs involve direct health system expenditures, direct transfers for welfare and carer expenses, indirect costs of lost earnings for individuals and their carers, and additional security related expenditures (e.g., for police, prisons, and legal costs). This chapter focuses on economic issues associated with health system expenditure and mental health.[1]

2.3 Economic issues in mental health

Richard Frank and Thomas McGuire's 2000 overview article on mental health in the Handbook of Health Economics provides a useful starting point of investigation. Frank and McGuire make the general point that mental illness is different from general health due to the nature of mental illness, the people affected with mental illness, and the different approach to treatment. Some of the economic issues raised by Frank and McGuire (2000), however, are specific to the US health financing environment and therefore are less germane to Australia. As such, the following discussion will draw on relevant topics from Frank and McGuire and others, and will later consider economic issues for Australia in section 2.5.

Frank and McGuire (2000) point out that the degree of severity in mental health is a key factor in treatment and finance arrangements; thus economic issues differ depending on the severity of illness. Issues for the severely mentally ill involve severe market failure, adverse selection and externalities; for these reasons severe mental illness usually involves publicly funded programs over private insurance funding arrangements. Severe mental illnesses like other chronic conditions are costly to treat; as often additional support for and coordination of services outside of the health sector are involved. This may include housing, social services, medical as well as psychiatric care.

Moderate to mild mental health disorders include directly delivered services such as community health and public hospital services, provided through both public and

[1] Two cost of illness studies, on bipolar disorders and schizophrenia, prepared by Access Economics and SANE Australia are available from: http://www.accesseconomics.com.au/

private insurance. The efficient function of insurance markets and design of optimal plans taking into account the problems of adverse selection and moral hazard is a major focus of mental health economics research in the United States, and several of these issues are covered by Frank and McGuire.

Moral hazard issues relate to the additional use of health care services due to insurance coverage (Gruber, 2005).[2] According to Frank and McGuire insurance companies' concern about cost-control due to over-use of psychotherapy led to higher co-payments for mental health coverage. These higher co-payments were supported by research evidence that showed greater price responsiveness, or price elasticity for mental health compared to general health services. Frank and McGuire summarise the findings from these studies, including the RAND Health Insurance Experiment conducted mainly during the 1980s. According to Gruber, moral hazard is also an issue in social insurance as over-use of health services has revenue-raising and tax implications.

Literature from other countries indicates that demand elasticity for mental health treatment may be more inelastic that previously found in the US literature. Evidence from a study in Denmark found that elasticity of demand for mental health medication depends on the perceived efficacy of the medicine (Emilien, 1997). Other researchers conclude that the demand elasticity for mental health treatment is inconclusive (Knapp et al, 2006).

Private health insurance research is also concerned with problems of adverse selection. In the insurance literature adverse selection relates to the effects of private information held by the insurance purchaser. A mental health insurance purchaser may not reveal the full extent of illness and subsequent use. Economic theory suggests that people with high health care needs have an incentive to reduce their potential financial loss by purchasing health insurance coverage. Insurance providers aim to minimise the extent of adverse selection in order to maximise profits. Adverse selection is less an issue for mental health in Australia because of universally

[2] The definition of moral hazard in health economics differs from the definition used in microeconomics. In microeconomics literature moral hazard refers to the problem in insurance markets where purchasers of insurance policies will not take an appropriate level of care (Varian 1992, 455).

available public insurance. However, private health insurance providers in Australia would be expected to adjust fees and benefits for mental health in light of concerns about adverse selection and moral hazard. To date no research has been conducted in Australia on the impact of private health insurance policies on the use of mental health services according to Williams and Doessel (2008).

More relevant to Australia are the incentives and responses created by fiscal federalism in funding for mental health care. The response by national, state government and private insurers to payment structures and regulation can lead to a ‘cascading cost-shifting game’. For example, Frank and McGuire make the point that cost shifting between national and state authorities in the US following the introduction of the national Medicaid program in 1965 hastened deinstitutionalisation since Medicaid funding wouldn’t cover long hospital stays for mental health.

In public-funded mental health, concerns are more likely to focus on quality of care and horizontal equity whereby equal healthcare is provided to those who are the same in a relevant respect (such as having the same 'need'). Health inequity is an important area of health economics especially in the UK where despite equal access to health care being ensured through the National Health Service, significant differences in access to health care and health outcomes exist between social classes (Dixon et al, 2007).[3]

Susan Ettner and Michael Schoenbaum (2006) raise demand-side issues unique to mental health. Mental health presents possible barriers to treatment due to the situation whereby mental disorders undermine patients’ ability to act as rational economic decision makers. Patients with mental disorders often lack family who act as their health care agents. Poor patient knowledge about mental disorders and appropriate treatment plus problems of social stigma are also barriers. Organizational and financial characteristics of the health care and insurance systems affect access. Without good information, patients rely on other players in health care system to serve as “agents”. For example, low educational levels and lack of capability limit treatment-seeking behaviour, and insufficient knowledge leads to underestimation of

[3] As the issue of equity is a minor theme in my thesis, I point interested readers in further investigation on equity to useful references provided in Dixon et al, 2007.

the value of the treatment. In addition, even if safety-net and targeted programs are available navigation through the health system may be a barrier.

Finally, economic research on mental health involves some important analytical issues to overcome: measurement problems and income endogeneity. Frank and Glied (2006) explain that the lack of biological markers for most mental health disorders contributes to challenges with appropriate treatment as well as measurement error in mental health research. Researchers need to be mindful of measurement issues when data rely on self-reports of condition.

Poor mental health is associated with financial pressure and unemployment, as well as poor health, lifestyle factors such as substance use, life events, and genetic factors. Economic research finds evidence of two-way causality between income and mental health. Frank and McGuire (2000) discuss evidence of a significant negative effect found in studies on the impact of mental health disorders on wages. Likewise studies using instrumental variables are able to establish a negative income gradient for mental health; people with high incomes are less likely to have mental health disorders (Ettner, 1996). Endogeneity issues can be addressed by more rigorous econometric analysis involving instrumental variables, natural experiments, or with panel data techniques.

2.4 Policy and institutional background for Australia

Australia's health care system is characterised as a mixed public-private system. Access to public hospitals is free of charge. Australia's universal health insurance, Medicare, covers a scheduled fee for doctor visits, with doctors entitled to set charges above scheduled fees, resulting in copayments. In 2006-07, 78.0 per cent of general practitioners charged no additional fees, or 'bulk-billed' Medicare directly (AIHW, 2008). Most specialist charges are above Medicare scheduled fee rates, and Medicare includes safety-net provisions for high-out-of-pocket medical payments. Pharmaceuticals are subsidised through the Pharmaceutical Benefits Scheme (PBS), which includes concession prices for people with low income and in receipt of other government benefit programs. PBS also includes safety net thresholds for both general patients and concession card holders. Optional private health insurance is available to cover hospital, dental and allied services. Tax and other incentives to the support the private health insurance sector has resulted in 43.5 per cent of Australians having basic private health insurance (AIHW, 2008).[4,5] In Australia, public hospital finance and operations are the responsibility of state and territorial governments, while the Commonwealth government is responsible for Medicare and PBS.

Ensuring equitable access to health care is a key policy priority in Australia. Addressing financial barriers to access health care was central to the introduction of Medicare in 1984, and its precursor Medibank in 1975 (Duckett, 2007). Due to the link between low income and mental health, affordable access is critical in the mental health sector.

The health care card in Australia provides assistance to low income earners, pensioners and other selected groups with access to concessional prices for PBS medicines and other health care costs such as ambulance, dental and eye care.[6,7] Annual report data from the Commonwealth Department of Families, Housing, Community Services and Indigenous Affairs indicates that approximately one third of Australia's population has a health card, either as a card holder or dependent.[8]

In addition to concessional prices provided by the health card and access to free doctor visits through 'bulk-billing' arrangements, safety net provisions are important for low income people facing high out-of-pocket health care costs associated with chronic conditions, including mental health disorders. Medicare safety net payments, PBS patient co-payments and safety net thresholds are annually indexed to the Consumer Price Index (CPI) (Australia Parliamentary Library, 2003).

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[4] For more details on Australia's health care system see the Australia Institute of Health and Welfare's *Australia's Health 2008*, or Stephen Duckett's 2007 book, *The Australian Health Care System*.

[5] Recent policy changes to private health insurance are not the focus of my thesis, as private health insurance in Australia tends to be concentrated in higher income groups.

[6] Further information on health care card benefits is available from the Centrelink website: http://www.centrelink.gov.au/internet/internet.nsf/payments/conc_cards_hcc.htm#benefits

[7] For brevity I will refer to the health care card as the health card for the remainder of in my thesis.

[8] FaHCSIA. 2009, 127, Table 2.5. Australia 2008 population data is available from ABS. 2010.

Medicare safety net provisions include cost recovery for out-of-pocket out-of-hospital expenses (such as specialist visits) when they exceed thresholds. In 2004, prior to introduction of the Extended Safety Net Program, the out-of-pocket thresholds were $300 in a calendar year for an individual and $700 for families (Australia Parliamentary Library, 2004).[9] Prior to 2004, the Medicare Safety Net program cost an estimated $10 million annually (Australian Government Department of Health and Ageing, 2009).

Safety net arrangements for large cumulative expenses for PBS listed medicines involve free payments once certain thresholds of expenditure are exceeded. In January 2005, the general patient safety net threshold was $874.90 and $239.20 for pensioners and concession card holders (Sweeny, 2007). PBS expenditure on the safety net program was $7.9 million in 2004-05 (Sweeney, 2007). In addition, a pharmaceutical allowance of approximately $150 per year is available for all pensioners, including part-pensioners, Veterans Affairs beneficiaries, sickness candidates and others receiving income support for at least 9 months (Australia Parliamentary Library, 2003).

The majority of mental health finance comes from state and Commonwealth governments. Private health insurance funds are mandated to include basic psychiatric services, and mainly provide coverage for private psychiatric hospitals (Whiteford et al, 2000). According to the latest government reports on national mental health expenditure for 2004-05, of the $3.9 billion spent in the mental health sector, the state and territorial government share was 61 per cent, the Commonwealth government share was 25 per cent and private health insurers accounted for 4 per cent (Department of Health and Ageing, 2007). Out-of-pocket payments would likely be incurred for visits to psychiatrists and psychologists, for PBS copayments and private hospital charges beyond private health insurance benefits. However, regular reporting on out-of-pocket expenses is not included in national mental health expenditure reports.[10] A recent review of the Extended Medicare Safety Net Program

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[9] Details on the original safety net program and the extended safety net program are provided in a recent government review of the Extended Safety Net Program (Australian Government Department of Health and Ageing, 2009).

[10] AIHW Health Expenditure series report out-of-pocket expenditure data at the health system level, but not for disease areas.

provides an annual estimate of mental health out-of pocket expenses in recent years at $317, which is three times that for other chronic conditions except cancer (Australian Government Department of Health and Ageing, 2009).

As a large contributor to Australia's disease burden, mental health accounts for a significant share of health expenditure.[11] The latest report on allocated health expenditure by disease group indicates that mental disorders amounted to $4.1 billion, accounting for 7.8 per cent of total expenditure allocated by disease group in 2004-05 (AIHW, 2009). Previous reports of health expenditure by disease and injury groups from 1993-94 and from 2000-01 show a consistent share of around 8 per cent of health system expenditure aimed at mental health disorders, indicating that mental health expenditure has kept pace with the total health expenditure growth of roughly 5 per cent per annum over the decade from 1993-4 to 2004-05 (AIHW, 2005a, 1998).[12] Some mental health advocates, however, indicate that expenditure for mental health needs to be increased to be commensurate with the high level of disability (Hickie et al, 2006).[13]

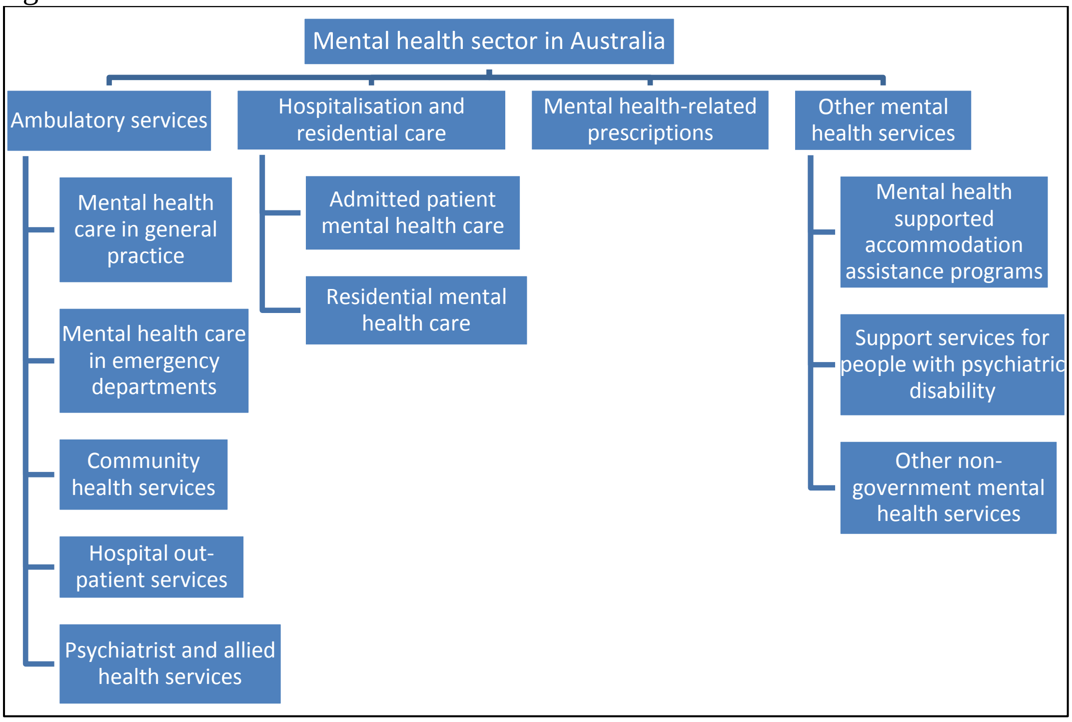
Figure 2.1 provides an overview of the mental health care sector. Hospitals and residential care are an important part of treatment for severe mental disorders, and requires greater fiscal expenditure than ambulatory care. Ambulatory care, which involves a range of treatments and services for those with less severe mental disorders has grown in importance since the early 1990s, after the introduction of the Mental Health Strategy in 1992, and is the focus of my research.

[11] Disease allocated expenditure is based on recurrent health expenditure. In 2004-05, the latest year allocated diseases expenditures were estimated, $52.7 billion of $76. 8 billion in total recurrent health expenditure was allocated to disease and injury groups. Total health expenditure in 2004-05 in current prices was $82,060 million (AIHW, 2009, 15, Table 2.7).

[12] Total health expenditure and GDP, constant prices (a), and annual growth rates, 1995–96 to 2005–06 (AIHW, 2008, 397, Table 8.2).

[13] Begg et al (2007, 39) provide a useful discussion on the limitation of equating health expenditure with specific disease burden as it does not account for total health opportunity costs.

Figure 2.1: Overview of the mental health sector in Australia

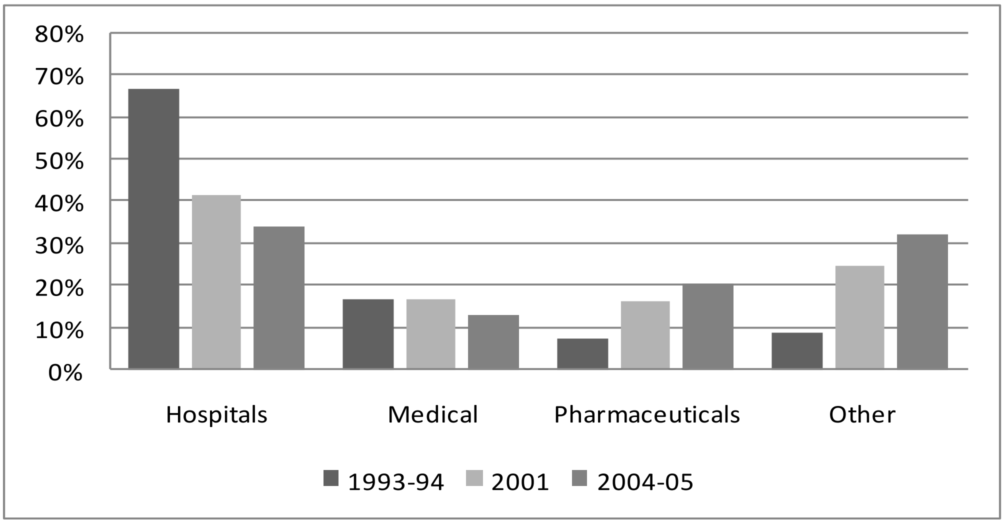


Adapted from: AIHW. 2007. *Mental health Services in Australia*, 2, Figure 1.1.

Reports on allocated health expenditure by disease group convey the significant changes in the composition of mental health expenditure since the start of the Mental Health Strategy. Figure 2.2 shows the change in the share of mental health spending by area of health expenditure. In 1993-94, hospital expenditure accounted for 66 per cent of mental health expenditure, which declined to 34 per cent in 2004-05. Over this period mental health expenditure for pharmaceuticals increased from 7 per cent of mental health expenditure to 21 per cent. In addition, expenditure related to community health services also grew significantly over this period, as captured in the other category.[14]

[14] Other mental health expenditure includes community, public health and research programs for mental health.

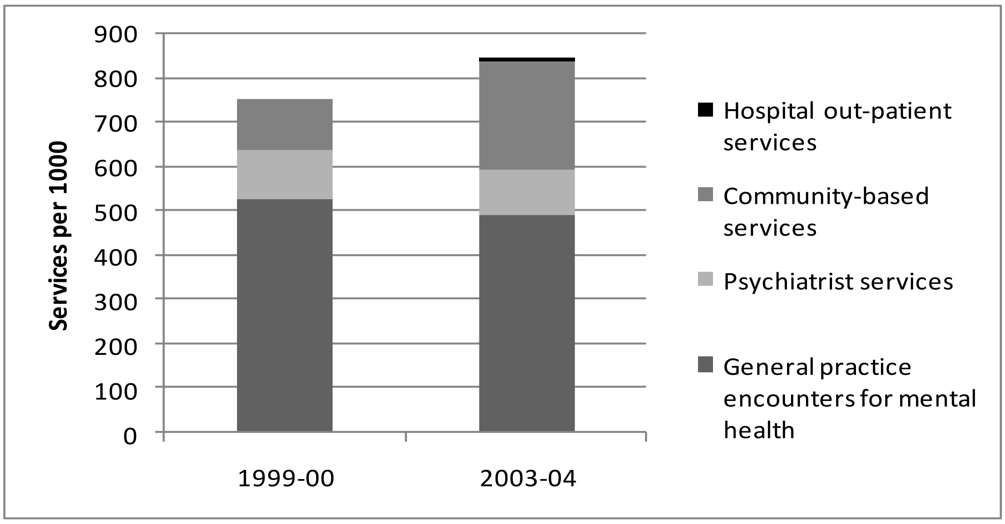
Figure 2.2: Share of total mental health expenditure by area of health expenditure, 1994-94, 2001 and 2004-05



Source: AIHW. 2008. *Australia's Health*; AIHW. 2005a. *Health system expenditure on disease and injury in Australia, 2000-01.*

Figure 2.3 shows further detail on the expansion of ambulatory services in mental health. While general practitioners (GPs) dominate ambulatory care, other community programs have been developed and expanded in recent years.

Figure 2.3: Per capita provision of ambulatory mental health services, 1999-00 and 2003-04



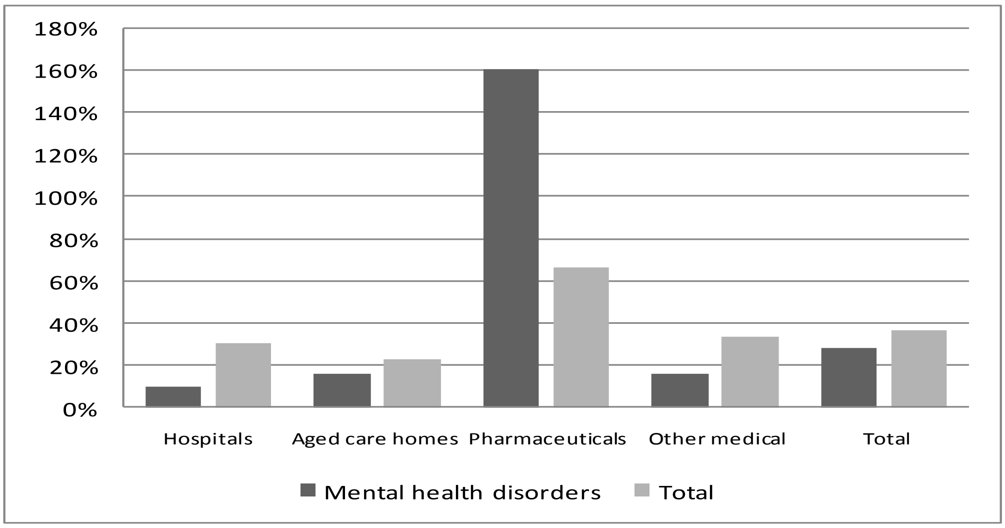
Source: AIHW. 2005b, 2000.*Mental health services in Australia*.

One view of the growth in ambulatory care is put forth in Frank and Glied (2006) in their overview of trends in mental health the United States, which were similar to Australia. Deinstitutionalisation led to more consumer choice in mental health care and market opportunities were exploited by drug companies, doctors and other mental practitioners.

The advent of new psychotropic medications during the early 1980s and 90s significantly expanded treatment for mental illness in Australia and other western countries (Frank and Glied, 2006; Mant et al, 2004; McManus et al, 2000). Analysis by Mant and others of drug sales data for Australia show a rapid period of increase from 1991 to 2002, which coincided with the entry of a major new class of compounds, namely the SSRIs, and later the serotonin–noradrenaline reuptake inhibitors and other new antidepressants. As a result of wider availability of medication-based treatment options, the majority of ambulatory mental health treatment is delivered by GPs. Data on mental health service use indicate that general practitioners prescribe 87 per cent of all medications for mental health (AIHW 2007).

Growth in pharmaceuticals for mental health was significantly greater than for the total pharmaceutical growth, especially between 1993-94 and 2001. Figure 2.4 summarises the changes in mental health expenditure growth compared to the total health system.

Figure 2.4: Change in health system expenditure for mental health disorders compared to changes in total health expenditure, 1993-94 to 2000-01, %, (inflation-adjusted)



Source: AIHW. 2005a. *Health system expenditure on disease and injury in Australia*, 26, Table 9.

2.5 Economic issues in mental health in Australia

Recent studies from Australia have focused more broadly on the role of socio-economic status and mental health service use and importantly, they were conducted since the mid-1990s covering the period of widespread availability of new pharmacotherapy options for mental health. These studies provide some evidence of equitable access to mental health treatment in Australia, but lack of detailed income data is a limitation to their analysis.

Utilising a behavioural framework with data from the 1997 National Survey of Mental Health and Wellbeing Ruth Parslow and Anthony Jorm conclude that socio-economic factors (or pre-disposing factors in the behavioural framework) are less important than need factors (Parslow and Jorm, 2001, 2000). Multiple logistic regressions are conducted for 5 types of mental health services on independent variables including need, predisposition factors (such as age gender, education, receiving a government allowance, employment and marital status) and enabling factors (including type of practitioner visited) they conclude that only age is an important factor in the type of health services used for mental health. They find that young people are more likely to receive psychological therapy and information whereas older groups are more likely to receive medication. Data on personal or household income was not available in their data set.

A more recent study by Andrew Page and colleagues (2009) using PBS administrative data by sex, age and statistical local area of prescription, finds sex and age to be significant factors in anti-depressant use, while socioeconomic status as measured by the economic resource index of the Socio-Economic Indexes for Areas (SEIFA) was not important. The economic resource index captures information about relative economic advantage by area of residence, but does not include household income levels. The authors concede that lack of data on individual income is a limitation of their investigation.

Gavin Andrews and other health researchers (2001a, 2001b, 2000), however, point to the high level of people with mental health disorders identified in the 1997 Survey of

Mental Health and Wellbeing (SMHWB) that do not seek treatment. According to the 1997 Survey, only 38 per cent of people with a mental health condition used a health service for mental health problems. Andrews and co-authors attribute low treatment for mental health disorders to problems of appropriate diagnosis and stigma, indicating that health system funding is not a factor (Andrews et al, 2001b).

Health economist Darrel Doessel and colleagues indicate a potential problem with 'structural imbalance' in Australia's mental health sector (Doessel, Williams and Nolan, 2008). Their analysis of data from the 1997 Survey of Mental Health and Wellbeing, points to a mismatch between the rate of those treated without actual mental health 'need', and the rate of non-treatment for those with a reported mental health care 'need'. An estimated 4.4 per cent of those surveyed are in the first group and an estimated 11 per cent in the second group. These findings point to possible inefficiency in Australia's mental health care sector. Doessel and authors (2008) indicate that this trend may be exacerbated by the introduction of the 2006 policy to include Medicare coverage for psychologists' services.

In reviewing the progress of reforms after ten years of the National Mental Health Strategy, Whiteford and Buckingham (2005) raise the issue of 'value for money' in the mental health sector. They argue that while program reforms and financial commitments are on track there is a lack of information on the level of efficiency and effectiveness in the sector. Their view and those expressed in the government's review of the Strategy recommend performance indicators and outcome measures to improve efforts to track efficiency and effectiveness in the sector (Department of Health and Ageing, 2007).

2.6 Data on mental health in Australia

Data sources for mental health economics research include the two main areas: population survey data and administrative data; the latter including health services and health expenditure data from government programs like Medicare and PBS. The following describes data sources that provide information on mental health and discusses some of the limitations of the data for economic analysis.

2.6.1 Population survey data sources

Two cross-section population surveys, the National Survey of Mental Health and Wellbeing and the National Health Survey provide the most comprehensive information on mental health prevalence and related health actions. Less detailed information on mental health disorders is available in two well-established longitudinal surveys, the Women's Health Survey and the Household, Income and Labour Dynamics in Australia (HILDA) Survey.

2.6.1.1 National Survey of Mental Health and Wellbeing

The 1997 National Survey of Mental Health and Wellbeing (SMHWB) was commissioned by the Commonwealth government to facilitate efforts by the National Mental Health Strategy to plan services and allocate resources for mental health (ABS, 1998a). The SMHWB was conducted by Australia's Bureau of Statistics (ABS) and is available for use by researchers as an ABS Confidential Unit Record File (CURF). ABS provides access to CURFs on CD-ROM or to CURFs with extended data through the Remote Access Data Laboratory (RADL). The survey is based on a nationally represented sample and provides data on 12 month prevalence and level of disability associated with selected major mental disorders as well as data on health services used and perceived need for help for the population over 18 years old at the national and state level.

The quality of mental health prevalence data is considered good as it is based on the Composite International Diagnostic Interview (CIDI) tool which translate the criteria for established mental disorders from the Diagnostic and Statistical Manual of Mental Disorders (DSM) into a set of questions which can be easily answered by the general population.[15] In addition, details are available on employment status,

[15] The Diagnostic and Statistical Manual of Mental Disorders (DSM) is published by the American Psychiatric Association and provides criteria for the classification of mental disorders. The current manual is DSM-IV-TR with the next major revision DSM-V expected in 2012. Further information is available from the American Psychiatric Association website (accessed 30 October 2010):

education and other characteristics, but income details were not collected as part of the SMHWB. Nor does the survey provide detail on household health expenditures. Further details on the survey can be found National Survey Mental Health and Wellbeing of Adults Users' Guide, 1997 Cat No. 4327.0 (ABS, 1998b).

A second National Survey of Mental Health and Wellbeing was conducted by the ABS in 2007 and provides similar information to the 1997 survey. It provides additional information on lifetime prevalence of mental health disorders, as well as data on personal and household income and financial stress. Many of the other variables are comparable with the earlier survey. Further details on differences between the two surveys are available from SMHWB Users' Guide, 2007 (ABS, 2009).

2.6.1.2 National Health Survey

The Australian Bureau of Statistics has undertaken nation-wide health surveys regularly over the past 3 decades. My research relies on surveys from 1989, 1995, 2001, and 2004-05. The latest survey from 2007-08 recently became available. In addition to providing a rich source of information on health status, risk factors and related actions, the National Health Surveys include details on demographics, education, work, income, health insurance/health cards and geography. While the aim of providing a representative snapshot of the state of health among Australians is consistent among the surveys, significant differences in questions and sampling methodology pose comparability challenges between the series. Comparability issues on mental health will be elaborated in Chapter 3.

The NHS information on mental health is not based on diagnostic interview tools like the SMHWB. Self-reports of a chronic condition (lasting 6 months or more) include a standardized list of major mental health conditions (e.g. depression, anxiety, mood problems, alcohol and drug problems, other mental and behavioural problems). In addition, all NHS surveys include a measure of short-term distress. In 2001 and 2004-05 information is included on current levels of distress as measured by the

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http://www.psych.org/mainmenu/research/dsmiv/dsmivtr.aspx

Kessler 10 (K10) Score, which is based on 10 questions that results in a K10 score between 0-50, with 50 indicating the highest level of current distress. Following interpretation of the K10 Score according to the ABS Mental Health & Wellbeing Survey, a score of 30-50 indicates a serious mental health condition (ABS, 1998a). Earlier National Health Surveys rely on other measures of current distress and therefore are not directly comparable. Medication use includes medications for mental health disorders, which also provide an indication of mental health disorder. NHS data is available on CURF on CDs or through RADL.

2.6.1.3 Australian Longitudinal Study on Women's Health

The Women's Health Survey tracks health issues in 3 cohorts of women, those aged 18-23, 45-50, and 70-75 at the beginning of the study in 1996. Five waves of data for all three groups is currently available. Characteristics data includes information on income and affordability, as well as health actions and medication use. Mental health information is based on self-reports of mental illness. Further information is available from the women's Health Australia website: www.alswh.org.au

2.6.1.4 HILDA

Nine waves of the HILDA Survey have been conducted and 7 waves are available through the Melbourne Institute of Applied Economic and Social Research. As well as tracking labour variables, each wave includes health status and well–being data based on the SF–36 Health Survey instrument, which includes the mental component summary score (MCS). In addition, the Kessler Psychological Distress Scale (K10) score, included for the first time in wave 7, will be available in future waves (Watson, 2009).

2.6.2 Administrative data sources

The Commonwealth Department of Health and Ageing (DOHA) oversees administration of national health programs (including Medicare and the Pharmaceutical Benefits Scheme) and makes available statistical data for these programs. De-identified individual service use data is available with special permission, but generally is not readily accessible The DOHA supports the Australian Institute of Health and Welfare whose main aim is to coordinate health data and information for Australia.

2.6.2.1 Medicare and PBS

Aggregate health service use and benefits data by state for major Medicare categories (e.g., professional services, diagnostic procedures) is available from the Medicare website: https://www.medicareaustralia.gov.au Demographic data is limited to age and gender. De-identified individual service use data is available with special permission, but generally is not readily accessible. The Medicare website also hosts statistics on the Pharmaceutical Benefits Scheme.

2.6.2.2 Mental health services in Australia series

Annual reports of the National Mental Health Strategy's implementation progress are prepared by the Australian Institute of Health and Welfare (AIHW). The AIHW provides annual reports on national mental health care data, detailing the activity and characteristics of mental health care services in Australia. The series starts in 1997-98, and includes data on ambulatory services (such as community-based services, emergency departments, private psychiatrists, allied health professionals and general practitioners), hospital and residential services and other services (such as supported accommodation services) In addition, information is provided on mental health-related prescriptions and mental health resources such as facilities, workforce and expenditure. Where possible, comprehensive data is provided for each state and territory (AIHW website, 2009). According to the AIHW website, service utilisation data has limitations in that it does not provide a complete picture of the incidence or prevalence of mental health. The data only covers those individuals who choose treatment. The number and pattern of services received can reflect admission or registration practices, and regional differences in service provision.

2.6.2.3 Mental health expenditure data

AIHW provides periodic reports of health expenditure data. The latest publication provides summary data on health system costs by area of health expenditure for broad disease and injury groups including mental disorders (AIHW 2008). In addition the latest publication provides time series data on health expenditure in Australia from 1996–97 to 2006–07. AIHW has also released a working paper comparing the expenditure on mental health disorders in Australia for 1993-94 with the expenditure of the United States of America, the Netherlands and Canada (AIHW 2003).

2.7 Data used in thesis

The National Health Survey Series was chosen for my thesis on income and mental health issues since it provides the most consistent dataset over time. It includes detailed income data and rich characteristics data, as well as details on health actions for a comprehensive set of health conditions. However, reflecting ongoing developments in health care, some disease definitions and medication types change between the NHS surveys, and effort is required to take these issues into account. My analytical papers involve data from four National Health Surveys conducted in 1989, 1995, 2001, and 2004-05. As the main focus of my thesis is demand for mental health medication use, I need to define the population at risk for mental health disorders, i.e., those with potential demand for mental health medication.

Several choices are available in the NHS with respect to defining the population at risk for mental health disorders. I derive a measure of mental health risk based on either a self report of a mental health chronic condition (lasting 6 months or more), or having a high level of short-term distress as measured by the Kessler Score (a very high score of 30-50) or indicating use of mental health medication (prescription drugs excluding sleeping pills). My population at risk is restricted to adults, as the Kessler Score questions are only asked for the population over 18 years. Details on the definition of mental health variables and comparability across the National Health Survey Series are discussed in Chapter 3.

2.8 Coverage of timeframe and topics

My timeframe captures the period of expansion of ambulatory services for mental health care from 1989 to 2004-05, which followed deinstitutionalisation of mental health care in Australia. The time period is also characterised by the increased availability and adoption of new psychotropic treatments. A recent development in mental health care – the policy change in November 2006 that expanded Medicare funding to cover psychological services – is not covered in my analysis. The latest National Health Survey conducted in 2008 became available in mid-2009 after most of my research was completed. Other health policy changes affecting the expansion of those eligible for the health card and concession prices for mental health medications are included in my study time period.

The focus of my thesis is on establishing the relationship between income and mental health risk and related mental health medication use in Australia. Using detailed socio-demographic characteristics from the National Health Survey, I am able to show that a significant negative income gradient exists for mental health in Australia (Chapter 3). In Chapter 4, I more closely investigate income and price effects on mental health medication use for people with mental health risk, and find that for people with a health card there is no price barrier for mental health medication use, but for those without a health card there is a positive income gradient. This later finding indicates that price may be a barrier in middle income groups. Finally, in Chapter 5 I explore the demand response of mid-high income seniors following income eligibility changes to the Commonwealth Seniors Health Card. I find no evidence of increased uptake of mental health medication compared to two control groups, and thus conclude there is no evidence of price effects among this group of mid-high income seniors.

2.9 Conclusion

Ensuring adequate access to mental health care is more challenging than for other health conditions. According to Frank and McGuire (2002) health financing issues related to moral hazard, externalities and adverse selection are more prominent for mental health than for general health. In addition, mental disorders can hamper rational demand decisions (Ettner and Schoenbaum, 2006). Investigating income and price barriers to mental health treatment requires attention to issues of endogeneity and measurement. Expansion of psychotropic treatments for mental health since the 1980s have changed the focus of treatment toward ambulatory care and community care in Australia and other developed countries, while lessening hospital-based mental health care. Australian mental health research provides evidence of equitable access to health care, although more rigorous analysis is needed. Other research has raised the problem of low treatment rates generally for mental health compared to other chronic conditions. Structural imbalance raised by health economist Darrel Doessel and colleagues (2008) points to a problem of operational inefficiency involving evidence of treatment for a significant share of people with no identified mental health condition and a significant level of non-treatment for people with a mental health condition. Mental health experts Harvey Whiteford and William Buckingham (2005) indicate that recent mental health sector reforms involving greater funding and availability of ambulatory care now require investigation on the effectiveness of these investments.

Australia’s health care system aims to provide equitable access to mental health care, but more research is needed to quantify that this aim is met. In the subsequent chapters, I investigate several of the equity and efficiency issues raised in mental health care financing in Australia.

Chapter 3

Mental health trends in Australia from 1989 to 2004-05

3.1 Introduction

This chapter explores three aspects of mental health in Australia. It aims to document mental health trends, establish socio-economic relationships in mental health, and account for factors that led to the recent increase in both mental health risk and mental health medication use. Few studies have investigated recent trends in mental health in Australia. My research contributes to the literature on the demand for mental health treatment in Australia by documenting the increased take-up of mental health medication between 1989 and 2004-05, by showing the negative association of low income with mental health risk and related medication use, and by providing evidence on the factors that have contributed to the increases in both.

My analysis shows an increase in the share of adults reporting mental health risk in the National Health Survey, from 8.99 per cent in 1989 to over 16.4 per cent in 2004-05. The share of people with mental health risk using mental health medication has nearly doubled from 26.6 per cent to 47.2 per cent in 2004-05. The chapter shows that the majority of people with mental health risk are in low income groups and that mental health medication use is also highest for people in low income groups in Australia. The chapter also provides evidence that Australia's policy of targeted income assistance through the health card has been an important factor in ensuring adoption of new psychotropic treatments for low income people with mental health risk. However, results from decomposition analysis of the growth in mental health risk and mental health medication use between 1989 and 2004-05 show that the characteristics of people with mental health risk and those who use mental health medication account for only a small share of the growth in the prevalence of mental health risk and related mental health medication use. Factors not included in my decomposition model such as the increased availability of new mental health treatments, cultural changes toward mental health stigma as well as changes in provider behaviour are all likely to have contributed to the growth in mental health risk and medication use in Australia.

The chapter is organised as follows. I begin with a background section on general trends in mental health in developed countries. This section includes a discussion of the literature on the socio-economic determinants of mental health risk, as well as literature on mental health treatment trends, which underscore the importance of policy changes on treatment trends. This section is followed by background on the National Health Survey data used in the analysis of mental health trends. The section focuses on comparability issues in the four NHS surveys used from 1989, 1995, 2001, and 2004-05. Section 3.4 provides an analysis of the trends in mental health in Australia between 1989 and 2004-05, and Section 3.5 includes decomposition analysis of the growth both in mental health risk and mental health medication use between 1989 and 2004-05. The conclusion provides a summary of the main findings in this chapter.

3.2 Background on mental health trends, determinants and related health actions

3.2.1 Introduction

The purpose of this section is to provide the context for mental health trends observed in Australia. Deinstitutionalisation of mental health care occurred in many countries starting in the 1950s until the 1990s. The mental health care structure that evolved since deinstitutionalisation is the focus of my examination. This section reviews recent trends in mental health in the United States where more research is published. In addition this section reviews the literature on the characteristics of people with mental health disorders, with special focus on the role of income for mental health risk and the importance of funding policies in providing access to treatment.

3.2.2 Trends in mental health prevalence

As mentioned in chapter 2 measuring mental health is complex due to the heterogeneous nature of mental health and the lack of biological markers for most mental disorders. As a result, few studies exist in the literature on inter-temporal trends. Frank and Glied (2006) provide a useful discussion of issues involved in trend analysis and discuss the results of intertemporal studies conducted in the United States. According to the authors, growing income over the past 50 years would be expected to lower mental health prevalence, yet over the same period there have been many new disorders added to the Diagnostic and Statistical Manual of Mental Disorders (DSM).[16] In their view this has resulted in the generally stable prevalence of mental health disorders over time. Based on a review of studies conducted in the United States since the 1950s, Frank and Glied (2006) estimate a prevalence range of 15 to 30 per cent of the US population having a diagnosable mental health condition over a twelve month period.

Few studies have documented trends in the prevalence of mental health disorders in Australia, but researchers here also point to a stable underlying prevalence of mental health disorders. Prevalence estimates for adults from two Surveys of Mental Health and Wellbeing (1997, 2007) fall within the range of 18 to 20 per cent. An examination of depression trends by McManus and co-authors (2000) discuss the increased reporting of depression observed in the 1995 NHS compared to 1989 NHS, and indicate that this reflects developments in the treatment for depression rather than a change in the underlying disease prevalence.

According to Frank and Glied, given the range of policy issues associated with different mental health disorders and their severity, research effort is better expended on an instrumental definition of mental health prevalence that relates to a policy concern. In concurrence with this view, my research focuses on Australia's non-

[16] See the previous footnote for details on the Diagnostic and Statistical Manual of Mental Disorders.

institutional, domiciled sub-population with mental health risk and access issues related to mental health medication use. The next section discusses the socio-economic characteristics associated with having mental health risk.

3.2.3 Socio-economic determinants of mental health risk

Frank and Glied (2006) provide an overview of the relationship between key socio-economic characteristics and mental disorders from a review of studies conducted in the United States over the past 50 years. In all studies, they find a consistent relationship between mental health and low socio-economic status, whether measured by income, education or occupation level. Income related inequalities in mental health disorders are also identified in Great Britain from a longitudinal study (Wildman, 2003). Wildman's study finds that both relative income and absolute income contribute to mental health differences by income group. There is consensus in the literature, however, that the relationship between income and mental health is bidirectional (Frank and McQuire, 2000; Ettner, 1996). Furthermore, the correlations between physical health, mental health, income, education, and occupation level make it difficult to isolate the direction of causality (Brown et al, 2004).

Frank and Glied (2006) identify other important associations with mental health disorders. The relationship for age is generally an inverted U-shaped, with younger and older adults having lower rates of mental health disorders compared to middle age adults. Older people, however, are more likely to experience greater disability due to mental health problems. Regarding gender, they conclude from the review that the prevalence of mental disorders is similar for women and men but type of disorder could affect the balance: women are more likely to have depressive and other affective disorders, while men are more likely to suffer from alcohol and drug related problems. Frank and Glied (2006) also conclude that there are no clear racial trends in the prevalence of mental disorders from the US studies.

3.2.4 Trends and determinants of mental health treatment

Mental health treatment trends have changed due to the influence of many factors, including: technological developments, health funding policies, market influences, medical practitioners' recommendations of appropriate treatment as well as consumer preferences. Deinstitutionalisation of mental health care opened the development of new community-based mental health treatments, including cognitive therapies during the 1970s and new psychotropic treatments during the 1980s for depression and anxiety disorders.[17] Many of the new psychotropic treatments introduced during the 1980s were found to be more efficacious drugs compared to previous drugs. In Australia and other countries, the government significantly expanded funding for these treatments, pharmaceutical companies invested in promotional activities of the new treatments, and prescribing rates of these treatments significantly increased (Frank et al, 2005).

According to Doessel and others (2005) deinstitutionalisation of mental health care occurred in Australia during the three decades prior to the 1980s, and the trend continued into the 1990s but at a much slower pace. The development of new psychotropic medicines, new providers of psychotherapy (social workers and counsellors) and expansion of psychiatric services enabled the development of community-based mental health care that characterises the mental health care system in Australia today. Medication is the most common form of treatment for many mental health conditions, and by 2007, mental health medications (including antidepressants, anti-anxiety and antipsychotic drugs) were the most commonly prescribed drug type, accounting for an estimated 21.7% of prescriptions written by general practitioners (AIHW, 2008).

Research by Peter McManus and colleagues (2000) document the increased use of anti-depressants in Australia from 1990 to 1998. They find that dispensing of antidepressant prescriptions nearly tripled between 1990 and 1998 and that by 1998 the level of antidepressant use in Australia was similar to United States. McManus and colleagues (2000) attribute the increased uptake to increased awareness of

[17] For further discussion on these advancements see Chapter 3. *The Evolving Technology of Mental Health Care*. Chapter 3, Frank and Glied (2006).

depression, along with promotion and increased availability of new psychotropic medications.

Frank, Conti and Goldman (2005) describe a similar trend toward increased mental health treatment with psychotropic drugs in the United States since 1990. Like Australia, expanded expenditure by third party payers (insurance companies and state managed Medicaid programs) for mental health medications supported increased availability and subsequent use.

In Australia, availability, price and funding of prescription drugs is administered by the Commonwealth Government through the Pharmaceutical Benefits Scheme (PBS). Increasing use of new medications since the 1990s has been a driver of health expenditure growth. The share of medication to total health expenditure has increased from 10 per cent in 1996-97 to nearly 14 per cent in 2006-07 (AIHW, 2008). Sweeny documents the significant growth in mental health medication expenditure during the 1990s, accounting for over 20 per cent of total PBS growth (Sweeny 2002).

Many studies find evidence of the importance of socioeconomic factors in the use of mental health treatment. Generally, people in higher income groups are more likely to consult medical specialists compared to other income groups (Steele et al, 2006; Alegria et al, 2000; Wells et al, 1986). Higher education and occupational groups also account for greater use of mental health care (Wells et al, 1986). A more recent study by Freiman and Zuvekas (2000) finds that expanded insurance coverage including Medicaid and Medicare are significantly related to both use of medical specialist and psychotropic medication. Several other studies from the United States point to the significant role of Medicaid in improving access to mental health care, and in particular access to medications (Frank and Glied, 2006; Frank et al, 2005; Zuvekas, 2005). Frank and Glied (2006) estimate that 60 per cent of the population with serious and persistent mental illness is covered by Medicaid and Medicare programs. Public insurance provision of medical care and subsidisation of pharmaceuticals also contribute to access to mental health care in Australia. However, economic analysis of the impact of health policy on access to mental health care has not been conducted here.

Previous studies from Australia have been focused more broadly on the role of socio-economic status and mental health service use. Parslow and Jorm (2001, 2000) conclude that socio-economic factors are less important than need factors. A recent study by Andrew Page and colleagues (2009) using PBS administrative data by sex, age and statistical local area of prescription, finds sex and age are significant factors in anti-depressant use, while socioeconomic status as measured by the economic resource index of the Socio-Economic Indexes for Areas (SEIFA) was not important. Data on personal or household income was not available in either study.

Other important factors that affect access to mental health treatment are proper diagnosis, patient knowledge, and stigma or cultural attitudes to mental health issues. Ettner and Schoenbaum (2006) make the point that if people are not properly diagnosed there are unlikely to be properly treated.

3.2.5 Concluding remarks

Based on review of studies over a 50 year period, Frank and Glied (2006) present the view that mental health prevalence has been fairly stable in the US population despite many economic and social developments, with approximately 15 – 30 per cent of the adult population experiencing a mental health disorder in any given year. Mental health treatment trends, however, have changed due to the influence of many factors, including: technological developments, health funding policies, market influences, medical practitioners' recommendations of appropriate treatment and ultimately patients' treatment preferences. Deinstitutionalisation of mental health care during the three decades prior to the 1980s opened development of new community-based mental health treatments. Many of the new psychotropic treatments introduced during the 1980s were found to be more efficacious compared to previous drugs. Governments in Australia and United States significantly expanded funding for these treatments, pharmaceutical companies invested in promotional activities of the new treatments, and prescribing rates of these treatments significantly increased. These factors resulted in greater use of mental health medication for people with mental disorders.

The aim of the remainder of this chapter is to investigate the characteristics of people with mental health risk in Australia, the factors that contribute to mental health medication use for people for with mental health risk, as well as key trends estimated from four National Health Surveys. The next section discusses the data from NHS surveys from 1989, 1995, 2001, and 2004-05.

3.3 Data from National Health Surveys 1989, 1995, 2001, and 2004-05

3.3.1 Introduction

The analysis in my thesis relies on data from four National Health Surveys (NHS). The Australia Bureau of Statistics has undertaken nation-wide health surveys regularly over the past three decades with the first Australian Health Surveys conducted in 1977-78 and 1983. These were followed in 5-year intervals with the National Health Surveys conducted in 1989-90 and 1995. In 2000, a new triennial health survey series was initiated, with a subsequent survey in 2004-05. The latest survey from 2007-08 recently became available after the much of my research was completed.

In addition to providing information on health status, risk factors and related actions, the National Health Surveys include details on demographics, education, work, income, health insurance/health cards and geography. While the aim of providing a representative snapshot of the state of health among Australians is consistent among the surveys, significant differences in questions and sampling methodology pose comparability challenges between the series. According to ABS documentation there generally is consistency between 2001 and 2004-05 surveys. Data, particularly related to chronic health conditions in earlier National Health Surveys, however, is not directly comparable with the later series starting in 2001 (ABS, 2006, 2003b, 2003d).[18] In addition, a greater number of variables and a great number of responses

[18] According to the ABS (2003c), the 2001 NHS questionnaire underwent significant revisions to provide more detailed information on several of the National Health Priority Areas. In their view the degree of comparability with earlier surveys has been affected somewhat for several National Health

to some variables exist in the later surveys. Generally, I found it was possible to combine variables or the level of detail within a variable in the later surveys to gain consistency with the early surveys.

Issues of comparability are paramount for trend analysis as key variables are compared across the 1989, 1995, 2001, and 2004-05. This section will discuss variable definition, comparability and adjustments across the four surveys in the following areas: mental health risk and mental health medication use, income, and socio-demographic variables.

Weights are provided in the NHS for the purpose of calibrating survey data with the Australia's benchmark population at the time of the National Health Survey. I utilise the weights in presenting descriptive statistics, such as variable means, in order to proximate results for the Australian population. However, all estimation models in my thesis are based on unweighted data. Following current practice, I estimated my models with both weighted and unweighted data, and found the results to be generally unaffected, and therefore chose not to use weighted data. According to Angrist and Pischke (2009) due to the lack of clear consensus on the use of weights in regression analysis my approach is reasonable. In addition, to account for possible heteroskedasticity in the unweighted data robust standard error techniques are used in the estimations.

Expanded Confidential Unit Record File (CURF) data with more detailed information is available for the 2001 and 2004-05 surveys through the ABS Remote Access Data Laboratory (RADL) website. Where possible I have utilised the expanded data for my thesis.

Priority Areas and other long-term conditions. However, other topic areas such as risk factors and health service use are largely unaffected by the changes to the NHS, and provide a stable time-series.

3.3.2 Definition and comparability of mental health variables

Defining mental health risk

Information on the state of Australia's mental health is captured in a limited way in the National Health Survey. First, the survey does not include two groups that may have serious and persistent mental illness: institutionalized people or homeless people. Excluding these groups from the sample provides for a somewhat more homogenous sample and potentially reduces possible unobservable heterogeneity. Second, unlike medical conditions where survey respondents are asked about a doctor's diagnosis of a condition, mental health status in the NHS relies on self-reports of a mental health chronic condition (lasting over six months) and questions or measures to determine current level of distress or happiness, in which different measures have been used over the years. Self reporting may lead to underreporting bias especially for people who attach a negative stigma to mental health disorders.

In general, the collection of information on the population with mental health disability is not consistent across the past four National Health Surveys. While a high degree of consistency exists between 2001 and 2004-05 on self-reported mental health status, different questions and measures were used in the earlier two surveys.[19] This section reports on the methodologies that I used to construct comparable measures of mental health risk and mental health medication use across the four surveys. The approach taken to determine mental risk is to consider all possible indications, such as a self-report of mental health chronic condition, a very high level of current distress, or use of mental health medication (the data reveals that mental health medication use occurs without indication of need, i.e., by the other two measures). These variables, although somewhat different, are available in all four surveys.

[19] According to the NHS Users' Guide mental health data from earlier National Health Surveys is not directly comparable with the later series starting in 2001 (see ABS 2003c).

Mental health long-term condition

All National Health Surveys ask respondents to indicate if they have health conditions that have lasted 6 months of more, which includes mental disorders such as: mood disorders (major depression, dysthymia, and mania); anxiety disorders (generalised anxiety disorder, panic disorder, simple phobia, social phobia, and agoraphobia); and substance use disorders (abuse of or dependence on either alcohol or drugs).

The methodology used to determine of type of illness in 1989 and 1995 and long-term condition in the later surveys poses a problem of comparability, according to the ABS (2003c). The list of conditions is standardized to the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) list for 2001 and 2004-05, while the 1989-90 and 1995 surveys have conditions coded more broadly classified by the ICD-9. The share of people reporting a mental health long-term chronic condition in the earlier NHS surveys were significantly lower at 5.36 per cent in 1989 and 6.05 per cent in 1995 compared to 11.22 per cent in 2001 and 13.13 per cent in 2004-05.

Current distress

In addition to long-term mental illness, the National Health Survey obtains information on the current level of distress or mental wellbeing. Three different measures have been used in the four surveys. In order to achieve comparability across the surveys, an approach taken in another published study to achieve comparability of two of the measures is relied upon. The Kessler 10 Score is used in 2001 and 2004-05, while the 1995 survey relies on the SF-36 Mental Health Component Summary Score. The 1989 NHS uses a self-assessed happiness score (ABS, 1998b).

The distress measure used in the later two surveys, the Kessler 10 Score (K10), is based on 10 questions on current level of distress with score ranging from 10 (indicating no distress) to 50 (indicating severe distress). The NHS records responses on a five-category scale, and were partitioned into four levels: low (10–15), moderate

(16–21), high (22–29) and very high (30–50) (ABS, 2003a). I restrict my definition of current distress in 2001 and 2004-05 to those with a very high K10 score.[20]

In 1995, the Short Form Health Survey (SF-36) was used to derive eight dimensions of health and wellbeing and aggregate into two measures: the Mental Component Summary (MCS) and the Physical Component Summary (PCS). Scores range from 0 to 100 and a higher score indicates better mental or physical health or wellbeing. According to a study by Eakert and co-authors (2004) a MCS score of 42 or less detects depression, which was used as my cut-off indicator of current distress.

In 1989, the current level of distress was assessed with a 4 point scale of self-reported happiness (ABS, 1992). The top two codes (3 and 4): unhappy and very unhappy were used in my indictor of current distress.

Current distress as measured by these indicators has risen from 4.58 per cent in 1989, to 8.39 per cent in 1995, 13.15 per cent in 2001, and 13.38 per cent in 2004-05.

Mental health medication

Questions on mental health medication use are included in all four National Health Surveys, with slight differences between the first two surveys compared to the later two. The approach taken for mental health medication use was to consider any prescription medication used for mental health conditions, excluding sleeping pills and pain medication.

The methodology used in the 1989 and 1995 relates use of a type of medication to a list of conditions. This allows for a precise measure of tranquilliser use for mental health disorders, for instance, as there is a high rate of tranquilliser use for non-mental health conditions. However, in these early surveys there are a limited number of medications included in the surveys. The1989 survey has tranquillisers and other medication; there is no tracking of anti-depressants, or anti-psychotics. In 1995,

[20] The ABS (2003a) report indicates that a very high K10 Score indicates a need to seek professional help.

tranquillisers, anxiety medication and other medications for mental health problems are used to construct the mental health medication variable.

In 2001 and 2004-05, specific questions are asked on medication use for mental wellbeing. For my variable, sleeping tablets are eliminated from the list of mental health medication, leaving: tablets for anxiety and nerves, tranquillisers, antidepressants, mood stabilisers and other medication for mental health.

For both 2001 and 2004-05 there was a small share that indicated use of a mental health medication but did not indicate a long-term mental health condition, or a very high level of short term distress. It is possible that mental health medication use without a mental health condition may be due to under-reporting of mental health conditions, but there is no way to verify this. Given the way the question was asked in 1989 and 1995, there were no observations using mental health medication without a mental health conditions.

Based on the results from the four NHS surveys, the share of the adult population using mental health medications increased significantly over the fifteen year period, from 2.4 per cent in 1989, 3.6 per cent in 1995, 6.8 per cent in 2001, and 8.4 per cent in 2004-05.

As a result, having mental health risk is derived from the following criteria: either a self-report of a mental health chronic condition, a very high K10 Score (or other distress score), or taking mental health prescription drugs, as defined above. The share of the population at risk for mental health problem has risen over the past 15 years from 8.9 in 1989, 13.3 per cent in 1995, 14.9 per cent in 2001, and 16.4 per cent in 2004-05. These trends are summarized in Section 3.4 in Table 1.

3.3.3 Definition and comparability of income variables

All four NHS surveys include data on income: personal, household and household equivalent income decile that the person belongs to. In order to provide consistency in the analysis across the years, I utilised the equivalised household income decile variable in this Chapter, although slight differences in measures of income equivalency are used in various survey years.

In the 1989 and 1995, equivalent income decile data is constructed with the same methodology and is based on a 2 adult and 1 child unit (ABS, 1995a). A similar equivalent income decile measure is available for 2001. Equivalised household income from the 2004-5 NHS has been standardised to a single person household, reflecting more recent use of the OECD scale (ABS, 2006a).[21] I convert decile income variables to income quintiles and include a dummy variable for missing income.

3.3.4 Definition and comparability of other chronic condition variables

In order to provide some comparison of mental health with other national disease priorities I identified consistent data on the following chronic conditions across the four surveys: heart problems, cancer, diabetes and asthma. Similar information on health actions were available in all four surveys, including: medication use, doctor, specialist and hospital visits, except use of cancer medication is not included in the 2004-05 NHS.

3.3.5 Definition and comparability of socio-demographic variables

Data on socio-demographic variables were mostly consistent across the four surveys. However, more detailed data from the later surveys needed adjusting for consistency with the 1989 survey. For instance, details on work status, part time and full time were not included in 1989, so a variable *WORKING* was used, which captures either working part time or full time. In addition, questions on highest level of post high school education were asked on a sub-sample in 1995 so the means of these variables in 1995 are not comparable to the full sample in the other surveys.

[21] For full discussion of comparability issues see the National Health Survey: Users' Guide 2004-05 (ABS, 2006a, 151).

Having a concession health card (*WHCARD*) in the 1989 NHS includes the Pensioners Concession Card, the Health Care Card and the Veterans Health Card. The Commonwealth Seniors Health Card was introduced in 1994 and therefore included in the definition of the health concession card in the 1995, 2001 and 2004-05 NHS. Policy changes affecting eligibility for some health cards would affect the share of people reporting having a health card across surveys. The effect of having a concession health card on mental health medication use is investigated in more detail in Chapters 4 and 5.

3.3.6 Concluding remarks

The National Health Survey provides a rich source of data on health status, health actions, income and other socio-demographic characteristics for Australia over time. Complete comparability of all variables is not possible, especially for mental health risk and mental health medication use. Data definitions of mental health risk and mental health medication use are consistent for the later two surveys. Every effort was made to adjust the different codes and definitions used for mental health variables in the 1989 and 1995 survey to be consistent with the later surveys. The subsequent section provides an indication of changes in self-reporting mental health risk and related medication use in NHS over the past four surveys.

3.4 Mental health trends in Australia from 1989 to 2004-05

3.4.1 Introduction

This section examines trends in mental health risk and mental health medication use in Australia from four National Health Surveys which previously have not been documented. First, an overview of the trends in those reporting mental health risk and mental health medication use in the NHS are presented. This is followed by trends in the income gradient for people with mental health risk and trends in the income gradient for related medication use. The data reveal that the negative income gradient observed for mental health risk is also observed for mental health medication use. These trends are confirmed for other chronic conditions, which suggests the potential importance of targeted support programs such as the health card to ensure treatment access for mental health and other chronic conditions in Australia, and points to the need for more in-depth research.

3.4.2 Overview

My analysis from four National Health Surveys provides new evidence on the increase in reporting of mental health risk and on the significant adoption of mental health medication from 1989 to 2004-05. My results are compared to similar data obtained from the Survey of Mental Health and Wellbeing. Consistency issues across the four NHS surveys are discussed. The results of my statistical analysis are presented with weighted data in order to report on population shares consistent with the Australian population at the time of each survey.[22]

Table 3.1 shows summary statistics for the Australian adult population with and without mental health risk. The table shows that the share of the adult population reporting mental health risk nearly doubled between 1989 and 2004-05 from 8.9 per cent to 16.4 per cent and that the share of the population using mental health medication more than tripled from 2.4 per cent in 1989 to 7.7 per cent in 2004-05. The share of the population using mental health medication increased from 26.6 per cent in 1989 to 47.2 per cent in 2004-05.

Table 3.1 also reveals that in 2001 and 2004-05 there was a segment of the population without mental health risk using mental health medication, approximately 3.3 per cent of those without mental health risk in 2001 and 2.3 per cent in 2004-05. This small share of the population reporting mental health medication without mental health risk may be attributable to measurement error due to under-reporting of mental health conditions, or it is plausible that some people may take mental health medication with insufficient mental health need, as indicated by research conducted by Doessel and colleagues (Doessel, Williams and Nolan, 2008). However, it is not possible to verify either explanation.

[22] ABS User Guides for each NHS provides details on benchmark population.

Table 3.1: Mental health risk trends for Australia's adult population

	Full Sample	Mental health risk	Without mental health Risk
1989			
Share with mental health risk	0.089	1.000	0.000
Share using mental health medication	0.024	0.266	0.000
Total Adult Population	11,861,085	1,058,850	10,802,235
1995			
Share with mental health risk	0.133	1.000	0.000
Share using mental health medication	0.036	0.268	0.000
Total Adult Population	13,389,881	1,778,972	11,610,909
2001			
Share with mental health risk	0.149	1.000	0.000
Share using mental health medication	0.068	0.454	0.033
Total Adult Population	14,181,410	2,116,893	12,064,517
2004-05			
Share with mental health risk	0.164	1.000	0.000
Share using mental health medication	0.077	0.472	0.023
Total Adult Population	14,963,100	2,450,978	12,512,122

Source: National Health Surveys 1989, 1995, 2001 and 2004-05
Notes: Numbers and means are weighted to reflect Australia's benchmark population at time of survey; 1989 is 20 years and older; all other years are 18 years and older.

Comparability with the Survey of Mental Health and Wellbeing

The Survey of Mental Health and Wellbeing (SMHWB) conducted in 1997 and 2007 provides a source of comparison for my estimates of trends in mental health, despite significant differences in approach and years involved (ABS, 2009, 1998a, 1998b). The SMHWB utilises the Composite International Diagnostic Interview (CIDI) to gain a more accurate estimate the prevalence of specific mental disorders. The SMHWB found that 17.7 per cent of Australian population (18 years and older) in 1997 had a mental disorder at some time during the 12 months prior to the survey, and in 2007 this increased to 20.0 per cent of adults (16-85 years old). In general, my estimates of the adult population having mental health risk are below the SMHWB: with 13.3 per cent in 1995, 14.9 per cent in 2001, and 16.4 per cent in 2004-05.

Both Surveys of Mental Health and Wellbeing also found higher rates of medication use, as indicated by the share of respondents who indicated their need for medication was fully met; which was 52.8 per cent in 1997 and increased to 58.5 per cent in 2007. My estimates of the share of the adult population with mental health risk using mental health medication were: 26.8 per cent in 1995, 45.4 per cent in 2001, and 47.2 per cent in 2004-05.

While my estimates differ from the SMHWB estimates, the trends are generally consistent. My lower prevalence of mental health disorders is likely due to self-reporting bias and lack of diagnostic interview tools.

Explanations for increased reporting of mental health risk

Several factors could account for the rising trend in mental health risk revealed in the National Health Surveys over the past 15 years. First, the national mental health policy of deinstitutionalisation that occurred during the 30-year period until the early 1980s and continued into the 1990s but at a slower rate could have had a lagged effect on the sample population.[23] This gradual shift toward community-based treatment may have contributed to the growth in the number of National Health Survey respondents in private residence with mental health risk between 1989 and 2004-05.

Second, the definitional adjustments between the surveys explained in Section 3.3.2 have impacted the trend toward increased mental health risk. The key factors include: the expanded medications for mental health over the four surveys, additional categories for mental health chronic conditions between 1989 and 1995 surveys, and the adoption of the Kessler 10 Score for the later surveys to gain a more accurate indication of current distress.

[23] The dates regarding the process of deinstitutionalisation are taken from Doessel et al 2005.

Third, the expansion of available mental health medications during the 1990s to treat depression, anxiety, and other mental disorders discussed in Section 3.2.4 could have resulted in increased demand for mental health treatment and the increased number of people reporting mental health problems in the NHS. McManus and co-authors (2000) attribute the increased reporting of depression in the 1995 NHS to greater awareness of depression due to the availability of new treatments and reduced stigma associated with reporting depression.

Fourth, measurement error related to underreporting, possibly due to stigma associated with having mental illness, may have impacted earlier surveys moreso compared with the later surveys.

Finally, the ABS (2003d) attributes the increased disclosure of mental disorders to improved interview techniques and a greater level of public awareness and acceptance of mental health disorders.

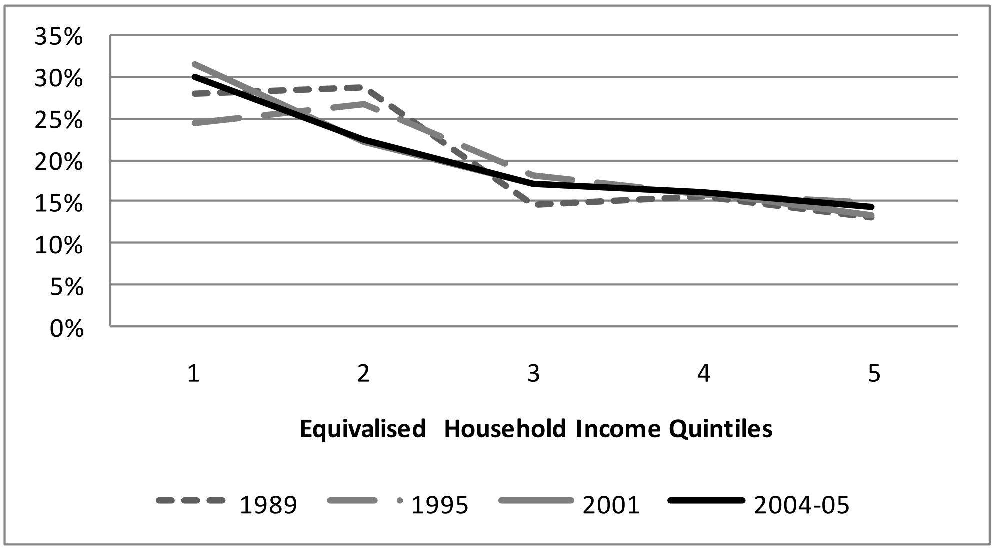
3.4.3 Income characteristics associated with mental health risk

This section provides a descriptive analysis of income characteristics associated with mental health risk and related medication use across the four National Health Surveys. It also provides a comparison of income and mental health associations with other chronic conditions. Data is shown for equivalent income by quintiles based on observations with reported income.

The following figures illustrate the stability of the negative income gradient for mental health risk and related medication use over the trend period. In addition, this negative income gradient is observed for other chronic conditions: heart problems, cancer, diabetes, and asthma, and for related medication use for those conditions.

Figure 3.1 shows the distribution of mental health risk by income quintile over the four surveys. The figure shows consistently higher rates of mental health risk in the lower income groups compared to the higher income groups. A shift from the second income quintile to the first income quintile is observed between the first two surveys and the later two. In 2004-05, 30 per cent of those with mental health risk are in income quintile 1 compared to 14.3 per cent in quintile 5.

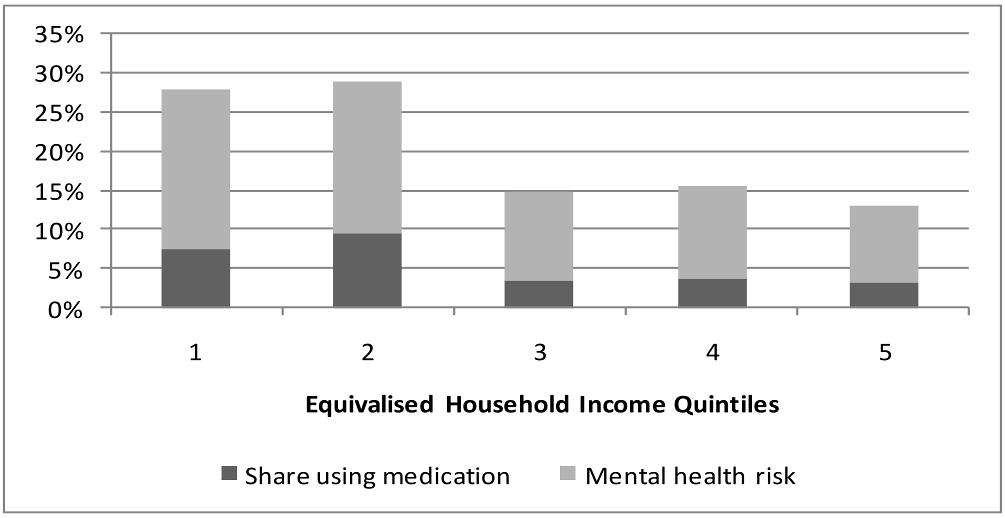
Figure 3.1: Mental health risk by income quintile for 1989, 1995, 2001, and 2004-05



Source: National Health Surveys 1989, 1995, 2001, 2004-05
Notes: Weighted data results, and adjusted for missing income observations.

Figure 3.2 shows the distribution of adults with mental health risk by income quintile in 1989 and the share of those using mental health medication. A similar comparison is shown for 2004-05 in Figure 3.3.

Figure 3.2: Mental health risk by income quintile and share using mental health medication in 1989

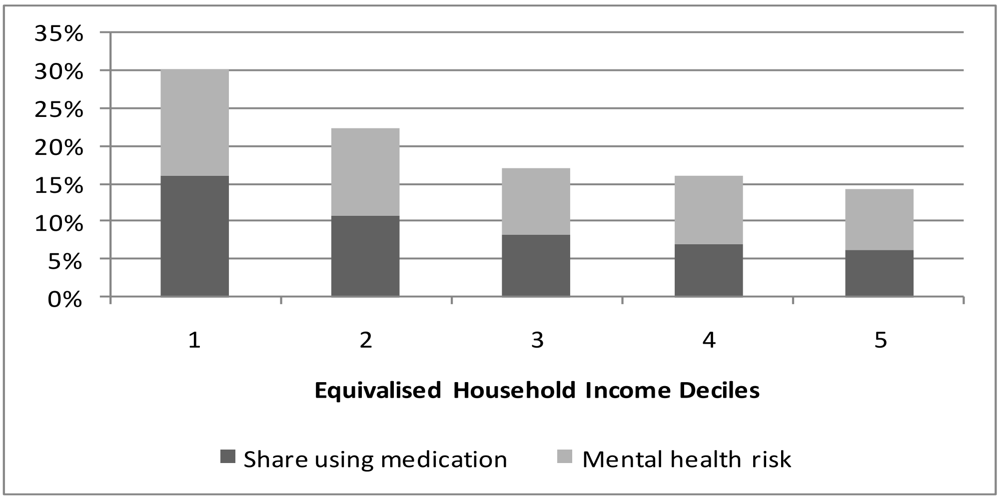


Source: National Health Survey 1989
Notes: Weighted data results, and adjusted for missing income observations.

Figure 3.2 shows that in 1989 27.8 per cent of people with mental health risk are in income quintile 1, compared to 13.0 per cent in income quintile 5. Similar shares using mental health medication are found across income groups, with 27.2 per cent of people with mental health risk in quintile 1 using mental health medication compared to 23.5 per cent in income quintile 5.

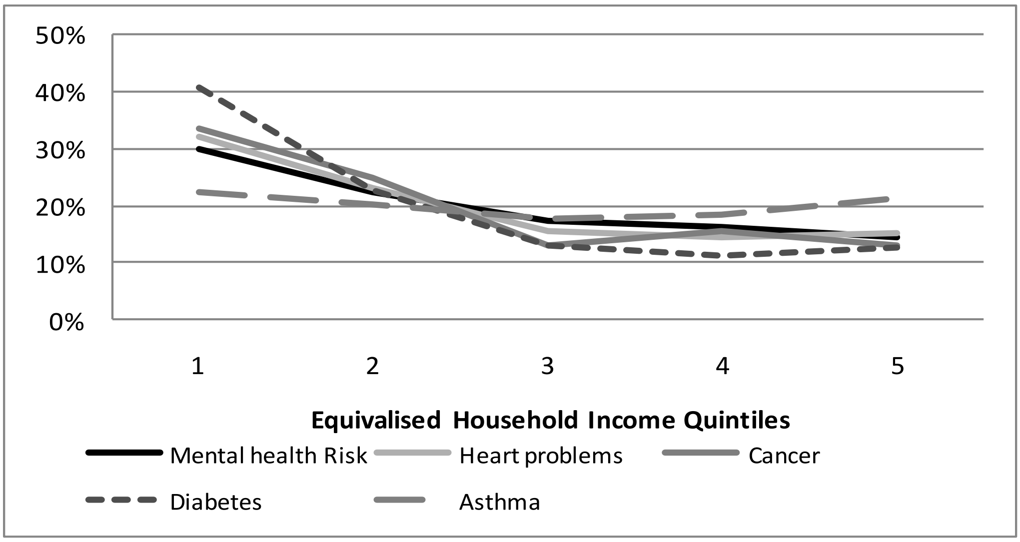
Figure 3.3 shows an increase in the share of people with mental health risk in income quintile 1 in 2004-05 compared to 1989, shown in Figure 3.2, as well as an increase in the share of those with mental health risk using mental health medication across all income quintiles in the later year. The figure shows that 30.0 per cent of people with mental health risk are in income quintile 1 compared to 14.3 per cent in income quintile 5. The share of those with mental health risk in income quintile 1 using mental health medication is 53.7 per cent compared to 43.4 per cent in income quintile 5.

Figure 3.3: Mental health risk by income quintile and share using mental health medication in 2004-05



Source: National Health Survey 2004-05
Notes: Weighted data results, and adjusted for missing income observations.

Figure 3.4: Mental health risk compared to other chronic conditions by income quintile in 2004-05



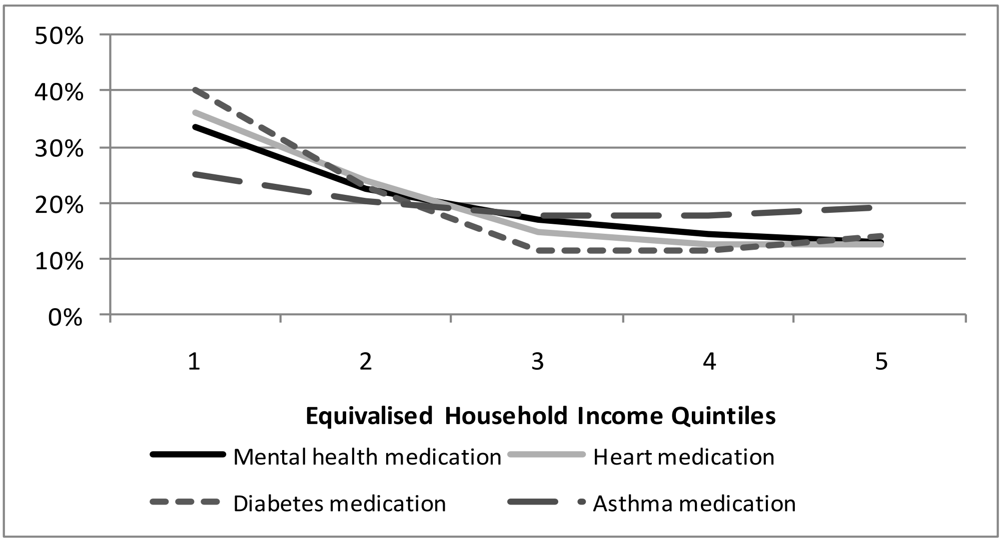
Source: National Health Surveys 1989, 1995, 2001 and 2004-05
Notes: Weighted data results, and adjusted for missing income observations.

Figure 3.4 shows the distribution of mental health risk by income quintile compared to other chronic conditions in 2004-05. A negative income gradient exists for these five conditions. The steepest gradient is for diabetes with 40.8 per cent of those with diabetes in quintile 1 and 12.4 per cent in quintile 5. Asthma is more evenly distributed with 22.5 per cent of people in quintile 1, 17.7 per cent in quintile 3 and 21.4 per cent in quintile 5. By comparison mental health risk is moderately sloped like heart problems and cancer.

The distribution of medication use for these chronic conditions (except cancer medication) by income quintile is shown in Figure 3.5.[24] The income gradient for medication use is similar to the income gradient for chronic conditions in previous figure.

[24] Cancer medication is not included in the 2004-05 NHS.

Figure 3.5: Mental health medication use by income quintile compared to medication use for other chronic conditions in 2004-05



Source: National Health Survey 2004-05
Notes: Weighted data results, and adjusted for missing income observations.

3.4.4 Concluding remarks

The preceding analysis shows both the expansion in the share of people with mental health risk and the share of those using mental health medication between 1989 and 2004-05. The data reveals that this expansion was concentrated among people in the lowest income group. While a negative income gradient is evident for mental health risk and mental health medication use, the analysis shows a similar negative income gradient for other chronic conditions, except asthma. Chapter 4 of my thesis provides a more in-depth investigation of the factors contributing to treatment access for people with mental health risk such as the health card. Further examination is suggested on the importance of targeted support programs such as the health card for accessing treatment for other chronic conditions in Australia. By providing the first documentation of these trends in mental health in Australia, my research makes an important contribution to health economics literature.

3.5 Factors associated with the growth in mental health risk and mental health medication use between 1989 and 2004-05

3.5.1 Introduction

This section uses decomposition analysis to show the factors that were associated with the growth in mental health risk from 8.9 per cent of the adult population in 1989 to 16.4 per cent in 2004-05, and the increase in the share of mental medication use among people with mental health risk from 26.6 per cent in 1989 to 52.8 per cent in 2004-05. An examination of the relative contribution of behavioural factors over socio-demographic characteristics to recent mental health trends has previously not been conducted. The analysis shows that both socio-demographic characteristics and behavioural factors were associated with the growth in the incidence of mental health risk, while behavioural factors were mainly associated with the growth in mental health medication use between 1989 and 2004-05.

3.5.2 Methodology

Decomposition analysis provides a method to determine the contribution of factors to the difference in an outcome variable over two time points or between two groups, such as males and females. Originally developed by Blinder (1973) and Oaxaca (1973) for linear regression, decomposition models have since been extended to nonlinear models, including probit models (Doiron and Riddell, 1994; Fairlie, 2005; Bauer, Hahn and Sinning, 2007; Bauer and Sinning, 2008).

With data on mental health risk and mental health medication use over time, decomposition analysis allows me to isolate the part of increased mental health risk or mental health medication use due to 1) changes in the differences in the characteristics of people with mental health risk or using medication between the two years: 1989 and 2004-05, and 2) the part that is attributable to behavioural factors. These two effects are also referred to as the “explained” or characteristics effect and the "unexplained" or coefficients effect. Decomposition analysis is applied in the same way and estimated separately for mental health risk and for mental health medication use. Discussion of the methodology will focus on mental health risk.

Using results from probit models for 1989 and 2004-05 on the determinants of mental health risk, the decomposition model is used to examine the contribution of these two effects to the increase in mental health risk over the 15 year time period.

The probit model for mental health risk is:

$$R_{it}^{*} = \beta_t X_{it} + \varepsilon_{it} \qquad \begin{cases} R_{it} = 1 \text{ if } R_{it}^{*} > 0 \\ R_{it} = 0 \text{ otherwise} \end{cases} \tag{3.1}$$

where R_{it}* is a continuous latent variable measuring mental health disorders and R_{it} is the observed mental health risk, where t=89, 05, X_{it} represents a vector of explanatory variables, and ε_{it} indicates unobserved factors which influence mental health risk and is assumed to be normally distributed with a mean equal to 0 and variance equal to 1.[25]

Equation 3.2 shows the decomposition equation for the difference in the mean outcome variable *Y*, a binary variable representing mental health risk, in the two time periods subscripts, t=89, 05, X is a vector of characteristics for individuals, i, N_t represents the size of the sample in t=89,05, Φ (.) indicates the cumulative density function for the standard normal distribution, and $\hat{\beta}$ represents the vector of coefficients from the probit estimation for each time period.

[25] A similar probit model is estimated for mental health medication use:

$$M_{it}^{*} = \gamma_t X_{it} + v_{it} \qquad \begin{cases} M_{it} = 1 \text{ if } M_{it}^{*} > 0 \,|\, R^* = 1 \\ M_{it} = 0 \,|\, R^* = 1 \text{ otherwise} \end{cases}$$

where M_i*is conditional on R* and is a continuous and latent variable measuring the utility gain of mental health medication use and M_i is the observed mental health medication use, where t=89, 05, and X_i represents a vector of explanatory variables and v_{it} indicates unobserved factors which influence mental health medication use and is assumed to be normally distributed with a mean equal to 0 and variance equal to 1.

$$\bar{Y}_{05} - \bar{Y}_{89} = \left[\frac{1}{N_{05}} \sum_{i=1}^{N_{05}} \Phi(X_{i05}\,\hat{\beta}_{05}) - \frac{1}{N_{89}} \sum_{i=1}^{N_{89}} \Phi(X_{i89}\,\hat{\beta}_{05}) \right] + \left[\frac{1}{N_{89}} \sum_{i=1}^{N_{89}} \Phi(X_{i89}\,\hat{\beta}_{05}) - \frac{1}{N_{89}} \sum_{i=1}^{N_{89}} \Phi(X_{i89}\,\hat{\beta}_{89}) \right] \quad (3.2)$$

The upper right-side term of the equation provides an estimation of the difference in mental health risk between the two years due to differences in the distribution of characteristics between the two years weighted by the coefficients from the later period, $\hat{\beta}_{05}$. This is referred to as the characteristic or endowment effect. The bottom right-side term considers the effect of the coefficients by holding constant the distribution of characteristics in t=89, X_{89}. The reference group chosen in the characteristics and coefficients parts of the equation will generally produce a different result in the decomposition analysis. It is therefore customary to consider the alternative specification as outlined below in (3.3), and to compare the results from both equations.

$$\bar{Y}_{05} - \bar{Y}_{89} = \left[\frac{1}{N_{05}} \sum_{i=1}^{N_{05}} \Phi(X_{i05}\,\hat{\beta}_{89}) - \frac{1}{N_{89}} \sum_{i=1}^{N_{89}} \Phi(X_{i89}\,\hat{\beta}_{89}) \right] + \left[\frac{1}{N_{05}} \sum_{i=1}^{N_{05}} \Phi(X_{i05}\,\hat{\beta}_{05}) - \frac{1}{N_{05}} \sum_{i=1}^{N_{05}} \Phi(X_{i05}\,\hat{\beta}_{89}) \right] \quad (3.3)$$

In specification (3.2), coefficients are set at 2004-05 levels for the characteristics effect; therefore 2004-05 is considered the base year for comparison. In equation (3.3), the coefficients from 1989 are considered the base year. The results will show that the distribution of the growth in mental health risk over the 15 year period attributable to the characteristics and the coefficients effects is slightly different but consistent for the two approaches.[26]

[26] Fairlie (2005, page 307) explains that technically the decomposition results from equations 3.2 and 3.3 will hold exactly for logit models due to the cumulative distribution function from the logistic distribution and will not hold exactly for probit models (due to the cumulative distribution function from the standard normal distribution), but he finds in empirical testing that probit results hold very closely.

Fairlie (2005) also developed a method to further explore the contribution of individual characteristics to the outcome differential. He contends that in a non-linear model the contribution of each characteristic to the gap is equal to the change in the predicted probability from replacing that one characteristic with the other group's (in this case time period) distribution while holding the distributions of the other characteristics constant. Fairlie's approach is based on coefficient estimates from a pooled sample, $\hat{\beta}^*$. In my model of mental health medication risk, the contribution of one characteristic, X_1, to the outcome differential mental health risk in the two periods can be expressed as follows:

$$\frac{1}{N_{89}} \sum_{i=1}^{N_{89}} \Phi(\hat{\alpha}^* + X_{1i05}\hat{\beta}^*{}_1 + X_{2i05}\hat{\beta}^*{}_2) - \Phi\left(\hat{\alpha}^* + X_{1i89}\hat{\beta}^*{}_1 + X_{2i05}\hat{\beta}^*{}_2\right) \tag{3.4}$$

Some researchers do not endorse this approach on the grounds that it produces arbitrary results due to the sensitivity in non-linear models to the ordering of the characteristics in decomposition (see footnote 7 in Bauer, Göhlmann and Sinning 2007). In order to address this issue, Fairlie's decomposition method in Stata 10 provides an option to randomise the order of the characteristics through replication.[27] An alternative approach would be to consider all possible variable ordering and average across them as outlined in Ham, Svejnar and Terrell (1998). Fairlie reports that random ordering of variables yields the same results as averaging (Fairlie, 2005). The approach involves a repeated sampling procedure to achieve a one-to-one matching in cases where the two groups are not equal in size (Fairlie, 2005).

3.5.3 Data

Behavioural models for mental health risk and mental health medication use are constructed using comparable data from the National Health Surveys for 1989 and 2004-05. The sample is based on the population of adults over 20 years of age due to the 5-year age categories in the 1989 NHS. Table 3.2 provides definitions of the variables used. Further detail on variable definitions is provided in Section 3.3.

[27] Stata 10 statistical software and related reference material was used in this paper.

Table 3.2: Variable definitions

Variable	**Definition**
MHRISK	1 if mental health chronic condition or very high current distress or taking mental health medication
MHMEDS	1 if taking prescription drug to treat mental health condition, excludes sleeping pills
INCQ1	1 if equivalent unit income quintile 1
INCQ2	1 if equivalent unit income quintile 2
INCQ3	1 if equivalent unit income quintile 3
INCQ4	1 if equivalent unit income quintile 4
INCQ5	1 if equivalent unit income quintile 5
INCQMIS	1 if missing income
AGE2024	1 if 20-24 years old
AGE2529	1 if 25-29 years old
AGE3034	1 if 30-34 years old
AGE3539	1 if 35-39 years old
AGE4044	1 if 40-44 years old
AGE4549	1 if 45-49 years old
AGE5054	1 if 50-54 years old
AGE5559	1 if 55-59 years old
AGE6064	1 if 60-64 years old
AGE6569	1 if 65-69 years old
AGE7074	1 if 70-74 years old
AGE7579	1 if 75-79 years old
AGE80PL	1 if 80 years old or more
FEMALE	1 if female
MARRIED	1 if married
WORKING	1 if working part time or full time
UNEMPLYD	1 if unemployed
NOTINLF	1 if not in the labour force
HIEDUC	1 if tertiary qualification
SOMEDUC	1 if trade or diploma qualification
NOEDUC	1 if no qualifications above high school
OTHCCON	1 if other chronic condition: heart problems, cancer, diabetes or asthma
CITY	1 if major city resident
WHCARD	1 if health card
WHI	1 if private health insurance
ENGLISH	1 if English main language spoken at home
AUBORN	1 if Australian born
NUBORN	1 if New Zealand or UK born
OTBORN	1 if other country born

Table 3.2 *continued*

FEXWORK	1 if female working part time or full time
FEXNILF	1 if female not in labour force
FEXUNE	1 if female unemployed
MAXWORK	1 if female working part time or full time
MAXNILF	1 if female not in labour force
MAXUNE	1 if female unemployed

3.5.4 Model and results for mental health risk

The dependent variable for having mental health risk is a binary variable, and therefore the model is estimated by probit regression. The model includes characteristics associated with mental health risk, with the main aim of accounting for the change in mental risk either due to changes in mean characteristics or behavioural factors. A causal model of the determinants of mental health risk would need to address endogeneity issues such as the relationship between low income and mental health risk, which is not the focus of the current analysis.

The model includes socio-economic factors associated with mental health risk identified in the literature previously discussed in Section 3.2.3. This includes variables for income, labour force status and education. Having a health card is included in the model as it is a general indication of low income, as low income is one of the eligibility criteria for the health card. Having private health insurance is also included in the model as it generally captures information about those with high income and/or wealth. In Australia, due to tax incentives people with high income are more likely to have private health insurance.

Other socio-demographic characteristics are included in the model. Age is entered for age groups to account for the inverted U-shape relationship with mental health risk. Gender differences with respect to labour force are expected and therefore the model includes female-labour status interaction terms. Having another chronic condition is included due to co-morbidity of chronic conditions such as diabetes, health disease, cancer and asthma with mental health risk. Being married is identified in the literature as having a protective effect for mental health disorders. Other covariates include area of residence (urban or non-urban), and cultural factors such as main language spoken at home and country of birth.

Table 3.3 indicates sample means for 1989 by comparing those with mental health risk to those without mental health risk. There are significant differences between the two groups for all factors considered, as shown by the *t*-test statistic in the last column. As expected the mental health risk group is more likely to be in the lower income groups, have a lower level of post high school education, more likely to be unemployed or not in the labour force. The share with a health card is 52.5 compared to 25.1 per cent for those without mental health risk, and the share with private health insurance is lower at 41.7 per cent compared to 53.5 per cent. The share of females with mental health risk is greater than males, and the share of females not in the work force with mental health risk is much great than the share of males. In 1989, those with mental health risk are on average 8 years older, at 51.5 compared to 43.7 for the group without mental health risk. A lower share of people with mental risk has English as their main language and fewer are Australian born compared to people without mental health risk.

Table 3.4 provides a similar comparison of the two groups in 2004-05. Most of the differences between those with mental health risk and those without remain although there is convergence on a few characteristics. The average age for those with mental health risk declined in 2004-05 to 48.8 years, which is nearly the same for the group without mental health risk. The share with the highest level of education increased for both groups and there is no gap in the share with some post-high school education between those with mental health risk and those without. A higher share in the mental health risk group has English as the main language spoken at home compared to 1989 and compared to the group without mental risk in 2004-05. In addition, in 2004-05 a higher share of those with mental health risk are Australian born compared with 1989.

Table 3.3: Sample means for 1989: sub-population with no mental health risk compared to sub-population with mental health risk, 20 years and older

Variable	**No mental health risk**	**With mental health risk**	**Difference**	**|*t*|-*value***
INCQ1	0.122	0.259	-0.137	22.115***
INCQ2	0.180	0.266	-0.086	12.106***
INCQ3	0.189	0.137	0.052	7.367***
INCQ4	0.208	0.145	0.063	8.649***
INCQ5	0.237	0.124	0.113	14.856***
INCQMIS	0.063	0.069	-0.006	1.323
AGE	43.699	51.546	-7.848	25.761***
FEMALE	0.507	0.571	-0.064	7.044***
MARRIED	0.705	0.578	0.127	15.143***
WORKING	0.633	0.369	0.264	30.090***
UNEMPLD	0.040	0.061	-0.021	5.771***
NOTINLF	0.326	0.570	-0.243	28.312***
HIEDUC	0.098	0.058	0.039	7.430***
SOMEDUC	0.371	0.309	0.062	7.035***
NOEDUC	0.532	0.633	-0.101	11.160***
OTHCCON	0.331	0.510	-0.179	20.781***
CITY	0.652	0.713	-0.061	7.056***
WHCARD	0.251	0.525	-0.273	34.089***
WHI	0.535	0.417	0.118	13.029***
ENGLISH	0.903	0.831	0.072	13.073***
AUBORN	0.722	0.666	0.056	6.818***
NUBORN	0.119	0.100	0.020	3.343***
OTBORN	0.159	0.234	-0.076	11.170***
FEXWORK	0.260	0.162	0.098	12.422***
FEXNILF	0.226	0.383	-0.157	20.232***
FEXUNE	0.021	0.026	-0.006	2.102**
MAXWORK	0.373	0.207	0.166	19.121***
MAXNILF	0.100	0.187	-0.087	15.348***
MAXUNE	0.019	0.035	-0.016	5.989***
MHMEDS	0.000	0.269	-0.269	30.231***
Observations	33,958	3,306		

Source: National Health Survey 1989

Notes: Unweighted data. ***Significant at 1% level, **significant at 5% level, *significant at 10% level.

Table 3.4: Sample means for 2004-05: sub-population with no mental health risk compared to sub-population with mental health risk, 20 years and older

Variable	**No mental health risk**	**With mental health risk**	**Difference**	***|t|-value***
INCQ1	0.191	0.316	-0.125	-16.369***
INCQ2	0.151	0.187	-0.036	-5.226***
INCQ3	0.153	0.142	0.012	1.756*
INCQ4	0.169	0.130	0.039	5.674***
INCQ5	0.194	0.113	0.081	11.377***
INCQMIS	0.141	0.113	0.028	4.409***
AGE	48.515	48.761	-0.246	-0.763
FEMALE	0.528	0.618	-0.090	-9.656***
MARRIED	0.519	0.396	0.124	13.277***
WORKING	0.638	0.472	0.166	18.290***
UNEMPLD	0.020	0.043	-0.023	-8.124***
NOTINLF	0.343	0.485	-0.143	-15.888***
HIEDUC	0.195	0.139	0.055	7.655***
SOMEDUC	0.334	0.330	0.004	0.453
NOEDUC	0.471	0.530	-0.059	-6.366***
CITY	0.634	0.612	0.022	2.449**
WHCARD	0.353	0.558	-0.205	-22.816***
OTHCCON	0.395	0.529	-0.134	-14.602***
WHI	0.522	0.402	0.120	12.927***
ENGLISH	0.931	0.942	-0.011	-2.318***
AUBORN	0.728	0.753	-0.025	-2.995***
NUBORN	0.125	0.117	0.007	1.198
OTBORN	0.147	0.129	0.017	2.655***
FEXWORK	0.292	0.269	0.023	2.697***
FEXNILF	0.227	0.326	-0.099	-12.401***
FEXUNE	0.010	0.023	-0.013	-6.453***
MAXWORK	0.346	0.203	0.143	16.489***
MAXNILF	0.116	0.159	-0.043	-6.999***
MAXUNE	0.010	0.020	-0.010	-4.949***
MHMEDS	0.023	0.499	-0.476	50.321
Observations	15,517	3,501		

Source: National Health Survey 2004-05

Notes: Unweighted data. ***Significant at 1% level, **significant at 5% level, *significant at 10% level.

Table 3.5 shows the estimation results for mental health risk for both years. All models are estimated with robust standard errors to account for possible heteroskedasticity. The results for 1989 show that many of the variables have the expected sign and are statistically significant. Low income quintile variables are positively associated with mental health risk as is living in a major city, being female, not in the labour force and unemployed. The interaction effect of female and labour status variables are also positive when compared to the omitted category working males. Having a chronic condition and having the health card are also positively associated with mental health risk. Having private health insurance, being married, and being in the youngest and oldest groups are negatively associated with mental health risk.

The estimation results for 2004-05 in Table 3.5 are consistent with the results for 1989, with a few exceptions. Except for the 20-24 year old group, many of the young to middle age groups are positive and significantly associated with mental health risk. Many of the variables are no longer statistically significant in 2004-05. This is consistent with the lower Pseudo R^2 of 0.067 compared with the Pseudo R^2 of 0.088 found in 1989.

By estimating the probit model of mental health risk with the data pooled and including interactions variables for each variable with 2004-05, a Wald test is used to test if the later year coefficients were jointly significantly different from zero and hence different from the 1989 estimated coefficients. The result of the Wald test shows that the 2004-05 estimated coefficients were jointly significant at the 1 per cent confidence level. This provides for the conclusion that the estimated coefficients on mental health risk are significantly different between the two years; a result also confirmed by the decomposition results.

Tests on the equality of the income coefficients in 1989 and 2004-05 were also conducted to account for the possible influence of an increase in real income over the time period. The results show that the income coefficients are the same across time periods, indicating there is no influence of the growth in real income in mental health risk model.

Table 3.5: Estimation results for mental health risk, persons 20 years and older

	1989		2004-05	
	Coefficient	Standard Error	Coefficient	Standard Error
INCQ1	0.163	0.043^{***}	0.131	0.048^{***}
INCQ2	0.118	0.038^{***}	0.115	0.045^{**}
INCQ3	0.056	0.035	0.130	0.042^{***}
INCQ4	0.105	0.034^{***}	0.098	0.041^{**}
INCQMIS	0.167	0.045^{***}	0.014	0.044
AGE2024	-0.611	0.052^{***}	-0.134	0.054^{**}
AGE2529	-0.432	0.047^{***}	0.043	0.050
AGE3034	-0.199	0.045^{***}	0.065	0.046
AGE3539	-0.180	0.045^{***}	0.177	0.044^{***}
AGE4044	-0.065	0.044	0.183	0.044^{***}
AGE5054	0.041	0.047	0.188	0.046^{***}
AGE5559	-0.036	0.049	0.135	0.046^{***}
AGE6064	-0.189	0.050^{***}	-0.119	0.050^{**}
AGE6569	-0.315	0.052^{***}	-0.552	0.058^{***}
AGE7074	-0.307	0.056^{***}	-0.610	0.062^{***}
AGE7579	-0.330	0.061^{***}	-0.463	0.068^{***}
AGE80PL	-0.385	0.065^{***}	-0.582	0.085^{***}
MARRIED	-0.313	0.023^{***}	-0.235	0.024^{***}
FEMALE	0.060	0.029^{**}	0.204	0.030^{***}
NOTINLF	0.340	0.040^{***}	0.360	0.045^{***}
UNEMPLYD	0.320	0.064^{***}	0.369	0.094^{***}
SOMEDUC	0.054	0.040	0.061	0.034^{*}
NOEDUC	0.097	0.040^{**}	0.052	0.034
OTHCCON	0.213	0.021^{***}	0.279	0.024^{***}
CITY	0.170	0.022^{***}	0.034	0.024
ENGLISH	-0.179	0.047^{***}	0.104	0.058^{*}
NUBORN	-0.101	0.032^{***}	-0.051	0.034
OTBORN	0.044	0.040	-0.067	0.041
WHI	-0.046	0.022	-0.091	0.025^{***}
WHCARD	0.306	0.031^{***}	0.340	0.035^{***}
FEXNILF	-0.120	0.042^{***}	-0.198	0.047^{***}
FEXUNE	-0.201	0.089^{**}	-0.067	0.127
Constant	-1.381	0.078^{***}	-1.458	0.082^{***}
Observations	37,264		19,018	
Pred. Probability	0.089		0.184	
Log Likelihood	-10,183.402		-8,472.750	
Pseudo R^2	0.088		0.067	
Wald test on income [a]	4.78	0.311		
Wald test [b]	822.61	0.000		

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Omitted categories include: *INCQ5, AGE4549, HIEDUC, AUBORN, MAXWORK.*
[a] Wald test on income coefficients 1989=2004-05 from pooled model: Chi^2 (4), p-value.
[b] Wald test in all coefficients 1989=2004-05 from pooled model: Chi^2 (32), p-value.

As indicated earlier, the aim of the probit estimation models for the two years is to enable the application of the analysis to decompose the increase in mental health risk between 1989 and 2004-05 into either the changes in characteristics (the means) or changes in the coefficients. The results of decomposition analysis are provided in Table 3.6. They indicate that most of the increase in mental health risk is associated with behavioural factors as captured by the coefficients effect. Based on decomposition analysis utilising different base year models from equation (3.2) and equation (3.3), the characteristics effect accounts for between 21.9 and 23.7 per cent of the increase in mental health risk, while the coefficients effect accounts for between 76.3 and 78.1 per cent of the growth. This indicates that there are factors missing from my model that may account for the increase in reporting of mental health risk. These factors may include changes in stigma and cultural factors related to increased willingness to report mental health risk, which may be due to the availability of new mental health treatments, or other reasons that are not captured in the data collected in the National Health Survey.

Table 3.6: Decomposition results for mental health risk (1989/2004-05)

	Characteristics of 1989 are combined with coefficients of 2004-05: Equation (3.2)		**Characteristics of 2004-05 are combined with coefficients of 1989: Equation (3.3)**	
	Coefficient	Standard Error	Coefficient	Standard Error
Change	0.096	0.003***	0.096	0.003***
Characteristics effect	0.023	0.002***	0.021	0.001***
in per cent	23.7		21.9	
Coefficients effect	0.073	0.003***	0.074	0.004***
in per cent	76.3		78.1	

*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 3.7 shows the result of further investigation into the contribution of each variable to the characteristics effect. The results indicate that changes in the means in the older age groups contributed to the characteristics effect for both decomposition equations. Other variables consistently significant in both equations were being in the low income groups, having another chronic condition, and having a health card.

Table 3.7: Mental health risk (1989/2004-05) decomposition by characteristics[a]

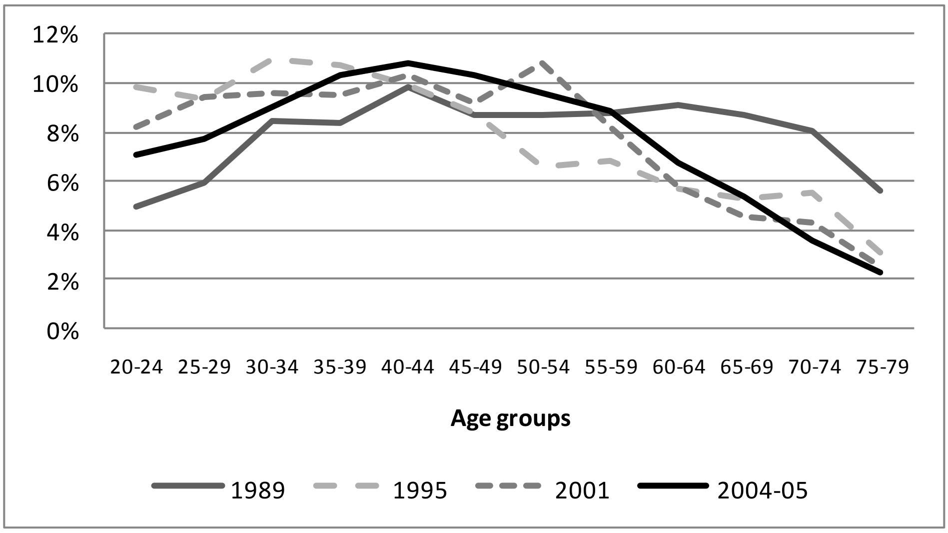
	Equation 3.1		**Equation 3.2**	
	Coefficient	Standard Error	Coefficient	Standard Error
INCQ1	-0.003	0.001**	-0.003	0.001***
INCQ2	0.001	0.000**	0.001	0.000***
INCQ3	0.001	0.000***	0.000	0.000
INCQ4	0.001	0.000**	0.001	0.000***
INCQMIS	0.000	0.000	-0.002	0.000***
AGE2024	-0.001	0.001**	-0.006	0.001***
AGE2529	0.000	0.000	-0.003	0.000***
AGE3034	0.000	0.000	-0.001	0.000***
AGE3539	0.000	0.000**	0.000	0.000
AGE4044	0.000	0.000***	0.000	0.000
AGE5054	-0.001	0.000***	0.000	0.000
AGE5559	-0.001	0.000***	0.000	0.000
AGE6064	0.000	0.000**	0.000	0.000
AGE6569	-0.005	0.001***	-0.001	0.000***
AGE7074	-0.003	0.000***	0.000	0.000***
AGE7579	-0.001	0.000***	0.000	0.000***
AGE80PL	-0.002	0.000***	-0.001	0.000***
MARRIED	-0.011	0.001***	-0.011	0.001***
FEMALE	-0.002	0.000***	0.000	0.000**
NOTINLF	0.002	0.001***	-0.001	0.000**
UNEMPLYD	0.002	0.001***	0.002	0.000***
SOMEDUC	0.000	0.000**	0.000	0.000
NOEDUC	0.001	0.001	0.001	0.000*
OTHCCON	-0.002	0.000***	-0.002	0.000***
CITY	0.000	0.000	0.002	0.000***
ENGLISH	-0.001	0.000*	0.002	0.000***
NUBORN	0.000	0.000	0.000	0.000***
OTBORN	0.000	0.000*	0.000	0.000
WHI	0.000	0.000	0.000	0.000
WHCARD	-0.009	0.001***	-0.006	0.001***
FEXNILF	0.001	0.001***	0.001	0.000*
FEXUNE	0.000	0.000	0.000	0.000***
Total explained	-0.023	0.002***	-0.021	0.001***

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Omitted categories include: *INCQ5, AGE4549, HIEDUC, AUBORN, MAXWORK.*

[a] Stata 10's *fairlie* decomposition command reverses the signs on the individual and total characteristics effect compared to those in Table 3.7, which were calculated by the *nldecompose* command.

One might expect an age cohort effect over the time period, based on the notion of the persistence of mental health disorders. Figure 3.6 shows the distribution of mental health risk over the four National Health Surveys. The figure shows a notable shift in the incidence of mental health risk away from older age groups between 1989 and 2004-05. An ageing cohort effect is evident between 1995 to 2004-05, with the bulge in people reporting mental health risk shifting from the 30-34 age group to the 40-44 age group.

Figure 3.6: Distribution of mental health risk by age group, 1989, 1995, 2001, and 2004-05



Source: National Health Surveys 1989, 1995, 2001 and 2004-05

While the results provide a limited explanation for the increase in the (unweighted) prevalence of mental health risk from 8.9 per cent in 1989 to 18.4 per cent in 2004-05, it is relevant to consider the effect of behaviour in 2004-05 on the earlier estimate of mental health risk. This involves backward projecting mental health risk prevalence in 1989 with the coefficients from the 2004-05 model. The result of this approach increases the prevalence of mental health risk to 15.2 per cent, indicating the large impact of the coefficients effect. The next section utilises the same decomposition approach to account for the increase in mental health medication use for those with mental health risk.

3.5.5 Model and results for mental health medication use

Similar estimations and decomposition analysis used for mental health risk was undertaken for mental health medication use among people with mental health risk. One would expect that only people with mental health risk would take mental health medication, so restricting the sample to the population with mental health risk provides more information about the factors affecting mental health medication use than sampling on the whole adult population. Table 3.4 does shows that for the 2004-05 sample, an estimated 2.3% of people without mental health risk take mental health medication, an estimated 356 observations. This is likely due to under-reporting of a mental health condition, but it is not possible to verify this. There are no observations in 1989 taking mental health medication without mental health risk as shown in Table 3.3. Medication use for this group nearly doubled, from 26.9 per cent in the sample using mental health medication in 1989 to 49.9 per cent in 2004-05. The estimation model includes the same variables for mental health risk, however, many of the factors that were statistically significant in the mental health risk model, are not statistically significant in the mental health medication model.

The differences between 1989 and 2004-05 for the sub-sample with mental health risk are highlighted in Table 3.8, with the *t*-test score result indicated in the last column. The share of people with mental health risk in the lowest income group significantly increased in 2004-05, as did the share being female, the share of people working, notably working females The share with a health card increased as did the share with a high level of education, and the share speaking English as their main language. There were reductions in mean age and the share of people married. There were no significant changes in the share of people with high income, private health insurance or with another chronic condition,

Table 3.8: Means for sub-sample with mental health risk: 1989 compared to 2004-05

	1989	2004-05	Difference	|*t* |-*value*
MHRISK[a]	0.088	0.184	0.095	33.139***
MHMEDS	0.269	0.499	0.230	20.066***
INCQ1	0.259	0.316	0.057	5.198***
INCQ2	0.266	0.187	-0.078	7.781***
INCQ3	0.137	0.142	0.004	0.517
INCQ4	0.145	0.130	-0.016	1.859*
INCQ5	0.124	0.113	-0.011	1.429
INCQMIS	0.069	0.113	0.044	6.278***
AGE	51.546	48.761	-2.785	6.860***
FEMALE	0.571	0.618	0.047	3.930***
MARRIED	0.578	0.396	-0.182	15.308***
WORKING	0.369	0.472	0.103	8.632***
UNEMPLYD	0.061	0.043	-0.019	3.454***
NOTINLF	0.570	0.485	-0.084	6.984***
HIEDUC	0.058	0.139	0.081	11.251***
SOMEDUC	0.309	0.330	0.021	1.887*
NOEDUC	0.633	0.530	-0.102	8.598***
CITY	0.713	0.612	-0.101	8.830***
WHCARD	0.525	0.558	0.034	2.784***
OTHCCON	0.510	0.529	0.020	1.618
WHI	0.417	0.402	-0.016	1.302
ENGLISH	0.831	0.942	0.111	14.774***
AUBORN	0.666	0.753	0.087	7.963***
NUBORN	0.100	0.117	0.018	2.369**
OTBORN	0.234	0.129	-0.105	11.368***
FEXWORK	0.162	0.269	0.107	10.758***
FEXNILF	0.383	0.326	-0.056	4.876***
FEXUNE	0.026	0.023	-0.003	0.923
MAXWORK	0.207	0.203	-0.004	0.697
MAXNILF	0.187	0.159	-0.028	3.304***
MAXUNE	0.035	0.020	-0.015	3.821***
Observations	3,306	3,501		

Source: National Health Surveys 1989 and 2004-05
Notes: Data are unweighted. *** Significant at 1% level, ** significant at 5% level,
* significant at 10% level.
[a] *MHRISK* is based on full sample over 20 years of age: 37,264 observations for 1989, and 19,018 observations for 2004-05.

The estimation results for mental health medication use for those with mental health risk for 1989 and 2004-05 are shown in Table 3.9. The results show that low income is negatively associated with mental health medication use, although it is not statistically significant. Income effects on mental health medication use may also be captured in the health card and health insurance variables; which are both positive and significant. Younger and older age groups are less likely to use mental medication compared to the missing category *AGE4549* in both years, although the size of the negative coefficients is smaller in 2004-05. Mental health medication use appears to be strongly associated with middle age, which may correspond with employment-related stress. The gender-employment status interaction terms provide some information that employment-related stress may be different for women than men. For example, the coefficient on *FEMALE* captures the association of mental health medication use for working females, compared to the omitted category working males. The coefficient is positive in 2004-05, perhaps reflecting increased mental health medication use related to job stress for working females. The coefficient on *NOTINLF* captures the association of mental health medication use for males not in the labour force compared to working males, which is positive in both years. It is possible that prolonged unemployment for males is related to mental health problems and related medication use. However, females not in the labour force appear to be less likely than working men to take mental health medication. Country of birth variables compared to Australian born indicates a negative association with mental health medication use. In 2004-05, having another chronic condition such as heart problems, cancer, diabetes, and asthma is also positively associated with mental health medication use, suggesting co-morbidity effects with mental health risk.

Estimating mental health medication use for the sub-sample with mental health risk could lead to biased estimates due to correlation of unobservable factors that affect both mental health risk and mental health medication use. For example, factors such as severity of mental health risk, not accounted for in my estimation model, could be correlated with both mental health risk and mental health medication use. A more appropriate approach would be to use a selection model that takes into account the correlation of unobservable factors as first developed by Heckman (1979) for linear models and further refined by Van de Ven and Van Praag (1981) for non-linear models. In this chapter, the analysis is descriptive and I do not attempt to correct for selection bias into the sub-sample of those with mental health risk. The estimation results should be interpreted as conditional on selection into the group of those with mental health risk. A selection model approach is utilised in the Chapter 4, which investigates in more depth the relationship between income and mental health medication use.

The issue of endogeneity of health card in the model for mental health medication use is a concern. Low income and pension age are among the criterion for health card eligibility, which could bias the estimates. The model was estimated by excluding the *WHCARD* variable and the results were not altered; none of the income variables were significant, nor were the age variables altered. Including the health card variable in the model provides information on its positive association with mental health medication use. Techniques to address endogeneity of health card with mental health medication use are investigated in Chapter 4.

By estimating the probit model of mental health medication use, conditional on mental health risk, with the data pooled and including interactions variables for each variable with 2004-05, a Wald test is used to test if the later year coefficients were jointly significantly different from zero and hence different from the 1989 estimated coefficients. The result of the Wald test shows that the 2004-05 estimated coefficients were jointly significant at the 1 per cent confidence level. This provides for the conclusion that the estimated coefficients on mental health medication use (conditional on mental health risk) are significantly different between the two years; a result also confirmed by the decomposition results.

Tests on the equality of the income coefficients in 1989 and 2004-05 were also conducted to account for the possible influence of an increase in real income over the time period. The results show that the income coefficients are the same across time periods, indicating there is no influence of the growth in real income in mental health medication model.

Table 3.9: Estimation results for mental health medication use, 20 yrs and older

	1989		2004-05	
	Coefficient	Standard Error	Coefficient	Standard Error
INCQ1	-0.108	0.111	-0.005	0.098
INCQ2	-0.065	0.102	-0.064	0.096
INCQ3	-0.045	0.102	-0.024	0.090
INCQ4	-0.048	0.098	-0.079	0.089
INCQMIS	-0.241	0.126	-0.148	0.097
AGE2024	-0.784	0.176***	-0.393	0.111***
AGE2529	-0.356	0.136***	-0.226	0.100**
AGE3034	-0.325	0.121***	-0.233	0.092**
AGE3539	-0.104	0.118	-0.167	0.085**
AGE4044	-0.036	0.111	-0.028	0.085
AGE5054	-0.052	0.115	0.001	0.088
AGE5559	-0.093	0.115	-0.023	0.088
AGE6064	0.055	0.115	0.038	0.097
AGE6569	-0.098	0.118	-0.076	0.120
AGE7074	-0.196	0.126	-0.246	0.127*
AGE7579	-0.221	0.136	-0.128	0.134
AGE80PL	-0.547	0.150***	-0.351	0.172**
MARRIED	0.033	0.056	0.021	0.047
FEMALE	0.095	0.088	0.409	0.064***
NOTINLF	0.423	0.098***	0.351	0.086***
UNEMPLYD	-0.052	0.171	0.103	0.167
SOMEDUC	-0.029	0.115	0.091	0.072
NOEDUC	-0.037	0.114	0.001	0.070
OTHCCON	0.073	0.051	0.105	0.047**
CITY	0.060	0.055	0.090	0.046*
ENGLISH	0.072	0.120	0.042	0.117
NUBORN	-0.177	0.084**	-0.024	0.068
OTBORN	-0.386	0.106***	-0.308	0.083***
WHI	0.136	0.055**	0.161	0.050***
WHCARD	0.279	0.075***	0.135	0.068**
FEXNILF	-0.020	0.109	-0.246	0.092***
FEXUNE	0.227	0.231	-0.231	0.219
Constant	-0.940	0.207***	-0.486	0.167***
Observations	3,306		3,501	
Pred. Probability	0.269		0.499	
Log Likelihood	-1794.515		-2330.805	
Pseudo R^2	0.068		0.040	
Wald test on income [a]	3.09	0.543		
Wald test [b]	334.98	0.000		

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Omitted categories include: *INCQ5, AGE4549, HIEDUC, AUBORN, MAXWORK.*
[a] Wald test on income coefficients 1989=2004-05 from pooled model: Chi^2 (4), p-value.
[b] Wald test in all coefficients 1989=2004-05 from pooled model: Chi^2 (32), p-value.

The results of decomposition analysis shown in Table 3.10 indicate that the characteristics effect accounts for even less of the increase in mental health medication use than for the increase in mental health risk discussed in the previous section. The large coefficients effect, over 90 per cent in both equations, indicates that significant behavioural changes with respect to taking mental health medication occurred between 1989 and 2004-05, which are not captured by the explanatory variables in the model. Likely factors have been already alluded to: the increased availability of new psychotropic treatments, promotion of new treatments by drug companies, providers' role in suggesting treatments for mental health disorders, and positive consumer attitudes towards new mental health treatments.

Table 3.10: Decomposition results for mental medication use (1989/2004-05)

	Characteristics of 1989 are combined with coefficients of 2004-05: Equation (3.2)		**Characteristics of 2004-05 are combined with coefficients of 1989: Equation (3.3)**	
	Coefficient	Standard Error	Coefficient	Standard Error
Change	0.231	0.011***	0.231	0.011***
Characteristics effect	0.017	0.009**	0.005	0.008
in per cent	7.4		2.1	
Coefficients effect	0.214	0.013***	0.226	0.013***
in per cent	92.6		97.9	

*** Significant at 1% level, ** significant at 5% level, * significant at 10% level.

In examining the contribution of the specific characteristics to the total characteristics effect, as shown in Table 3.11, several positive contributors stand out from the decomposition analysis based on equation (3.2). Working females, females not in the labour force, having a chronic condition, being born outside of Australia, UK or New Zealand, and having a health card all contributed to the increase in medication use between 1989 and 2004-05. Characteristics such as being in the youngest and oldest groups, men out of the work force, living in a major city and having health insurance had a counter effect on the increase in mental health medication use.

Table 3.11: Mental health medication use (1989/2004-05) decomposition by characteristics[a]

	Equation 3.1		**Equation 3.2**	
	Coefficient	Standard Error	Coefficient	Standard Error
INCQ1	0.000	0.002	0.003	0.002
INCQ2	-0.002	0.003	-0.002	0.003
INCQ3	0.000	0.000	0.000	0.000
INCQ4	0.000	0.001	0.000	0.000
INCQMIS	0.002	0.002	0.002	0.001
AGE2024	0.000	0.000**	-0.002	0.001***
AGE2529	0.001	0.000***	0.000	0.000
AGE3034	0.000	0.000*	0.000	0.000
AGE3539	0.002	0.001*	0.001	0.001
AGE4044	0.000	0.000	0.000	0.001
AGE5054	0.000	0.000	0.000	0.001
AGE5559	0.000	0.000	0.000	0.000
AGE6064	0.000	0.001	0.000	0.001
AGE6569	-0.001	0.002	-0.002	0.002
AGE7074	-0.004	0.002*	-0.003	0.002
AGE7579	-0.001	0.001	-0.002	0.001*
AGE80PL	-0.004	0.002**	-0.005	0.001***
MARRIED	0.001	0.003	0.002	0.003
FEMALE	-0.007	0.001***	-0.001	0.001
NOTINLF	0.011	0.003***	0.011	0.002***
UNEMPLYD	0.001	0.001	0.000	0.001
SOMEDUC	-0.001	0.001	0.000	0.000
NOEDUC	0.000	0.003	-0.001	0.003
OTHCCON	-0.001	0.000**	-0.001	0.000
CITY	0.003	0.002**	0.001	0.001
ENGLISH	-0.002	0.004	-0.001	0.002
NUBORN	0.000	0.000	0.001	0.000**
OTBORN	-0.011	0.003***	-0.008	0.002***
WHI	0.001	0.000***	0.000	0.000***
WHCARD	-0.002	0.001*	0.000	0.001
FEXNILF	-0.006	0.002***	0.000	0.002
FEXUNE	0.000	0.000	0.000	0.001
Total explained	0.017	0.009***	0.005	.008

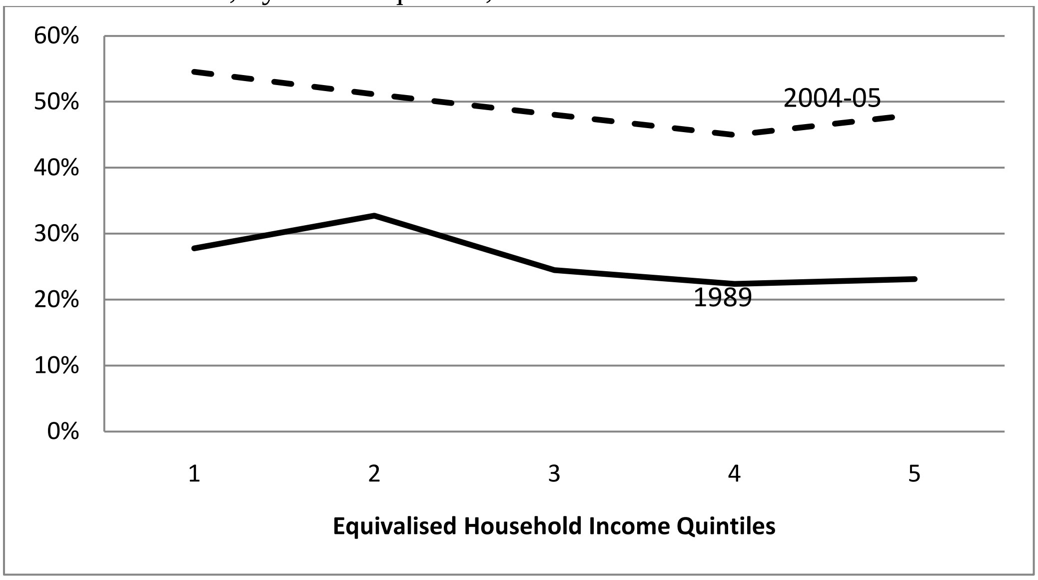
Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level. Omitted categories include: *INCQ5, AGE4549, HIEDUC, AUBORN, MAXWORK.*

[a] Stata 10's *fairlie* decomposition command reverses the signs on the individual and total characteristics effect compared to those in Table 3.11, which were calculated by the *nldecompose* command.

Predicted probabilities from the estimated models provide further indication of changes in mental health medication use between 1989 and 2004-05. Figure 3.7

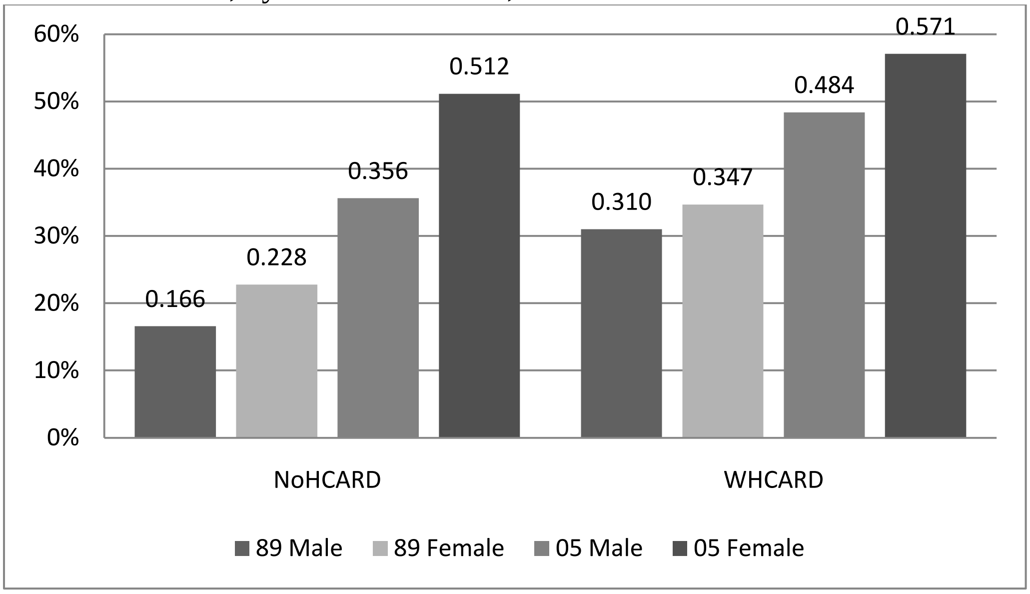
shows predicted mental health medication use, conditional on mental health risk, by equivalent income quintile. As well as higher use for all income groups in 2004-05, medication use for income quintiles 1 and 5 indicate notable deviations from the trend in 1989.

Figure 3.7: Predicted probability of mental health medication use, conditional on mental health risk, by income quintile, 1989 and 2004-05



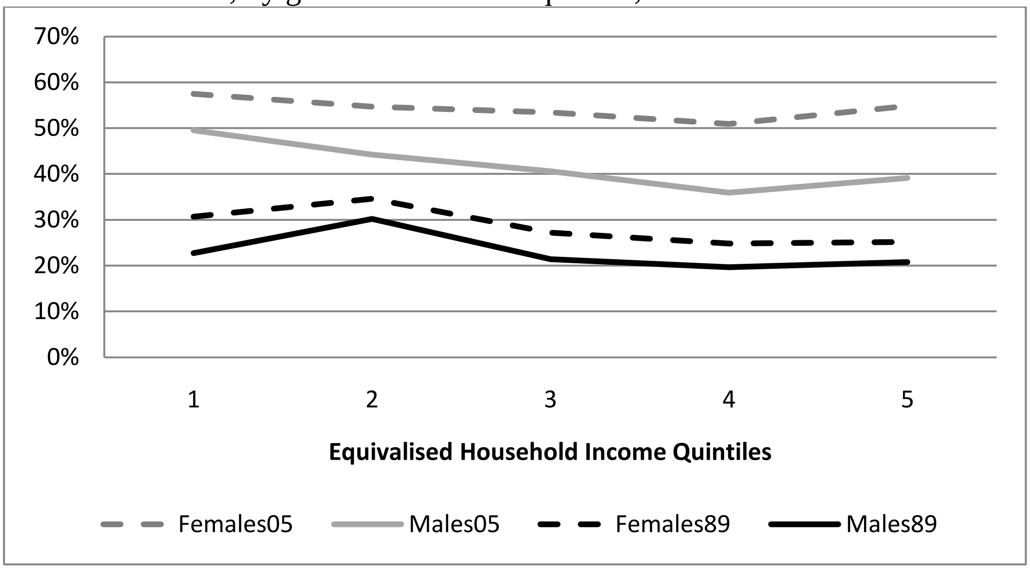
Due to concession prices for prescription drugs associated with having a health card, higher mental health medication use is predicted for health card holders compared to those without a health card. This is shown in Figure 3.8. The figure also shows that the rate of increase in predicted mental health medication use between 1989 and 2004-05 was greater for people without a health card compared to those with a health card.

Figure 3.8: Predicted probability of mental health medication use, conditional on mental health risk, by health card status, 1989 and 2004-05



Finally, it is worth noting the much higher predicted use of mental health medication for females compared to males in both time periods, shown in Figure 3.9. In addition to overall use being greater, the difference in use between the time periods for females is greatest for the higher income groups. Further study on factors contributing to higher mental health medication use for females in higher income groups is needed.

Figure 3.9: Predicted probability of mental health medication use, conditional on mental health risk, by gender and income quintile, 1989 and 2004-05



3.5.6 Concluding remarks

This section explored three aspects of mental health in Australia which previously have been unavailable in the health economics literature. Utilising data from the National Health Survey series, I documented mental health trends, established socio-economic relationships in mental health, and accounted for factors that led to the recent increase in both mental health risk and mental health medication use. My analysis showed a doubling of adults reporting mental health risk in the National Health Survey, from 8.99 per cent in 1989 to over 16.4 per cent in 2004-05. The share of people with mental health risk using mental health medication has also nearly doubled from 26.6 per cent to 47.2 per cent in 2004-05. The section revealed that the majority of people with mental health risk are in low income groups and that mental health medication use is also highest for people in low income groups in Australia. Some evidence was provided that Australia's policy of targeted income assistance through the health card has been an important factor in ensuring the adoption of new psychotropic treatments for low income people with mental health disorders. However, results from decomposition analysis of the growth in mental health risk and mental health medication use found that the characteristics of people with mental health risk and those who use mental health medication accounted for only a small share of the growth in the prevalence of mental health risk and related mental health medication use. Other factors, for which data is not readily available, such as the increased availability of new treatments, cultural changes toward stigma and provider behaviour are likely to be important factors in accounting for both the growth in mental health risk and as well as mental health medication use in Australia.

3.6 Conclusion

Deinstitutionalisation of mental health care occurred in many countries starting in the 1950s until the 1990s. The mental health care structure that evolved since deinstitutionalisation is the focus my examination of recent trends in mental health in Australia. In a review of recent trends in mental health in United States where more research is published, the availability of new psychotropic treatments for many mental health disorders and increased insurance funding for these treatments have become notable features of current mental health care. Increased PBS expenditure during the 1990s for mental health drugs has been documented in Australia, however, limited health economic studies have been published on the demand factors associated with increased mental health medication use. The research presented in this chapter contributes to this knowledge gap.

Evidence across many countries indicates that the majority of people with mental health disorders are likely to be in low socio-economic groups. The relationship between low income and related socio-economic factors such as education and occupation are complex. Job loss, health shocks and family crisis, as well as genetic factors also contribute to mental health problems. A review of prevalence rates from 50 years of studies in the United States concludes that the prevalence of mental health disorders is fairly stable, affecting between 15 and 30 per cent of the adult population in a given year. The same study finds, however, that take-up of mental health treatment is more variable, and is highly responsive to policy changes that affect access to treatment.

My investigation of data from the past four National Health Surveys provides a more in-depth examination of mental health trends in Australia, which previously has been unavailable. Increased reporting of mental health disorders and related use of mental health medication between 1989 and 2004-05 likely reflects a significant positive response to the expansion of community-based treatments for mental health disorders, including innovations in drug therapies and counselling. Australia's policy of targeted income assistance through the health card has likely contributed to the adoption of new psychotropic treatments for low income people with mental health disorders. Further investigation on factors such as cultural changes toward mental health stigma, provider behaviours toward mental health diagnosis and treatment, and price effects of various mental health treatments at different income levels would be important to consider in future research on accounting for recent trends in mental health risk and related medication use in Australia. The latter would require consideration of the impact of government health funding policies on access to mental health care, as well as private health insurance policies.

The recent release of the 2007-08 NHS provides an opportunity to update and verify the mental health trends established in this chapter. Likewise, the addition of another NHS provides opportunities to conduct further decomposition analysis of the increase in mental health risk and mental health medication and on the trends in the association between income and mental health risk and related medication use. Investigation of other data sources is needed, though, to provide further information on important behavioural factors that were associated with these recent trends. The National Health Survey does not collect data on health care attitudes and preferences nor does it include information on providers' behaviours and other supply side factors that were likely contributors to increased mental health medication use since 1989.

Chapter 4

Income and price barriers to mental health medication use

4.1 Introduction

Ensuring access to treatment is a special challenge in the area of mental health. Mental health sufferers are more likely to be in low income groups and often lack the financial, educational and social resources required to seek appropriate treatment. Evidence from other countries indicates that price responsiveness is greater for mental health compared to general medical care. This finding points to a concern about treatment accessibility, as high prices for mental health care may lead to low treatment rates. In Australia, there are several health policies aimed at reducing financial barriers to access treatment, including universal health care through Medicare, targeted subsidies for pharmaceuticals and other safety net programs to reduce out-of-pocket health care expenses. Despite these efforts, many health experts express concern that more funding is required to improve treatment rates for mental health, and that better targeting is needed to ensure that those most in need get treated. Little is known about the effects of income and price on access to mental health treatment in Australia, and as such would be an important starting point to address the issue of adequate treatment rates for mental health.

Data analysis in Chapter 3 showed a negative relationship between income and mental health disorders in Australia with the prevalence of mental health disorders greater among low income people compared to high income groups. Use of mental health medication among people with mental health risk is higher in low income groups, which may be due to the Australian health card which provides targeted assistance to low income people by significantly lowering the price they pay for prescription drugs. The aim of this study is to consider whether there is evidence of a differential impact on the take-up of mental health medication for those with the health card compared to those without the health card. If so, this provides important information to policy makers on how to improve access to mental health treatment in Australia, especially on the appropriate eligibility for the health card.

Previous studies in Australia have not considered the importance of targeted assistance such as health card status in access to mental health treatment. No studies have examined income barriers to mental health medication use for those who lack a health card and who have a card. My contribution to this knowledge gap is three-fold. First, I provide evidence on the role of income in accessing mental health medication after controlling for the association of income with mental health risk. Second, my results confirm the importance of the health card in ameliorating the impact of income on mental health medication use. And third, I show a possible income barrier for mental health sufferers without a health card.

Using data from the 2004-05 National Health Survey (NHS), I develop a model to estimate the probability of mental health medication use for people with mental health risk. My main variable of interest is household income and its association with mental health medication use. I estimate the model for adults below pension age (the full sample) and for sub-samples of people with and without a health card. I address selection bias with a censored probit model, and utilise a novel approach to identify the model by using personal income in the mental health risk equation and only household income in the outcome equation for mental health medication.

With the data pooled, results show evidence of a positive income gradient for mental health medication use; people with low income are less likely to use medication after controlling for mental health risk factors. When the sample is split for those with a health card, the income gradient for medication use flattens, and for the sample without a health card, the positive income gradient remains, as predicted by economic theory. This implies that a significant cost difference may lie within the group of people around the income threshold for the health card. My estimation results confirm this significant discontinuity.

These results have important policy implications. Policy changes aimed at addressing low treatment rates for mental health in Australia need to consider access issues for those just above thresholds for the health card in low-middle income groups. In addition, policy changes to increase copayments for pharmaceuticals need to take into account the importance of concession prices for those with mental health disorders.

4.2 Background

4.2.1 Recent studies

Chapter 2 provides a review of several studies in the United States that have determined that the price elasticity for mental health care is more responsive than for general medical care. The findings point to a concern about treatment accessibility, as high prices for mental health care may lead to low treatment rates. Health experts in Australia have expressed concern about low treatment rates for mental health in the general population. Chapter 2 also reviewed cost-sharing arrangements for mental health treatment in Australia and found a prevailing view that universal health insurance and additional safety-net provisions would be expected to ameliorate affordability issues. Generally there has been little attention given to investigating possible income and price barriers in mental health treatment in Australia.

A review by Lexchin and Grootendorst (2004) of studies on the effect of user fees for prescription drugs concludes that cost sharing leads patients to forgo essential medications and also leads to a negative impact on health status. The majority of studies reviewed were conducted in Canada and the United States. While none of the studies focused on mental health medication use, many looked at low income people with chronic conditions. High price elasticity was observed in several studies, specifically for the elderly with low income.

The studies on access and utilisation of prescription drug use in Australia have focused on two issues. First, a few studies have investigated the general affordability of medications and second, several studies have examined the effect on medicine use following increases in Pharmaceutical Benefit Scheme (PBS) copayments in 2005.

Two telephone surveys on access to health care conducted by the Commonwealth Fund identified cost concerns with filling prescriptions in Australia (Blendon et al, 2002; Schoen et al, 2005). In the 2005 study, Australia had a slightly higher share of respondents (22 per cent) indicating cost was a barrier to filling a prescription compared to four other OECD countries (Canada, Germany, New Zealand and the UK). Likewise, a survey conducted in non-metropolitan NSW found that 69 per cent of respondents had a concern with meeting prescription costs (Doran et al, 2003). These surveys did not distinguish affordability differences for people with and without a health card, and given the small samples involved the findings may not be statistically significant.

An empirical investigation of the impact of the 2005 change that increased PBS copayments by 24 per cent found a decline in dispensings of medicines across 17 medicine categories, with a greater drop in dispensings for social security beneficiaries (health card holders) compared to general beneficiaries (non-health card holders) (Hynd et al, 2008). The study utilised trend data on national aggregate monthly prescription dispensing prior to the policy change to predict utilisation rates without the policy change. The predicted levels of prescription dispensing were compared to actual dispensing data by patient type: general or concessional patient. The limitation of the study is that individual behaviour and characteristics were not accounted for, nor were the effects of other policy and economic factors controlled for. According to Russell (2007) PBS policies to remove some medicines from PBS over this period as well trends in prescribing practices (eg, less prescribing of antibiotics) may have also impacted dispensing trends.

Using microsimulation model analysis, the National Centre for Social and Economic Modelling considered the distributional impact of a hypothetical 25 per cent increase in the PBS copayment (Walker, 1999). Inputs to the model included data from the 1995 National Health Survey, the 1993-94 Health Expenditure Survey and PBS administrative data. The findings show a higher household budgetary impact of the copayment increase for general patients (those without a health card) in low income quintiles compared to concessional patients (those with a health card) in low income quintiles. The study signals affordability concerns for those in low-middle income groups without access to the health card.

Regarding access to mental health treatment in Australia, health researchers have documented low treatment rates for those with mental health conditions as discussed in Chapter 2, while very limited economic analysis has been conducted. Ruth Williams and Darrel Doessel are among the few economists working in the field of mental health, and in addition to their own research, they have documented the dearth of economic research in this area (Williams and Doessel, 2008, 2006).

A recent study by Doessel and co-authors (2007) provides an analysis of patient and provider response to Medicare policy changes affecting both benefits and fees in the mid 1990s aimed at limiting annual psychiatric visits to a maximum of 50. Utilising Medicare data in time series analysis, they conclude that annual visits were reduced to the maximum following the policy changes, and that financial incentives may be a more effective policy tool than regulation.

Several studies by Andrews and others (2001a, 2001b, 2000) have utilised the 1997 Survey of Mental Health and Wellbeing (SMHWB,1997), and explore the finding that across the majority of mental health disorders less than 40 per cent of sufferers sought treatment. While the 1997 SMHWB does not include detailed income data, which limits empirical analysis on price and income effects, Andrews and co-authors (2001b, 145) nonetheless conclude that, "As Australia has a universal health insurance scheme, the barriers to effective care must be patient knowledge and physician competence."

Chapter 5 of my thesis investigates the effect of policy changes in 1996 – which increased income limits for the Commonwealth Seniors Health Card – on the take-up of mental health medication. Using difference-in-difference analysis, I did not find evidence of an increased take-up of mental health medication for mid-high income seniors newly eligible for the health card. The group of seniors eligible for the

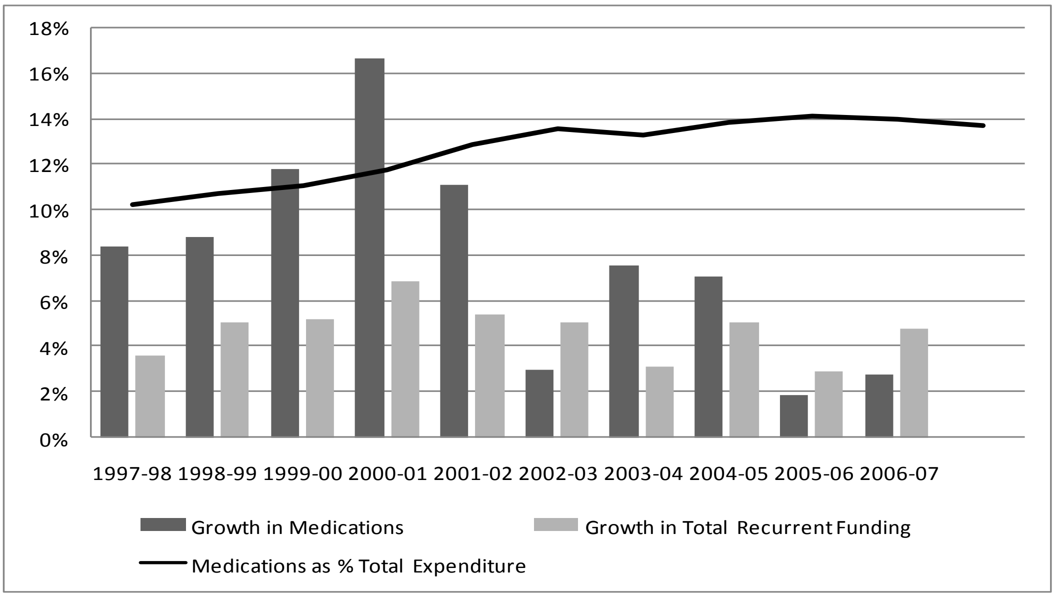
Commonwealth Seniors Health Card are in the top two income deciles compared to other seniors, and may be less responsive to price changes than those in low income groups. The full study is provided in the next chapter of my thesis.

My current study aims to build on these previous studies by considering the impact of income on the use of mental health medication, and to determine if there is a differential impact for people with the health card compared to those without the health card for the adult population below pension age. A priori, income would not be expected to impact medication use for those with a health card. In addition, at low income levels just above health card eligibility levels, predicted use of mental health medication would be much lower for those without a health card in the same income group. To date, no examination of income barriers to mental medication use in Australia has been undertaken. Utilising the 2004-05 National Health Survey, which captures the expansion of new psychotropic medicines during the 1990s, and controlling for selection bias, my study provides an up-to-date and rigorous finding that the Australian health card ameliorates the impact of low income on mental health medication use.

4.2.2 Institutional Setting

Increasing use of new medications since the 1990s has been a driver of health expenditure growth in Australia. Figure 4.1 illustrates that annual growth in expenditure for medications significantly exceeded total health expenditure growth in Australia over the period from 1997 to 2002. As a result, the share of medication to total health expenditure has increased from 10 per cent in 1996-97 to nearly 14 per cent in 2006-07 (AIHW, 2008). Sweeny (2002) documents the significant growth in mental health medication expenditure during the 1990s, accounting for over 20 per cent of total PBS expenditure growth.

Figure 4.1: Growth in funding for total recurrent health expenditure and medications, 1997-98 to 2006-07



Source: Australian Institute of Health and Welfare, 2008

In Australia, the majority of prescription drug costs are covered by the Commonwealth government. Patient contributions are estimated at 20 per cent of total pharmaceutical expenditure, amounting to an estimated $1.2 billion in 2007 (Department of Health Ageing website). Patient prices for medications are regulated through the Commonwealth government's Pharmaceutical Benefits Scheme (PBS). Prices are adjusted annually for inflation, plus significant one-off increases were imposed in 1990, 1997 and 2005. There are two prices: one for concessional patients and one for general patients. In 2005, the prices were $4.60 per prescription for concessional patients and $28.60 for general patients.[28] Eligibility for concessional prices is based on having a health card, which provides a range of benefits to cardholders. Various health card programs are available to low income earners, people with disabilities and pensioners. The income eligibility limits for the different health card programs are discussed in more detail in the Data section.

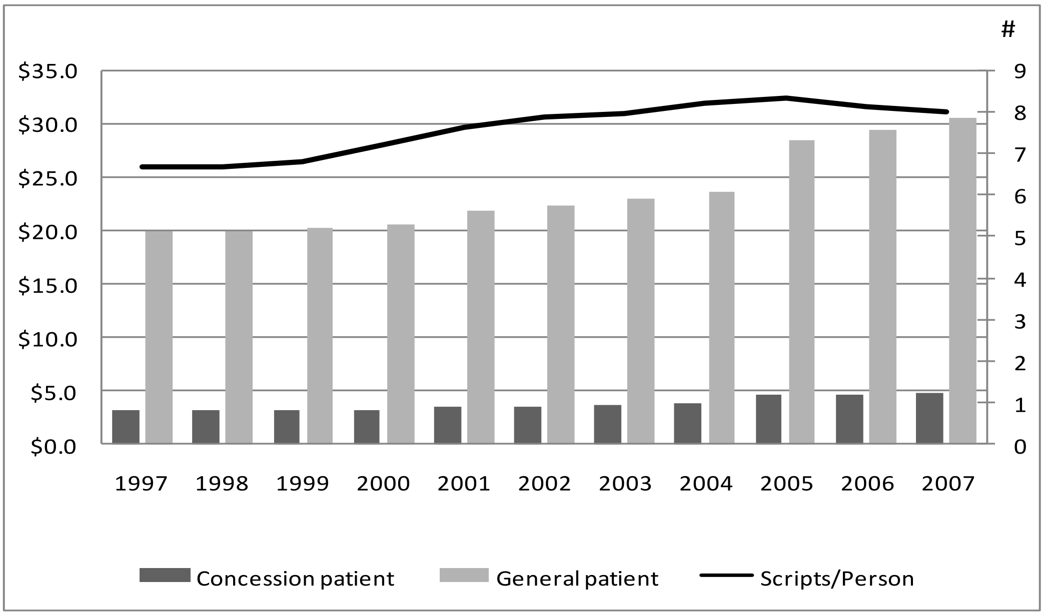
In addition to subsidised prices, PBS also includes safety-net provisions for people with large cumulative out-of-pocket medicine expenses. Safety net arrangements involve free payments once certain thresholds of expenditure are exceeded. In January 2005, the general patient safety net threshold was $874.90 and $239.20 for

28 NHS interviews straddle the PBS price increase on 01 January 2005. Those interviewed in 2004 would face lower prices of $3.80 for concession patients and $23.70 for general patients.

pensioners and concession card holders, which is equivalent to approximately 30 scripts for general patients and 52 for concession card holders. A pharmaceutical allowance of approximately $150 per year is also available for all pensioners, including part-pensioners, Veterans Affairs beneficiaries, sickness candidates and others receiving income support for at least 9 months (Australia Parliamentary Library, 2003).

In response to increasing pharmaceutical expenditure, the government has steadily increased consumer co-payments over the past couple of decades. As discussed in the previous section, some evidence indicates that increasing co-payments have led to declining medication use. Figure 4.2 shows some slowdown in the growth in the number of scripts per person over the past decade, which may be attributable to increasing co-payments.

Figure 4.2: Trends in co-payments for general and concession patients ($) and scripts per person (#), 1997 to 2007



Source: Department of Health and Ageing website:
http://www.health.gov.au/internet/main/publishing.nsf/Content/pbs-pbbexp-archive

Analysis in Chapter 3 showed the significant increase in take-up of mental health medication since the early 1990s. The slow-down observed in prescription drug volumes in recent years may extend to a slow-down in mental health medication use due to increasing co-payments, but the evidence is lacking. Based on Walker's 1999 findings, the impact of increased copayments is more likely to affect low to middle income general patients compared to health card holders. While not the main focus of my study, my analysis provides some evidence on the importance of health card status in the demand for mental health medication, which is an important contributor to total PBS expenditure.

4.3 Estimation approach

An investigation of the impact of income on mental health medication use can be modelled for the sub-sample of people with mental health risk. However, if there are factors that influence both mental health medication use and mental health risk that are not captured by the explanatory variables in the mental health medication use model, the parameter estimates may be inconsistent and biased. For example, severity of mental health disorder could be correlated with the decision to use mental health medication. Data is not included in the NHS on severity of mental health disorder so it can not be included as a control variable in the model of mental health medication use. A selection model provides an approach that both tests and corrects for possible bias due to the correlation of unobserved factors that jointly affect mental health medication use and mental health risk.

The approach follows Heckman's (1979) selection model, which explicitly models the selection equation (having mental health risk) and the outcome model (taking mental health medication), and by estimating a correlation coefficient that captures the correlation of unobservable factors allows for consistent estimation of the outcome model. Since my dependent variable is a binary variable, I apply a censored probit model introduced by Van de Ven and Van Praag (1981), which is a bivariate probit model following the spirit of Heckman's selection model.

The main outcome of interest is the use of mental health medication of person *i*, which is represented by the following latent variable specification:

$$M_i^* = \beta_0 Y_i + \beta X_i + \varepsilon_i \qquad \begin{cases} M_i = 1 \text{ if } M_i^* > 0 \\ M_i = 0 \text{ otherwise} \end{cases} \tag{4.1}$$

where M_i* is a continuous and latent variable measuring the utility gain of mental health medication use and M_i is the observed mental health medication use, Y_i denotes household income, X_i represents a vector of explanatory variables, and ε_i indicates unobserved factors that influence mental health medication use and is assumed to be normally distributed with a mean equal to 0 and variance equal to 1. Explanatory variables include socio-demographic characteristics such as age, marital status, gender, geographic location, employment status, and education. Other factors that may impact demand for mental health medication are also included such as having other chronic conditions, which might impact an overall budget constraint for pharmaceutical purchases, and health card status, which affects the price of medication. Note that if there was no selection bias, i.e. in the case where the occurrence of mental health disorders is purely random and unrelated to the medication use, this model can be consistently estimated by a standard binary choice model such as a probit model.

The censored probit model relates observations of mental health medication use, the main outcome of interest, to the condition of having mental risk and is represented by:

$$M_i^* = \beta_0 Y_i + \beta_1 X_i + \varepsilon_{1i} \ \text{ if } \ R_i^* > 0 \tag{4.2}$$

where M_i* is a continuous and latent variable measuring the utility gain of mental health medication use and, as above, M_i is the observed mental health medication use when M_i* is greater than 1 and equals 0 otherwise, R_i* is a continuous latent variable measuring the mental health disorders, Y_i denotes household income, X_i represents a vector of explanatory variables, and ε_{1i} indicates unobserved factors which influence mental health medication use.

The selection equation for mental health risk is:

$$R_i^* = \gamma_0 Y_i + \gamma_1 X_i + \gamma_2 I_i + \varepsilon_{2i} \qquad \begin{cases} R_i = 1 \ \text{ if } \ R_i^* > 0 \\ R_i = 0 \ \text{ otherwise} \end{cases} \tag{4.3}$$

where R_i* is a continuous latent variable measuring the mental health disorders and R_i is the observed mental health risk, Y_i denotes household income, X_i represents a vector of socio-demographic variables including household income, $I_{i,}$ is personal income, and ε_{2i} indicates unobserved factors for mental health risk. ε_{1i} and ε_{2i} are assumed to be jointly normally distributed, with a correlation coefficient of ρ.

For a censored probit model to be identified the selection equation needs to satisfy the exclusion restriction, i.e. it must have at least one variable that is not in the outcome equation and be statistically significant (Wooldridge, 2002, 571). My approach uses personal income in the mental health risk equation to identify the model. Since household purchases like medication depends on household income, I use household income in the outcome equation. Likewise, eligibility for the health card and associated concessional prices for prescription drugs is based on household income. The assumption is that personal income does not impact on medication use over and above the effect of household income, whereas personal income is assumed to affect the predilection of mental health risk. Tests included in Appendix A results show that personal income is significant for mental health risk over and above the effect of household income on mental health risk, but this is not the case for mental health medication use. This identification approach relies on the assumption of homogeneous treatment effects in the sample. The instrument will have more effect for the group of married households but this group constitutes 49% of the sample with mental health risk, hence it is a large group with sufficient within-group variation. Further justification of the approach is based on the fact that household and personal income are not perfectly correlated; the test of correlation for the married subgroup is 0.793.

Over-identification tests were conducted to confirm the reasonableness of the identification strategy and are included in Appendix B. The over-identification test results provide some indication that that the identification strategy is reasonable, but that personal income may be a weak instrument. Murray (2006) indicates that weak instruments can result in biased estimates and incorrect standard errors which affect hypothesis testing and inference. Methods to improve upon the standards errors in weak instrument models involve constructing conditional likelihood ratio-based confidence intervals (Murray, 2006). Another method is limited information maximum likelihood estimation (LIML). Programming limitations of the ABS Remote Data Access Laboratory did not allow me to explore these procedures.

The censored probit model provides a test of whether the two equations are correlated by estimating a coefficient of correlation, ρ, between the error terms:

$$corr(\varepsilon_{1i}, \varepsilon_{2i}) = \rho$$

When $\rho \neq 0$ the censored probit model specification is necessary to correct the selection bias; $\rho = 0$ indicates the standard probit model would provide consistent parameter estimates. The maximum likelihood estimation (MLE) procedure treats the coefficient of correlation as an estimated parameter and therefore provides consistent parameter estimates for the full sample conditional on the distributional assumptions.[29]

Based on the estimation results, the probability of using mental health medication conditional on mental health risk is:

$$\Pr(M_i = 1 \mid R_i = 1) = \frac{\Pr(M_i = 1, R_i = 1)}{\Pr(R_i = 1)}$$
$$= \frac{\Phi_2(X_{iM}\beta_M, X_{iR}\beta_R; \rho)}{\Phi(X_{iR}\beta_R)} \tag{4.4}$$

where $X_{iM}\beta_M$ is the index score from the mental health medication outcome equation including household income variables and socio-demographic control variables; $X_{iR}\beta_R$ indicates the index score from mental health risk selection equation including household income variables, socio-demographic control variables and personal income variables; Φ_2 is the bivariate normal distribution and Φ the standard normal distribution.

The outcome equation for mental health medication use and the selection equation for mental health risk include the same set of control variables except personal

[29] The Stata 10 command *heckprob* was used to estimate the censored probit model.

income decile variables, which are only included in the selection equation. The censored probit estimation approach parses the effect of the explanatory variables on mental health medication use after controlling for the effect of the explanatory variables on mental health risk. In this way, it is possible to isolate the factors that are important for medication use, as separate from their impact on mental health risk.

Another important consideration in the model is the possible endogeneity of having a health card with the mental health medication use, which could possibly bias the parameter estimates. For example, the severity of mental health condition, which necessitates mental health medication use, is unobserved and may be correlated with health card status. A test of endogeneity of the health card utilising a bivariate probit model is included in Appendix C. Based on the variables used in the model, the results on the correlation coefficient in Table C1 confirm endogeneity between mental health medication use and health card status. Lack of convincing instrument for health card status makes instrumental variable (IV) estimation impossible. I therefore estimate separate models on subsamples based on health card status and compare results. These results must be interpreted as conditional on health card status.

The estimation strategy is as follows. First, I assess the impact of income on mental health medication use for those with mental health risk. Next, I estimate the impact of price on mental health medication use by estimating models for sub-samples with and without a health card. As a validity check, the main results from the censored probit model are compared with a censored linear probability model.

4.4 Data

My analysis relies on data from the National Health Survey conducted in 2004-05 (2004-05 NHS), and is restricted to the adult population under pension age. This section discusses definitional issues and sample size adjustments related to key variables for mental health risk, mental health medication, income and health card. A more detailed explanation of the National Health Survey data and variable definitions is provided in Chapter 3.

Mental health risk and mental health medication

For my analysis, mental health risk is defined as either having a self-reported mental health chronic condition or a high K10 Score, greater than 22. The share of the adult population under pension age in 2004-05 with mental health risk from my sample (unweighted) is estimated at 20 per cent, which is consistent with the 1997 Survey of Mental Health and Wellbeing.

Details are provided in the 2004-05 NHS on types of medications used for mental health. For my analysis mental health medication used for all mental health conditions is restricted to pharmaceutical products, excluding sleeping pills, vitamins and minerals. The share of adults below pension age using mental health medication is 9 per cent. For those with mental health risk the share is 29 per cent.

Approximately 2.3 per cent of adults below pension age indicate use of mental health medication without mental health risk. These people have indicated a level of current distress below the K10 score cut-off I use to indicate mental health risk. Since I am interested in the effect of income and price on mental health medication use for those with mental health risk, I exclude observations without mental health risk from my estimations.

Income

I utilise personal and household income on the basis of income deciles in the 2004-05 NHS, which allows for relative comparisons between income groups. Since the focus of my analysis is on low income deciles, the middle income deciles 6-8 are merged as binary variable *MIDPY* for personal income, and binary variable *MIDEH* for equivalent household income. Likewise personal and household income deciles 9-10 are merged to form binary variables *HIDPY* and *HIDEH*. Assignment of observations in decile 8 to *MIDPY* and *MIDEH* instead of *HIDPY* and *HIDEH* was based on *t*-tests comparisons with observations in income deciles, 7, 8 and 9 across a number of characteristics. Note that decile income cut-offs are defined for the full sample and remain fixed in my sample; therefore the decile categories used in my analysis should not be interpreted as actual income deciles for my sub-samples.

The 2004-05 NHS contains many missing observations for income. Household income information is missing for an estimated 14 per cent of the sample over age 18 and under pension age, and 10 per cent of the same group report missing personal income. This is not unusual for surveys where the emphasis is not on the collection of income, wealth and expenditure data. Instead of dropping these observations, I created dummy variables for missing personal income, *DPYMIS*, and for missing household income, *DEHMIS*.[30] A sensitivity test of the estimation results without missing income observations is included in Appendix D.

My main variable of interest is the effect of household income decile on mental health medication use. In the 2004-05 NHS equivalised income for households has been standardised to a single person household, thereby accounting for the number of people in a household.

Health card

A variety of government allowance programs entitle recipients to a health card, which provides access to concession prices for prescription drugs. Concession drug prices are significantly less than those paid by general patients. In the 2004 the prices

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[30] A common solution to accommodate missing income is to replace these data with mean income values. Due to the emphasis in my analysis on decile income groups, this approach is inappropriate.. Alternatively, if one is certain that the missing observations are randomly selected, it is considered acceptable to drop the observations. Without certainty on the direction of potential bias, dropping the observations with missing income was not considered.

were: $3.80 for concession card holders and $23.70 for general patients. These prices were increased on 01 January 2005 to $4.60 and $28.60 (Sweeny, 2007).

Eligibility for a health card is means tested and for some programs such as the Disability Support Pension there is an asset test. Table 4.1 provides information on income eligibility for different health cards through Centrelink at the time of the 2004-05 NHS. For example, low income earners receiving various government program allowances are eligible for the Health Care Card. Age pensioners receive a Pension Concession Card as do people receiving a disability pension or supporting a disabled family member. The Commonwealth Seniors Health Card is available to age pensioners whose income is above the age pension income cut-off but below the income limit set-out below.

Table 4.1: Income limits for health cards (2004)

Card type	Annual income limit
Health Care Card (through Newstart, Youth Allowance, Parenting Payment programs)	$17,472 (single)
	$29,068 (couple)
	$30,836 (single/couple with one child)
	Plus $1,768 (for each extra child)
Health Care Card (through Family Tax Benefit A)	$31,755 (family)
Pension Concession Card (age pensioners, and disability support pensioners)	$32,929 (single)
	$33,569 (single with one child)
	$55,029 (couple)
	Plus $640 (for each extra child)
Commonwealth Seniors Health Card (self funded retirees)	$50,000 (single)
	$80,000 (couple)
	$100,000 (couple if separated by illness, care of gaol)

Source: Parliament of Australia. Health Legislation Amendment (Medicare) Bill 2003 (Bills Digest, no 85, 2003-04) available from http://www.aph.gov.au/library/pubs/bd/2003-04/04bd085.htm

The NHS 2004-05 asks respondents if they have a health card issued either by Centrelink or the Department of Veterans Affairs (DVA). Having a health card in the 2004-05 NHS refers to one of the following types of health card:

- Pensioner Concession Card;
- Commonwealth Seniors Health Card;
- Health Care Card; or
- Repatriation Health Card or Repatriation Pharmaceutical Benefits Card (issued by the Department of Veteran Affairs)

The majority of people of pension age in Australia receive a health card. In the 2004-05 NHS sample, the share of the pension age population with a health card is 92 per cent. While mental health risk prevalence for the pension age population is slightly less than for the whole population, their rate of medication use is slightly higher. In fact pensioners comprise over 40 per cent of the group taking mental health medication without mental health risk. Due to the high rate of health card among the pension age group, my analysis is restricted to the adult population below pension age. Pension age in my sample is defined as females and males over 65 years of age.[31] Sample size and proportions are shown in Table 4.2.

[31] Due to pension age eligibility some females 63 and 64 years may be eligible for the age pension. Since age pension is also based on financial circumstances these females were not dropped from the final sample.

Table 4.2: Sample summary 18 and over population

	Mental health risk	Without mental health risk	Total
Not pension age	3,348	12,303	15,651
With health card	1,525	2,513	4,038
% with health card	*45.55%*	*20.43%*	*25.80%*
Pension age	619	3,231	3,850
With health card	591	2,946	3,957
% with health card	*95.48%*	*91.18%*	*91.87%*
No mental health risk using mental health medication	0	361	361
% of total			*2.3%*
Final sample	3,348	11,942	15,290
With health card	1,525	2,368	3,893
% with health card	*45.55%*	*19.83%*	*23.91%*

Additional characteristics of people with a health card can be obtained from a related question in the 2004-05 NHS on type of government allowance. A cross check of health card and type of government allowance reveals that there are a significant number of people who receive some type of government allowance but do not receive a health card.[32] For example, of those people reporting a Disability Support Pension, 30 per cent do not have a health card. Generally, people with low income are more likely to have a health card, and people with mental health risk are more likely to have a health card than people without mental health risk. Based on the sample data for the adult population below pension age nearly 46 per cent of people with mental health risk have a health card compared to 20 per cent of people without mental health risk.

Safety-net provisions for large cumulative out-of-pocket medicine expenses are not means tested and provide assistance to people requiring numerous prescriptions often due to co-morbidities. Assistance through the PBS safety-net program for middle and high income earners would be expected to positively impact the uptake of mental health medication use, but it is not possible to quantify this effect with available data. The 2004-05 NHS provides information on the number of medication types taken but not the cumulative number of annual prescriptions, which could assist with identification non-health card holders eligible for threshold programs.

[32] Multiple responses are allowed for type of government allowance.

Other variables and sample summary statistics

Table 4.3 provides definitions for all variables considered in my analysis and shows the mean value of the variables for the adult population below pension age with mental health risk compared to those without mental health risk.

Those in the mental health risk group tend to be in the lower personal and household income groups. Greater shares of people with mental health risk are in income deciles 1, 2 and 3, represented by personal income variables *DPY1*, *DPY2*, and *DPY3* as well as household income variables, *DEH1*, *DEH2* and *DEH3* compared to being in the highest income deciles, represented by the variable *HIDPY* for personal income and *HIDEH* for household income. The means for these income variables do not correspond to relative income deciles because of the reduced sample, i.e., removing the pension age population from my sample.

Mean age is not different for the mental health risk group compared to the general population or those without mental health risk. Those in the mental health risk group are much less likely to be married, more likely to be female and more likely to have another chronic condition, *OTHCCON*. As expected based on low income eligibility criteria a greater share of people with mental health risk have a health care card, *WHCARD*: nearly 40 per cent compared to 16 per cent of people without mental health risk. As for labour force status, over 30 per cent with mental health risk are not in the labour force and the unemployment rate is double that of the general population. The level of post-secondary education is lower for people with mental health risk. Geographical area of residence, *CITY*, *TOWN* and *COUNTRY* conforms to the general population; however, as measured by an index of relative socio-economic disadvantage, *AREADIS*, people with mental health risk are more likely to live in a Census Division of relative disadvantage. The variables *AREADIS* and *AGE* are continuous variables, while all others are dummy variables.

Table 4.3: Variable definitions and means
*indicates the omitted variable category in the estimation models

Variable name	**Definition**	**Full sample**	**Mental health risk**	**Without mental health risk**
MHRISK	Mental health long term condition or high or very high current distress: Kessler Score (K10) 22-50	0.198	1.000	0.000
MHMEDS	Taking prescription mental health medication (excludes sleeping pills, vitamins/minerals/herbal/ natural medications)	0.072	0.277	0.022
DPY1	Decile 1: less than $150/week	0.069	0.085	0.065
DPY2	Decile 2: $150-$199/week	0.059	0.105	0.048
DPY3	Decile 3: $200-$249/week	0.054	0.108	0.040
DPY4	Decile 4: $250-$353/week	0.073	0.111	0.064
DPY5	Decile 5: $354-$499/week	0.091	0.101	0.088
MIDPY	Deciles 6-8: $500-$958/week	0.301	0.254	0.313
*HIDPY**	Deciles 9-10: $959 or more/week	0.234	0.138	0.258
DPYMIS	Not applicable, not stated or not known personal income	0.119	0.097	0.124
DEH1	Decile1: less than $238/week	0.059	0.110	0.047
DEH2	Decile 2: $238-$294/week	0.051	0.097	0.039
DEH3	Decile 3: $295-$379/week	0.057	0.084	0.050
DEH4	Decile 4: $380-$479/week	0.073	0.078	0.071
DEH5	Decile 5: $480-$584/week	0.083	0.083	0.083
MIDEH	Deciles 6-8: $585-$996/week	0.284	0.246	0.293
*HIDEH**	Deciles 9-10: $997 or more/week	0.220	0.132	0.242
DEHMIS	Not stated or not known household income	0.174	0.169	0.175
AGE	Continuous variable	39.138	39.144	39.136
MARRIED	In a registered or defacto marriage	0.580	0.492	0.602
*WORKFT**	Working full time	0.558	0.397	0.597
WORKPT	Working part time	0.217	0.222	0.216
UNEMPLYD	Unemployed	0.032	0.066	0.024
NOTINLF	Not in labour force	0.193	0.315	0.163

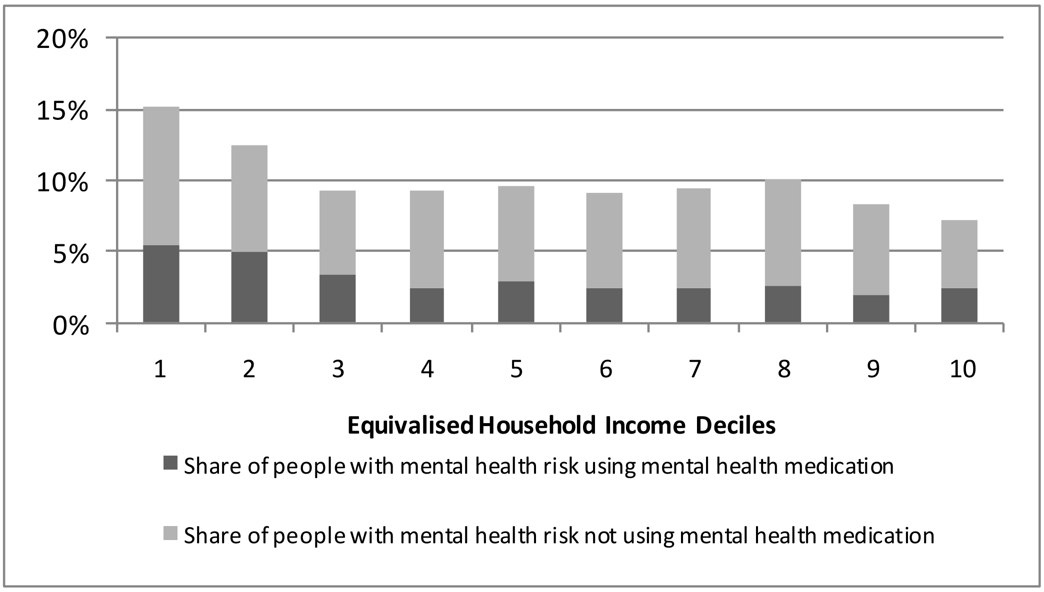
Table 4.3 *Continued*

Variable name	**Definition**	**Full sample**	**Mental health risk**	**Without mental health risk**
*HIEDUC**	Post-grad degree/graduate diploma or certificate or bachelor degree	0.205	0.147	0.219
SOMEDUC	Advanced diploma or certificate	0.354	0.344	0.357
NOEDUC	No post-school qualification or level not determined	0.441	0.509	0.424
FEMALE	Female gender	0.483	0.552	0.466
OTHCCON	Other chronic conditions: heart problems, high cholesterol, diabetes, cancer, asthma	0.302	0.403	0.277
CITY	Major city	0.688	0.672	0.692
*TOWN**	Inner regional	0.192	0.204	0.190
COUNTRY	Other areas	0.119	0.124	0.118
WHCARD	Government health concession card	0.205	0.399	0.158
AREADIS	Index of disadvantage based on socio-economic factors at the census division level (deciles) continuous values 1-10 1=most disadvantage, 10=least disadvantage	5.726	5.164	5.868
ENGLISH	English main language spoken at home	0.909	0.905	0.910
*AUBORN**	Australian born	0.728	0.739	0.725
NUBORN	New Zealand or UK born	0.090	0.082	0.092
SEBORN	Southern Europe born	0.040	0.046	0.038
WEBORN	Western Europe born	0.014	0.008	0.015
ASBORN	South Asia born	0.077	0.062	0.080
OTBORN	Other country born	0.052	0.060	0.050
Sample size *(unweighted)*		15,290	3,348	11,942

Note: The means in the table are weighted to represent the Australian population at the time of the survey.

Figure 4.3 shows higher mental health risk for people in the lower income deciles. While average mental health medication use for those with mental health risk is 30 per cent, the rate of use for people in the lower income deciles is closer to 40 per cent. The mental health medication use rate for the middle income groups is average or below and for Decile 10 the rate is 35 per cent. The following analysis focuses on whether income is a barrier to medication use, even though the data reveals lower income deciles are relatively high users, and secondly, the contributing factors to the mental health medication use; the health card in particular.

Figure 4.3: Share of people with mental health risk and mental health medication use by household income decile



Summary statistics for health card sub-samples

Summary statistics for those with mental health risk having a health card and not having one shown in Table 4.4 indicate significant income differences between the two sub-samples, with the majority of people with mental health risk without a health card in the middle and high income categories. Likewise being unemployed or not in the labour force account for 70 per cent of the health card sub-sample compared to 60 per cent being employed full-time in the no health card sample. In addition, mental health medication use is higher for the sub-sample with a health card, at 35 per cent compared to 23 per cent. Also noteworthy is the higher share with another chronic condition in the health card sub-sample, 48 per cent compared to 35 per cent for the sub-sample without a health card.

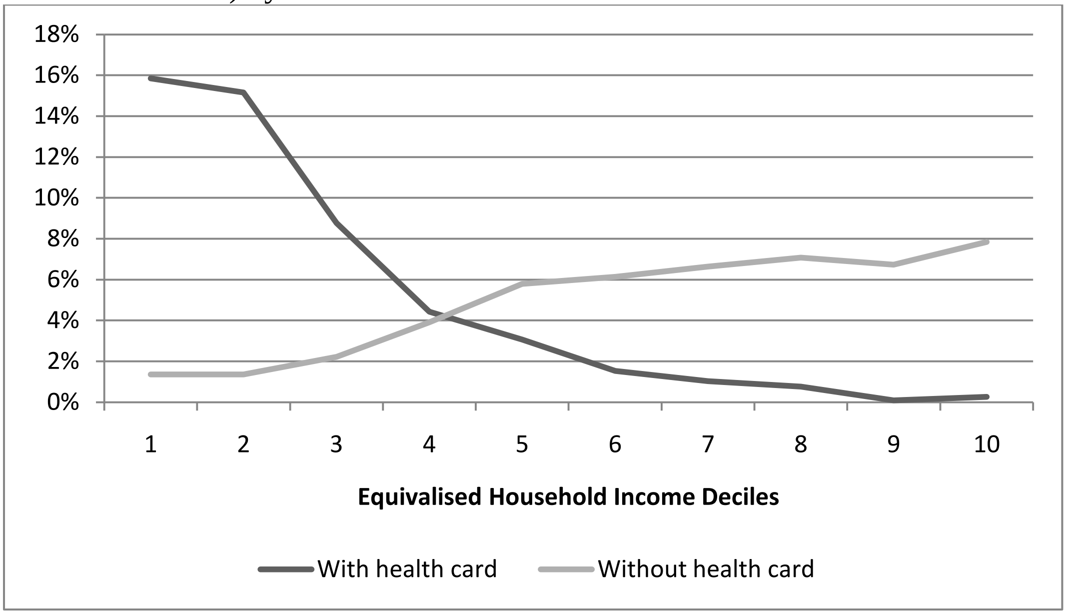
Table 4.4: Means for mental health risk group in sub-samples with a health card and without a health card

	Health card sub-sample	**Without health card sub-sample**
Sample size (unweighted)	1,525	1,823
MHMEDS	0.350	0.228
DPY1	0.091	0.081
DPY2	0.227	0.025
DPY3	0.232	0.026
DPY4	0.171	0.072
DPY5	0.115	0.092
MIDPY	0.105	0.353
HIDPY	0.014	0.220
DPYMIS	0.046	0.132
DEH1	0.236	0.026
DEH2	0.223	0.014
DEH3	0.167	0.029
DEH4	0.078	0.078
DEH5	0.053	0.103
MIDEH	0.081	0.356
HIDEH	0.012	0.212
DEHMIS	0.150	0.182
AGE	40.256	38.406
MARRIED	0.371	0.573
WORKFT	0.091	0.601
WORKPT	0.206	0.233
UNEMPLYD	0.122	0.028
NOTINLF	0.581	0.138
HIEDUC	0.066	0.200
SOMEDUC	0.331	0.353
NOEDUC	0.603	0.447
FEMALE	0.549	0.554
OTHCCON	0.484	0.349
CITY	0.619	0.707
TOWN	0.213	0.198
COUNTRY	0.168	0.095
AREADIS	4.129	5.776
ENGLISH	0.877	0.925
AUBORN	0.734	0.743
NUBORN	0.077	0.087
SEBORN	0.059	0.039
WEBORN	0.004	0.012
ASBORN	0.053	0.068
OTBORN	0.074	0.051

Note: The means in the table are weighted to represent the Australian population at the time of the survey.

A plot of mental health medication use for the health card sub-sample compared to the no health card sub-sample in Figure 4.4 shows two distinct patterns: much higher medication use for the 3 lowest income groups in the health card sub-sample, and an increasing trend of mental health medication among the higher income groups for the sub-sample without a heath card. From these data, one can postulate that income is not a barrier to access medication for low income people with a health card, and yet income may be a barrier to mental health medication use for those without a health card, particularly those just above health card income eligibility limits in income deciles 4 and 5.

Figure 4.4: Distribution of people using mental health medication (conditional on mental health risk) by health card status and household income decile



Note: the shares of the income deciles under the lines sum to 100%.

A point of clarification is needed. While one would expect that all low income people in Australia are eligible for the health card this is not necessarily the case. Some allowance program criteria include residency requirements, some include an asset test, a few programs require an application, such as for the low income health card, and several programs restrict eligibility to permanent residents. A cross check of health card and type government allowance confirm that a significant number of people who receive some type of government allowance do not receive a health card. For example, of those people reporting a Disability Support Pension in the 2004-05 NHS, 30 per cent do not have a health card. Low income people with mental health risk without a health card using mental health medication could comprise of international students, recent immigrants, low income earners with a house (e.g., recently divorced individuals), or others that have neglected to apply for program benefits.

Table 4.5 shows the distribution of the sample with mental health risk by income group and health card status. The table highlights that the majority of people with mental health risk are in the low income groups and have a health card, while the majority of those with mental health risk in the middle and high income groups are in the sample without a health card.

Table 4.5: Mental health risk sub-samples by household income groups

	Full sample	**With health card sub-sample**	**Without health card sub-sample**
DEH1	490	442	48
DEH2	434	404	30
DEH3	292	237	55
DEH4	258	123	135
DEH5	268	71	197
MIDEH	771	87	684
HIDEH	429	16	413
DEHMIS	406	145	261
Total	3,348	1,525	1,823

4.5 Results

4.5.1 Main estimation results

Table 4.6 presents marginal effects, standard errors and significance levels for the determinants of mental health medication use for all adults below pension age estimated by two approaches: standard probit estimation and censored probit estimation. All models are estimated with robust standard errors to account for possible heteroskedasticity. Discussion of the results will first focus on specification issues for the censored probit model, followed by a comparison of coefficient results from the probit and censored probit models.

As previously explained, personal income variables are included in the mental health risk equation to identify in the censored probit model. The results show that the low personal income decile variables are positive and highly significant, which provide an indication that the model specification is appropriate.

The ρ coefficient is negative and significant, which indicates that selection is not random. The ρ coefficient captures information about the correlation between unobservable factors that predict both mental health risk and mental health medication use. Several explanations are plausible for the negative coefficient of correlation. One factor not accounted for in the model is severity of mental health risk, which may contribute to a negative sign on ρ. In other words, people with severe mental health problems may be less inclined to seek treatment, and likewise people with less severe mental health problems may have a more proactive approach to health. Secondly, missing information on severity of other chronic health condition could also be a factor. Severe mental illness combined with serious physical illness could impact medication use in the following way. People with several chronic conditions who also have mental health risk may require a number of prescription medications. Given a budget constraint, it is possible medication purchases are prioritised with mental health medication receiving lower priority. In addition, attitudes to health care and 'self-management' are not captured in the dataset and may also affect possible negative correlation between mental health risk and mental health medication use.

Comparison of the standard probit model and the censored probit model reveals limitations with the standard probit approach. Several factors indicated in the probit model as significantly impacting mental health medication use are factors mostly associated with mental health risk as indicated in the censored probit model. Importantly, the low household income deciles are negative and not significant determinants of mental health medication use in the probit model, but these low income decile variables are negative and significant in the censored probit model after controlling for the effect of low personal income on mental health risk. In addition, other factors predicted to impact mental health medication use such as being out of the labour force, having another chronic condition, age and having a health card, are significantly associated with mental health risk and not mental health medication use in the censored probit model.

The predicted probabilities of mental health mediation use shown in Table 4.6 are conditional on having mental health risk. The predicted probabilities are evaluated at the means for all variables. Slightly lower predicted probability of mental health medication use is found for the censored probit model compared to the standard probit model since the censored probit model calculation adjusts for the negative correlation of unobservables, ρ, between mental health medication use and mental health risk.

The main results of the censored probit model for all adults below pension age indicate that low household income is negatively associated with mental health medication use after controlling for selection bias. A Wald test of joint significance for the variables *DEH1, DEH2 and DEH3* is nearly statistically significant. This negative association is also evident in decile 4 and the middle income groups. However, there is no clear linear positive relationship between mental health medication use and household income probably because low income people in Australia are eligible for a health card that entitles them to concession prices on medications. To clarify this point and provide additional insight into the relationship between income and mental health medication use, I estimate the model separately for those with and without a health card.

Table 4.6: Estimation results for full sample - adults below pension age

	Probit		Censored Probit			
	MHMEDS		***MHMEDS***		***MHRISK***	
	Mar. Eff.	Std. Err.	Mar. Eff.	Std. Err.	Coef.	Std. Err.
DEH1	-0.060	0.119	-0.090	0.101**	0.053	0.068
DEH2	-0.028	0.120	-0.072	0.106*	0.143	0.068**
DEH3	-0.035	0.123	-0.058	0.108	0.059	0.067
DEH4	-0.088	0.120	-0.097	0.104***	0.025	0.064
DEH5	-0.014	0.117	-0.037	0.101	0.089	0.058
MIDEH	-0.030	0.089	-0.051	0.073**	0.103	0.042**
DEHMIS	-0.067	0.101*	-0.074	0.089**	0.102	0.056**
AGE	0.021	0.012***	0.009	0.020	0.061	0.008***
AGE2	0.000	0.000***	0.000	0.000	-0.001	0.000***
MARRIED	-0.036	0.053**	0.015	0.066	-0.259	0.029***
WORKPT	0.020	0.077	-0.001	0.067	0.036	0.040
UNEMPLYD	0.031	0.120	-0.047	0.123	0.328	0.000***
NOTINLF	0.110	0.079***	0.034	0.107	0.285	0.044***
SOMEDUC	-0.010	0.080	-0.027	0.068	0.089	0.037**
NOEDUC	-0.052	0.074**	-0.065	0.065***	0.074	0.036**
FEMALE	0.061	0.050***	0.037	0.054*	0.103	0.029***
OTHCCON	0.057	0.051***	-0.008	0.077	0.323	0.030***
CITY	-0.002	0.060	-0.007	0.056	0.041	0.037
COUNTRY	-0.029	0.083	-0.019	0.074	-0.035	0.045
WHCARD	0.079	0.075***	0.000	0.100	0.339	0.040***
AREADIS	0.003	0.011	0.006	0.008*	-0.014	0.006***
Constant		0.357***		0.672	-2.289	0.151***
DPY1					0.165	0.067**
DPY2					0.249	0.070***
DPY3					0.433	0.069***
DPY4					0.245	0.063***
DPY5					0.133	0.059**
MIDPY					0.068	0.050
DPYMIS					-0.050	0.066
Observations		3,348	15,290			
Censored observations			11,942			
Uncensored. observations			3,348			
Predicted Prob. (cond)		0.308	0.272			
Pseudo R^2		0.044				
ρ			-0.543			
Wald test $\rho = 0$ [a]			0.034			
DEH1,2,3,4,5,MID = 0 [b]		0.344	0.168			
DEH1,2,3 = 0		0.448	0.105			
DEH4,5,MID = 0		0.142	0.058			
DPY1,2,3,4,5,MID = 0					0.000	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] p-value is shown.[b] Wald test that variables are jointly = 0; p-value is shown.
Omitted variable categories are: *HIDEH, WORKFT, HIEDUC, TOWN and HIDPY.*

Probit and censored probit estimation results for the health card sub-sample and the no-health-card sub-sample are shown in Table 4.7 and Table 4.8, respectively. First, ρ remains negative and significant, indicating that the specification is appropriate, and that the negative correlation of unobservables affecting mental health medication and mental health risk remains. The coefficients on the low income variables in the mental health medication use equation of the censored probit model are positive, although not statistically significant. Nor are the joint tests on the household income variables significant. This confirms the *a priori* notion that income is not a barrier for low income people with mental health risk for the sub-sample with a health card.

As expected the predicted probabilities shown in Table 4.7 for the health card sample are much higher compared to the results for the sub-sample without a health card shown in Table 4.8 For the censored probit model, the predicted probability of mental health medication use for those with a health card is 34.1 per cent compared to 24.4 per cent for those without a health card.

Estimation results for the sub-sample without a health card in Table 4.8 indicate that the ρ in the censored probit specification passes statistical significance, but the value of ρ may indicate a problem. According to Wooldridge (2002, 570), high collinearity between the outcome and selection equations could indicate lack of identification in the censored probit specification. The fact that very few of the personal income group variables in the selection equation, except for *DPY1*, are statistically significant suggests that identification may not be achieved in the censored probit model for the sub-sample without a health card. The null hypothesis that the identifying restrictions are jointly zero cannot be rejected. The coefficients on household income groups in the medication equation show a negative association between household income and mental health medication, with the middle income variables being statistically significant. However, due to the problem with identification the results should be interpreted with caution.

Table 4.7: Estimation results for sub-sample with a health card

	Probit		**Censored Probit**			
	MHMEDS		***MHMEDS***		***MHRISK***	
	Mar. Eff.	Std. Err.	Mar. Eff.	Std. Err.	Coef.	Std. Err.
DEH1	0.084	0.398	0.026	0.350	0.255	0.202
DEH2	0.112	0.399	0.041	0.354	0.355	0.201*
DEH3	0.128	0.394	0.067	0.355	0.354	0.202*
DEH4	0.067	0.404	0.028	0.356	0.298	0.206
DEH5	0.258	0.411*	0.191	0.376	0.340	0.213
MIDEH	0.162	0.412	0.110	0.363	0.318	0.201
DEHMIS	0.078	0.399	0.032	0.355	0.412	0.210**
AGE	0.030	0.025***	0.016	0.027	0.084	0.012***
AGE2	0.000	0.000***	0.000	0.000	-0.001	0.000***
MARRIED	-0.051	0.082*	-0.003	0.093	-0.277	0.053***
WORKPT	0.043	0.161	0.012	0.148	0.116	0.086
UNEMPLYD	0.075	0.188	-0.004	0.187	0.325	0.106***
NOTINLF	0.185	0.148***	0.091	0.188	0.417	0.084***
SOMEDUC	0.022	0.149	0.015	0.133	0.040	0.092
NOEDUC	-0.015	0.146	-0.011	0.130	-0.015	0.090
FEMALE	0.005	0.077	0.031	0.071	-0.146	0.050***
OTHCCON	0.084	0.073***	0.002	0.114	0.478	0.048***
CITY	0.021	0.086	0.000	0.081	0.146	0.054***
COUNTRY	-0.009	0.107	-0.009	0.097	0.033	0.067
AREADIS	0.002	0.014	0.004	0.012	-0.017	0.009*
Constant		0.559***		0.926	-2.390	0.313***
DPY1					0.102	0.195
DPY2					0.193	0.188
DPY3					0.344	0.186*
DPY4					0.110	0.184
DPY5					-0.012	0.186
MIDPY					-0.145	0.179
DPYMIS					-0.363	0.208*
Observations		1,525	3,893			
Censored observations			2,368			
Uncensored. observations			1,525			
Predicted Prob.(cond.)		0.374	0.338			
Pseudo R^2		0.045				
ρ			-0.524			
Wald test ρ = 0 [a]			0.062			
DEH1,2,3,4,5,MID = 0 [b]		0.115	0.124			
DEH1,2,3 = 0		0.575	0.748			
DEH4,5,MID = 0		0.048	0.107			
DPY1,2,3,4,5,MID = 0					0.000	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] p-value is shown.[b] Wald test that variables are jointly =0; p-value is shown.
Omitted variable categories are: *HIDEH, WORKFT, HIEDUC, TOWN and HIDPY.*

Table 4.8: Estimation results for sub-sample without a health card

	Probit		Censored Probit			
	MHMEDS		***MHMEDS***		***MHRISK***	
	Mar. Eff.	Std. Err.	Mar. Eff.	Std. Err.	Coef.	Std. Err.
DEH1	-0.046	0.224	-0.039	0.125	0.127	0.106
DEH2	0.102	0.257	-0.038	0.176	0.308	0.135**
DEH3	-0.020	0.243	-0.020	0.118	0.035	0.094
DEH4	-0.052	0.149	-0.034	0.083**	0.087	0.069
DEH5	-0.040	0.127	-0.035	0.068**	0.121	0.058**
MIDEH	-0.028	0.094	-0.030	0.048***	0.114	0.041***
DEHMIS	-0.053	0.115	-0.023	0.065*	0.084	0.056
AGE	0.012	0.021*	-0.006	0.016*	0.050	0.009***
AGE2	0.000	0.000	0.000	0.000**	-0.001	0.000***
MARRIED	-0.019	0.078	0.041	0.050***	-0.256	0.032***
WORKPT	0.009	0.086	-0.010	0.048	0.043	0.041
UNEMPLYD	0.029	0.241	0.041	0.152**	0.438	0.127***
NOTINLF	0.019	0.108	-0.030	0.064**	0.196	0.056***
SOMEDUC	-0.013	0.089	-0.022	0.048**	0.103	0.041***
NOEDUC	-0.067	0.090**	-0.038	0.057***	0.111	0.043***
FEMALE	0.106	0.072***	-0.014	0.098	0.221	0.034***
OTHCCON	0.031	0.076	-0.040	0.056***	0.251	0.035***
CITY	-0.020	0.083	-0.001	0.049	-0.009	0.038
COUNTRY	-0.052	0.121	0.001	0.078	-0.074	0.062
AREADIS	0.005	0.013	0.003	0.007**	-0.013	0.006**
Constant		0.434***		0.475***	-2.068	0.198***
DPY1					0.107	0.057*
DPY2					-0.038	0.083
DPY3					0.164	0.093*
DPY4					0.107	0.084
DPY5					0.073	0.056
MIDPY					0.033	0.034
DPYMIS					-0.042	0.053
Observations		1,823	11,397			
Censored observations			9,574			
Uncensored. observations			1,823			
Predicted Prob.(cond.)		0.255	0.245			
Pseudo R^2		0.035				
ρ			-0.973			
Wald test $\rho = 0$ [a]			0.102			
DEH1,2,3,4,5,MID = 0 [b]		0.614	0.061			
DEH1,2,3 = 0		0.546	0.296			
DEH4,5,MID = 0		0.602	0.010			
DPY1,2,3,4,5,MID = 0					0.286	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] p-value is shown [b] Wald test that variables are jointly =0; p-value is shown.
Omitted variable categories are: *HIDEH, WORKFT, HIEDUC, TOWN and HIDPY.*

A useful test of model validity is to compare nonlinear results with similar linear probability models, as demonstrated in Angrist and Pischke (2009). Correct standard errors for the probit marginal effects are needed for direct comparisons. The ABS Remote Data Access Laboratory does not allow programming commands such as the delta method (Greene, 2000) or bootstrapping methods, that would enable me to construct correct standard errors for the marginal effects.

The following tables show marginal effects on the income variables from the censored probit models compared with the coefficients from the censored linear model for three models: the full sample, the sub-sample with a health card and the sub-sample without health card. The standard errors for the censored probit models are from the coefficient estimates. The marginal effects from the censored probit model are very similar to the coefficient estimates for the censored linear specification.

Table 4.9: Estimation results for full sample – censored probit model compared with censored linear probability model

	Censored Probit		**Censored Linear**	
	MHMEDS		***MHMEDS***	
	Mar. Eff.	Std. Err.	Coef.	Std. Err.
DEH1	-0.090	0.101**	-0.081	0.038**
DEH2	-0.072	0.106*	-0.054	0.040
DEH3	-0.058	0.108	-0.042	0.040
DEH4	-0.097	0.104***	-0.085	0.037**
DEH5	-0.037	0.101	-0.025	0.069
MIDEH	-0.051	0.073**	-0.041	0.027
DEHMIS	-0.074	0.089**	-0.066	0.032**
ρ	-0.543		-0.248	
Wald test $\rho = 0$ [a]	0.034		0.000	
DEH1,2,3,4,5,MID = 0 [b]	0.168		0.314	
DEH1,2,3 = 0	0.105		0.224	
DEH4,5,MID = 0	0.058		0.139	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] p-value is shown.[b] Wald test that variables are jointly = 0; p-value is shown.
Omitted variable category is *HIDEH*.

Table 4.10: Estimation results for sub-sample with a health card– censored probit model compared with censored linear probability model

	Censored Probit		**Censored Linear**	
	MHMEDS		***MHMEDS***	
	Mar. Eff.	Std. Err.	Coef.	Std. Err.
DEH1	0.026	0.350	0.030	0.105
DEH2	0.041	0.354	0.052	0.106
DEH3	0.067	0.355	0.083	0.106
DEH4	0.028	0.356	0.053	0.108
DEH5	0.191	0.376	0.216	0.116
MIDEH	0.110	0.363	0.106	0.103
DEHMIS	0.032	0.355	0.044	0.108
ρ	-0.524		-0.283	
Wald test $\rho = 0$ [a]	0.062		0.000	
DEH1,2,3,4,5,MID = 0 [b]	0.124		0.114	
DEH1,2,3 = 0	0.748		0.557	
DEH4,5,MID = 0	0.107		0.097	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] p-value is shown.[b] Wald test that variables are jointly = 0; p-value is shown.
Omitted variable category is *HIDEH.*

Table 4.11: Estimation results for sub-sample without a health card – censored probit model compared with censored linear probability model

	Censored Probit		**Censored Linear**	
	MHMEDS		***MHMEDS***	
	Mar. Eff.	Std. Err.	Coef.	Std. Err.
DEH1	-0.039	0.125	-0.052	0.072
DEH2	-0.038	0.176	0.075	0.090
DEH3	-0.020	0.118	-0.026	0.063
DEH4	-0.034	0.083**	-0.065	0.045
DEH5	-0.035	0.068**	-0.054	0.038
MIDEH	-0.030	0.048***	-0.039	0.028
DEHMIS	-0.023	0.065*	-0.058	0.035*
ρ	-0.973		-0.157	
Wald test $\rho = 0$ [a]	0.102		0.017	
DEH1,2,3,4,5,MID=0 [b]	0.061		0.537	
DEH1,2,3=0	0.296		0.669	
DEH4,5,MID=0	0.010		0.362	

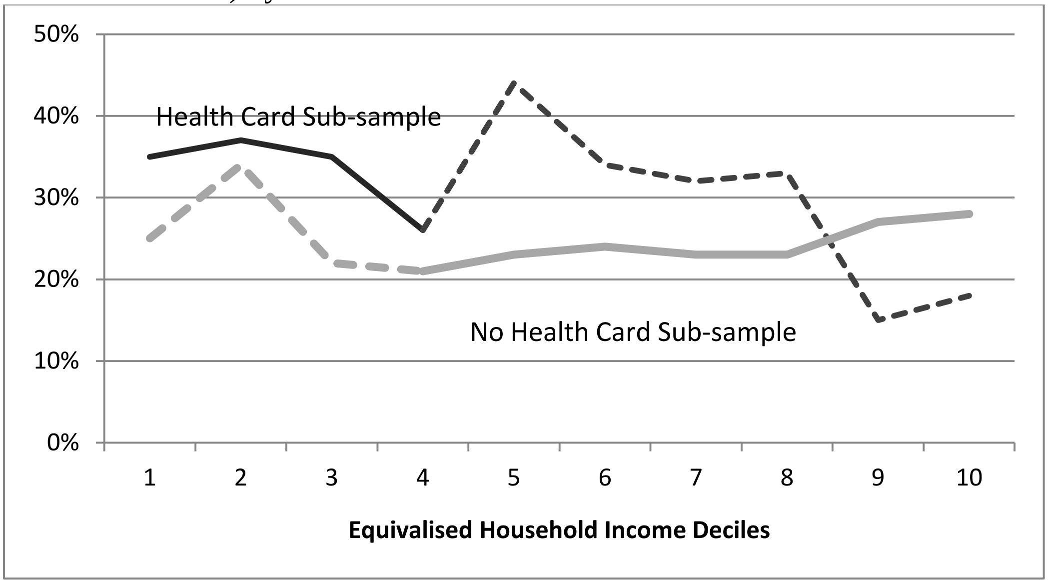
***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] p-value is shown.[b] Wald test that variables are jointly = 0; p-value is shown.
Omitted variable category is *HIDEH.*

Figure 4.5 shows the predicted probability of mental health medication use conditional on mental health risk by household income decile for those with a health card and for those without a health card. The conditional predicted probabilities (based on equation 4.4) were calculated for each observation based on their income decile and then averaged across each income decile; the approach does not control for differences in other characteristics.

The solid part of the lines indicates areas across the income decile distribution with more observations relative to the dotted part of the lines. For example, as indicated in Table 4.5, few people without a health card are observed in the low income deciles, and likewise, few people with a health card are observed above decile 4. Generally, the figure shows higher predicted use of mental health medication for low income groups due to having a health card. For this group, use is greatest in decile 2 and then declines to decile 4, which corresponds to income eligibility for the health card. Predicted mental health medication use is comparatively lower for people in middle income groups without a health card and there is evidence of a positive gradient beyond income decile 4.

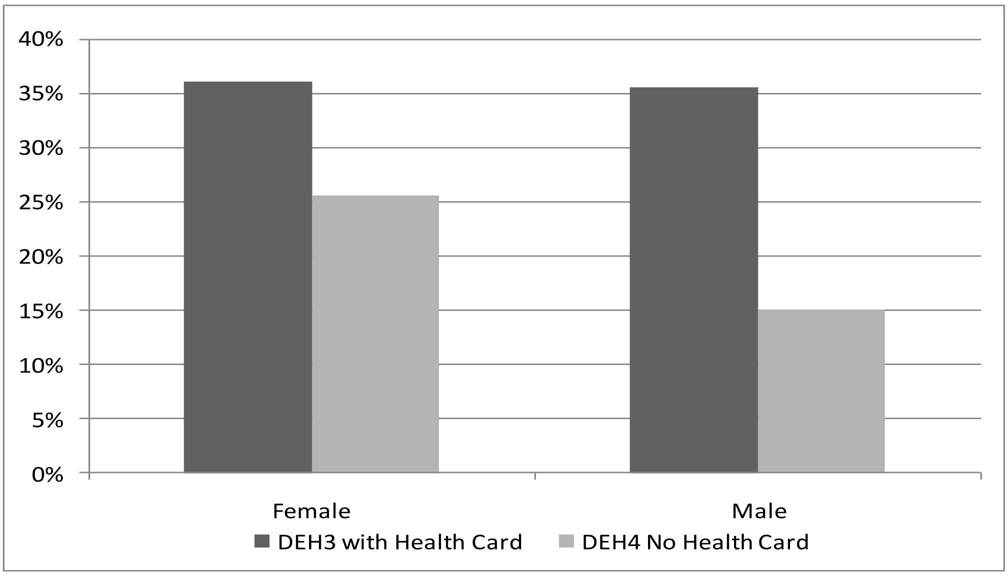
The 'lumpiness' of predicted use for the health card sub-sample is presumably due to differential income cut-off criteria associated with various government allowance programs. For example, the income cut-off for single beneficiaries receiving the health care card due to the unemployment benefits falls within household income decile 3, thus creating a spike in decile 4. Other program benefit criteria may account for the peak in decile 5, such as use related to Veteran's Affairs programs.

Figure 4.5: Predicted probability of mental health medication use (conditional on mental health risk) by household income decile



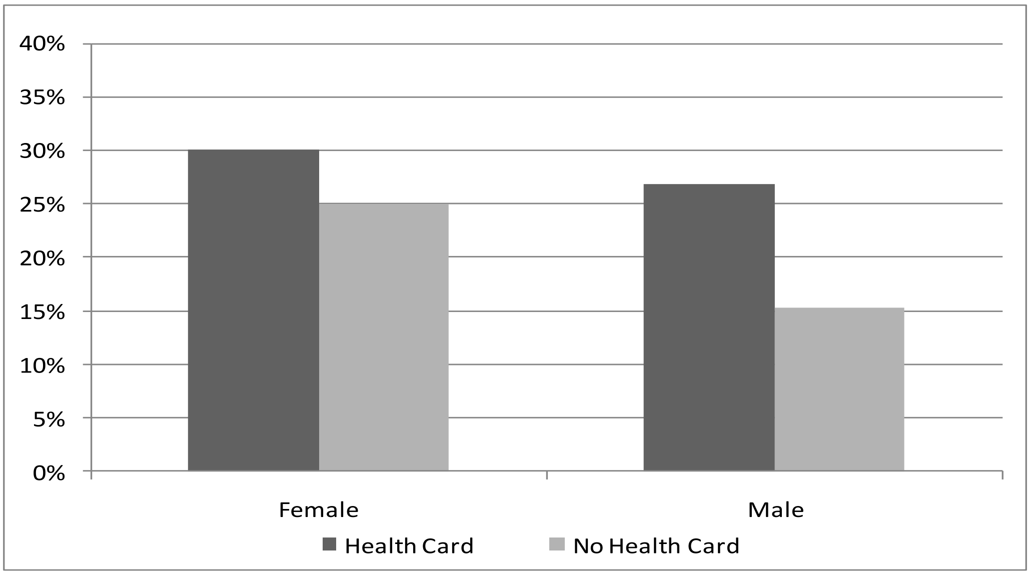
To provide more in-depth analysis of the effect of having a health card on mental health medication use for those with mental health risk, it is helpful to consider some representative individuals. The first scenario considers the effect of the health card for a single individual with a health card in household income decile 3 compared to someone without a health card in household income decile 4 where the individual is no longer eligible for a health card; differences in other characteristics are not controlled for. It is important to bear in mind that different income eligibility cut-offs for unemployment programs versus for long disability pensions: in 2005 the cut-off for singles is nearly double for the latter ($336 compared to $633 as shown in Table 4.1). The following analysis does not try to distinguish between the type of government allowance programs associated with the health card. In addition there are other program criteria that are not means tested (e.g., Veteran Affairs). These factors may affect predicted probability results. Predicted probabilities are estimated separately for females and males due to generally higher rates of mental risk and mental health medication use for females compared to males. The results presented in Figure 4.6 show an approximately 10 percentage point drop in predicted medication use for females and 20 per cent reduction in mental health medication use for males going from household income decile 3 to 4. This significant drop is likely due to lack of health card in household income decile 4.

Figure 4.6: Predicted probability of mental health medication use (conditional on mental health risk) in household income decile 3 compared to decile 4, females and males



The second scenario looks at married individuals in household income decile 4, in which most low income couples would still be eligible for health card benefits if they met other program criteria. The results show significant differences for both females and males in the health card group versus the no health card group. For females medication usage is 5 percentage points less for the no health card group, and for males the difference in usage between having a health card and not having a health card is more than 10 percentage points.

Figure 4.7: Predicted probability of mental health medication use (conditional on mental health risk) for couples with and without a health card in income decile 4



The results generally show that having a health card is a strong predictor of mental health medication use. The results also show some evidence of a positive income gradient on mental health medication use for middle income people without a health card; suggesting that income could be a barrier to mental health medication use for middle income people without a health card.

4.5.2 Sensitivity tests

Alternative specifications based on the censored probit model were tested to determine the model's sensitivity. Tests were conducted for the following: male and female subsamples, possible omitted variables, excluding observations with missing income, alternative exclusion restriction variables, and an application of the model to another chronic condition: heart medication use. What follows is a brief discussion of the findings from the tests. Details from the estimation results are provided in Appendix D.

In addition to testing gender interaction terms on the income variables in the full sample of adults, which didn't alter the model, gender sub-samples were also estimated. Results for the female sub-sample are shown in Table C1 and Table C2 shows the results for males. The main results were slightly improved for the female sub-sample compared to the full sample of adults. The ρ variable was similar to results for the full sample previously discussed, and several of the coefficients on income were more precisely estimated. The female results were also consistent for the health card and no health card sub-samples compared to the main results previously discussed.

The male results generally performed less well compared to the main results for the full sample of adults and for the health card and no health card sub-samples. For males in the full sample model the ρ coefficient was not significant, and several of the income variables in the medication equation were not statistically significant. Likewise, in the health card sub-sample ρ was not significant, and in the sub-sample without a health card, the model did not converge after many iterations.

All models, full sample, health card and no health card sub-samples, were tested for possible missing key variables, country of birth and if English was the main language spoken at home. Some of the country of birth variables were negative statistically significant in both mental health risk and mental health medication use equations, but overall the main findings were preserved, as shown in Table C.3.

Presence of children and household size would be expected to play a role in demand for mental health medication. However, this could not be tested with the current specification due to the equivalised household income variable already accounting for household size.

The effect of measurement error due to the high number of observations with missing income was tested by dropping observations with missing income. Overall the results are consistent between the two models leading to the conclusion that including observations with missing income does not alter the main results. Table C.4 shows improved precision in the full sample model as a result of dropping observations with missing income. For the health card sub-sample, the low income variables remain positive but not statistically significant, which is consistent with the main findings previously discussed. The results for the sub-sample without a health card also remain the same.

In addition, several modifications were considered for identification of the censored probit model, with particular focus on the sub sample without a health card. The modifications focused on alternative formulations of the personal income decile variables. Interaction variables with personal income deciles and characteristics such as female, married, and female and married together did not change the results of the value and significance of the ρ coefficient. Nor did a parsimonious approach prove more effective. When continuous income and continuous income squared were used in place of the personal income decile variables the results showed the income variables to be jointly significant, but ρ was not significant in the sub-sample without a health card model. As a result, the specification put forth for the sub-sample without a health card in the main results is the best that could be achieved given the limited availability of exclusion restrictions.[33]

The censored probit model was also tested for its relevance in assessing possible income barriers to medication use for another chronic condition: heart medication taken for heart conditions. While 27.7 per cent of people with mental health risk take mental health medication (see Table 4.3), the share of people with heart condition taking heart medication is much higher at 58.3 per cent (see Table C.5). Results from the censored probit regressions are shown in Table C.6. In the full sample of adults under pension age, household income is negatively associated with heart medication use; yet many of the variables are not statistically significant. The ρ coefficient was not statistically significant, which could mean there is no correlation between unobservable factors affecting both heart medication use and health disease in the full sample, or that some important variables are missing from the model. The sub-sample with a health card did not converge, which could be due to the high share of people with heart condition taking heart medication in the health card subsample (65.8 per cent in the weighted sample results in Table C.5). The results for the sub-sample without a health card are similar to those for the full sample. Few of the coefficients for the personal income variables in the heart disease selection equation were statistically significant, indicating that income may not play the same role in heart disease as for mental health risk.

[33] The results for alternative specifications of the identifying restriction discussed are available upon request.

To summarise the results of the sensitivity tests: the findings of the censored probit model are generally robust for the impact of income on mental health medication use among the full sample of adults and in the health card and no health card sub-samples. The model proved less robust for the males without a health card, and extending the approach to other chronic conditions may not be suitable.

4.5.3 Threats to validity

The results support the notion that Australia's health care system is equitable and that safety net provisions such as the health card improves access to mental health care for people with low income. The results also reveal that there may be income barriers to mental health treatment for people just above health card income thresholds. This section considers limitations of the current model and findings due to possible omitted variables, selection bias and specification issues. Suggestions for future research are also discussed.

For people with a health card low income is not a deterrent to medication use, while it may be for people without a health card. We know that health card holders pay significantly less for each medication. But is the price paid by general patients likely to be a significant factor? Medication costs may not be an issue for individuals or families with few ailments. However, for individuals or families with a severe mental health condition or co-morbidity with other serious chronic conditions, requiring many medications, the cumulative cost of prescription drugs may be an important factor. A small portion, an estimated 2.5 per cent of these people may be eligible for reduced prescription prices through the PBS safety-net program after reaching program thresholds, which would not affect my results.[34] Future research on the price and income effects on the demand for mental health medication should consider total prescription costs and the effect of the PBS safety-net program. The NHS includes data on number of medications for many health conditions, so it may be possible to extend the analysis with NHS data or from other sources such as PBS data.

[34] Sweeney (2007, page 5) estimates that 2.5 percent of general patients were eligible for a PBS safety net card in 2006.

Information is also missing in the model about individual mental health treatment preferences and the influence of providers on treatment. It may be the case that a provider's awareness of a patient's health card status induces providers to recommend medication as a component of treatment. Any difference in treatment preferences between those with a health card compared to those without a health card would impact the results. For example, some people may prefer counselling or alternative therapies (such as natural herbs and vitamins) instead of taking prescription drugs for mental health conditions. Studies based on 1997 Survey of Mental Health and Wellbeing identified a need to improve access to specialist and counselling services for people with mental health disorders in Australia (Andrews et al, 2000). In 2006, expanded Medicare coverage for counselling services was passed. Prior to this policy change medication was the predominant type of medical treatment for mental health disorders. In addition my model does not capture supply constraints, such as the availability of mental health specialists offering counselling services (which can be both a substitute and complement for medication). Finally other variables may be missing from the model including attitudes about mental health such as stigma, which may prevent people from seeking treatment, or attitudes towards health care and preferences for 'self-management' of mental health conditions. Non-random preferences against mental health medication use among those without a health card may bias my results, and would be an important area to try to gain more information on in future research.

In addition to omitted variable bias, new selection bias is introduced when the sample is split into having a health card and not having a health card. There may be endogeneity of mental health risk with having a health card, i.e., selection into health card status based on mental health risk status. A bivariate probit test of mental health risk and health card found significant positive correlation of the error terms, which suggests that an additional dimension of selection bias is possible in my model. These results are included in Panel 2 of Appendix Table B.2. Maximum likelihood estimation involving three stages – mental health medication, mental health risk and health card status could be estimated and the results compared to the current model: a possible extension to consider in future research.

Identification poses a challenge in selection models. It is especially difficult to think of variables affecting mental risk and not mental health medication use. I was able to achieve reasonable results with a novel approach of using personal income to identify the selection effect on mental health medication use. However, based on the strength of instruments test (in Appendix B) potential weak instrument problems need to be acknowledged. Nevertheless, the selection model provides a useful approach to distinguish between the effects of the explanatory variables on mental health medication use from the effects of these variables on mental health risk, which is recommended for future research with different datasets where stronger exclusion restrictions may exist. For example, longitudinal data with data on income and price shocks or mental health shocks (associated with job loss or divorce) could improve the specification of the model with respect to selection and the analysis of factors affecting demand for mental health treatment. The Australian Longitudinal Study on Women's Health which includes mental health, medication use and income data, may provide an appropriate dataset to verify the results on this analysis.

4.6 Conclusion

Ensuring access to treatment is a special challenge in the area of mental health. Mental health sufferers are more likely to be in low income groups and often lack the financial, educational and social resources required to seek appropriate treatment. Evidence from other countries indicates that price responsiveness is greater for mental health compared to general medical care. This finding points to a concern about accessibility, as high prices for mental health care may lead to low treatment rates. In Australia, there are several health policies aimed at reducing financial barriers to access treatment. Despite these policies, many health experts express concern that more effort is required to improve treatment rates for mental health, and that better targeting is needed to ensure that those most in need get treated. Little is known about the effect of price and income on access to mental health treatment in Australia, and as such would be an important starting point to address the issue of adequate treatment rates for mental health.

Previous studies in Australia have not considered the importance of targeted assistance such as health card status in access to mental health treatment. No studies have examined income barriers to mental health medication use for those who lack a health card and who have a card. My contribution to this knowledge gap is three-fold. First, I provide evidence on the role of income in accessing mental health medication after controlling for the association of income with mental health risk. I address selection bias with a censored probit model, and utilise a novel approach to identify the model by using personal income in the mental health risk equation and household income in the outcome equation for mental health medication. Second, my results confirm the importance of the health card in ameliorating the impact on income on mental health medication use, and third, I show a possible income barrier for mental health sufferers without a health card.

These results have important policy implications. Policy changes aimed at addressing low treatment rates for mental health in Australia need to consider access issues for those just above thresholds for the health card in low-middle income groups. In addition, policy changes to increase copayments for pharmaceuticals need to take into account the importance of concession prices for those with mental health disorders.

Further investigation of the impact of income thresholds for the health card on mental health medication use would be beneficial. Regression discontinuity estimation methods utilising continuous income data in the 2004-05 NHS could assist in this regard.[35]

[35] A useful overview of regression discontinuity methods is provided in Imbens and Lemieux (2006).

Appendix A: Importance of income

Tests were conducted to determine the relative importance of personal income or household income for mental health medication use and mental health risk. Table A1 shows the results of probit regressions with Panel 1 including personal income decile variables and Panel 2 including equivalent household income decile variables. All models include control variables for age, gender, having another chronic condition, marital, employment, education status as well as having a health card.

Table A.1: Estimation results for income variables, mental health medication use and mental health risk

	MHMEDS		**_MHRISK_**	
1				
	Coefficient	Standard Error	Coefficient	Standard Error
DPY1	0.080	0.126	0.166	0.062***
DPY2	-0.085	0.124	0.297	0.063***
DPY3	0.094	0.115	0.467	0.060***
DPY4	0.000	0.113	0.286	0.057***
DPY5	-0.107	0.114	0.183	0.053***
MIDPY	-0.053	0.083	0.117	0.037***
DPYMIS	-0.230	0.117*	0.000	0.051
Observations	3,348		15,290	
Pseudo R^2	0.044		0.090	
DPY1,2,3,4,5,MID=0 [a]	0.284		0.000	
2				
DEH1	-0.202	0.114*	0.210	0.057***
DEH2	-0.112	0.116	0.280	0.060***
DEH3	-0.111	0.118	0.126	0.059**
DEH4	-0.241	0.117*	0.105	0.055*
DEH5	-0.057	0.110	0.128	0.051*
MIDEH	-0.095	0.084	0.139	0.037**
DEHMIS	-0.203	0.101*	0.057	0.045
Observations	3,348		15,290	
Pseudo R^2	0.043		0.087	
DEH1,2,3,4,5,MID=0 [a]	0.428		0.000	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Wald test that variables are jointly = 0; p-value shown.
Omitted variables: *HIDEH, HIDPY*.

The results show that personal income variables are positive and significantly associated with mental health risk compared to mental health medication use. The results also show that household income has a somewhat stronger negative association with mental health medication use compared to personal income. Joint significance tests of the income variables are also included in Table A1. These tests show the stronger association of income with mental health risk compared to mental health medication use. When income variables are combined for mental health medication use, neither personal income variables or household income variables pass joint tests of significance.

Specifications with both income variables included were estimated for mental health risk to test if personal income was significant over and above household income. The estimation includes all the control variables previously mentioned. The results in Table A2 show that personal income was significant for mental health risk over and above household income.

Table A.2: Estimation results for income variables and mental health risk

	MHRISK	
	Coefficient	Standard Error
DPY1	0.134	0.067**
DPY2	0.257	0.068***
DPY3	0.430	0.066***
DPY4	0.244	0.062***
DPY5	0.146	0.057**
MIDPY	0.080	0.040**
DPYMIS	-0.049	0.064
DEH1	0.053	0.064
DEH2	0.144	0.065**
DEH3	0.039	0.062
DEH4	0.038	0.058
DEH5	0.078	0.054
MIDEH	0.102	0.040**
DEHMIS	0.093	0.055*
Observations	15,290	
Pseudo R^2	0.091	
DPY1,2,3,4,5,MID=0 [a]	0.000	
DEH1,2,3,4,5,MID=0 [a]	0.084	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Wald test that variables are jointly = 0; p-value shown
Omitted variables: *HIDEH, HIDPY*.

Appendix B: Over-identification and weak instrument tests

Over-identification and weak instrument tests are standard post-estimation procedures for two-stage least square (2SLS) models to assess the validity of exclusion restrictions. I conduct these tests with the two-stage least squares regression since over-identification tests are not available for probit models.

The over-identification test requires more instruments than endogenous variables in the first stage – the *MHRISK* equation.[36] The test assumes that one instrument is valid, and then tests for the validity of the other instruments (i.e., whether the instruments are uncorrelated with the error term in the second stage – the *MHMEDS* equation). To test the validity of personal income as valid instrument in my model, I include dummy interaction variables between main source of income and personal income. The main source of income variables groups are: employment income (*EMPEY*), business and other income (*BUSYO*) and government income and missing or no income (*GOVTY*). Since all of the instruments are drawn from the same concept – personal income – one would expect that either all instruments, or no instruments, would be valid.

The strength of the instruments is tested by the R^2 statistic – or goodness of fit – from the first-stage equation and by the F-test on the joint significance of all the instruments in the first-stage equation. A high R^2 and an F-test statistic over 10 are required to suggest that the instruments are sufficiently strong (Stata 10, 2010).

The following tables show the results of the *MHRISK* equation from the 2SLS model for *MHMEDS*. The tables show the results for models using different combinations of the interaction variables. The results show that the coefficients for some of the interaction variables are statistically significant in all models. The R^2 indicates that the goodness of fit for the first stage equation is reasonable. However, the joint test of significance – the F-test statistic does not pass 10 in any of the models, providing evidence of a weak instrument. The over-identification test score (the Sargan score

[36] This approach follows Angrist, Joshua D. and Alan B. Krueger. 1991. Does compulsory school attendance affect schooling and earnings? *The Quarterly Journal of Economics*, 106 (4): 979-1014.

shown in the second last row of the tables) is based on the null hypothesis that the instruments are valid. The results in every model indicate that the null cannot be rejected. This result provides some evidence that the identification strategy is valid but based on the F-test results, it may be weak.

Table B.1: Over-identification test results: I and II

	I [a]			**II** [b]	
MHRISK	Coef.	Std. Err.	***MHRISK***	Coef.	Std. Err.
DEH1	0.021	0.019	*DEH1*	0.019	0.019
DEH2	0.049	0.020**	*DEH2*	0.049	0.020**
DEH3	0.023	0.018	*DEH3*	0.023	0.018
DEH4	0.003	0.016	*DEH4*	0.003	0.016
DEH5	0.030	0.014**	*DEH5*	0.031	0.014**
MIDEH	0.028	0.010***	*MIDEH*	0.029	0.010***
DEHMIS	0.031	0.015**	*DEHMIS*	0.030	0.015**
DPY1	0.004	0.029	*DPY1*	0.015	0.026
DPY2	0.027	0.051	*DPY2*	0.001	0.036
DPY3	0.023	0.049	*DPY3*	0.060	0.032*
DPY4	0.032	0.035	*DPY4*	0.052	0.022**
DPY5	0.032	0.027	*DPY5*	0.031	0.017*
MIDPY	-0.002	0.020	*MIDPY*	0.019	0.011*
DPYMIS	-0.008	0.021	*DPYMIS*	-0.011	0.018
EMPXY1	0.054	0.046	*BUSXY1*	0.009	0.049
EMPXY2	-0.025	0.062	*BUSXY2*	0.043	0.081
EMPXY3	0.063	0.058	*BUSXY3*	-0.002	0.082
EMPXY4	0.030	0.038	*BUSXY4*	-0.019	0.054
EMPXY5	0.006	0.027	*BUSXY5*	0.016	0.035
EMPXYM	0.025	0.016	*BUSXYM*	-0.061	0.024**
EMPXYS	-0.013	0.024	*BUSXYS*	-0.009	0.034
GOVXY1	0.059	0.031**	*GOVXY1*	0.048	0.030
GOVXY2	0.082	0.051	*GOVXY2*	0.107	0.039***
GOVXY3	0.156	0.049***	*GOVXY3*	0.120	0.035***
GOVXY4	0.082	0.037**	*GOVXY4*	0.062	0.027**
GOVXY5	0.014	0.033	*GOVXY5*	0.015	0.028
GOVXYM	0.024	0.036	*GOVXYM*	0.001	0.033
GOVXYS	-0.035	0.043	*GOVXYS*	-0.031	0.043
constant	-0.214	0.044***	*constant*	-0.214	0.044***
R^2	0.099		R^2	0.099	
F (21, 15,290)	4.72		F (21, 15,290)	4.78	
Prob>F	0.000		Prob>F	0.000	
Score Chi^2 (20)	22.825		Score Chi^2 (20)	18.414	
p value	0.298		p value	0.560	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Omitted variables: *HIDEH, HIDPY, EMPXYH, GOVXYH*
[b] Omitted variables: *HIDEH, HIDPY, BUSXYH, GOVXYH*

Table B.2 Over-identification tests results: III

	III [a]	
MHRISK	Coef.	Std. Err.
DEH1	0.022	0.019
DEH2	0.055	0.019***
DEH3	0.025	0.018
DEH4	0.003	0.016
DEH5	0.031	0.014**
MIDEH	0.029	0.010***
DEHMIS	0.031	0.015**
DPY1	0.034	0.025
DPY2	0.089	0.027***
DPY3	0.153	0.026***
DPY4	0.088	0.026***
DPY5	0.023	0.027
MIDPY	0.014	0.023
DPYMIS	-0.015	0.023
BUSXY1	-0.013	0.047
BUSXY2	-0.047	0.076
BUSXY3	-0.098	0.079
BUSXY4	-0.057	0.054
BUSXY5	0.023	0.038
BUSXYM	-0.057	0.028**
BUSXYS	-0.006	0.035
EMPXY1	0.020	0.043
EMPXY2	-0.092	0.044**
EMPXY3	-0.073	0.040*
EMPXY4	-0.031	0.028
EMPXY5	0.011	0.025
EMPXYM	0.003	0.018
EMPXYS	-0.009	0.025
constant	-0.222	0.044***
R^2	0.098	
F (21, 15,290)	4.07	
Prob>F	0.000	
Score Chi2 (22)	13.941	
p value	0.833	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Omitted variables: *HIDEH, HIDPY*, *BUSXYH*, *EMPXYH*

Appendix C: Tests for endogeneity

Bivariate estimation is used to associations between two sets of key variables: mental health medication use and having a health card, and having a health card and mental health risk. The estimation results show that the correlation coefficient ρ is statistically significant in both cases, and thus provides an indication of correlation. However, according to Greene (2000, 854) if the bivariate estimation model has omitted variables the correlation may be due misspecification.

Table C.1: Estimation results from bivariate probit regressions (1) for mental medication use and health card and (2) health card and mental health risk

1			**2**		
	Coefficient	Standard Error		Coefficient	Standard Error
MHMEDS			*WHCARD*		
DEH1	0.223	0.074***	*DEH1*	1.894	0.072***
DEH2	0.345	0.075***	*DEH2*	2.288	0.080***
DEH3	0.220	0.077***	*DEH3*	1.754	0.072***
DEH4	0.039	0.078	*DEH4*	1.090	0.069***
DEH5	0.090	0.073	*DEH5*	0.626	0.071***
MIDEH	0.052	0.055	*MIDEH*	0.248	0.063***
DEHMIS	-0.027	0.066	*DEHMIS*	0.736	0.064***
AGE	0.083	0.010***	*AGE*	-0.005	0.008
AGE2	-0.001	0.000***	*AGE2*	0.000	0.000
MARRIED	-0.310	0.035***	*MARRIED*	-0.622	0.032***
WORKPT	0.179	0.048***	*WORKPT*	0.683	0.040***
UNEMPLYD	0.430	0.088***	*UNEMPLYD*	1.326	0.079***
NOTINLF	0.536	0.050***	*NOTINLF*	1.191	0.042***
SOMEDUC	0.065	0.049	*SOMEDUC*	0.293	0.049***
NOEDUC	0.003	0.049	*NOEDUC*	0.334	0.048***
FEMALE	0.152	0.036***	*FEMALE*	0.001	0.033
OTHCCON	0.349	0.035***	*OTHCCON*	0.241	0.033***
CITY	0.027	0.041	*CITY*	-0.113	0.037***
COUNTRY	-0.071	0.056	*COUNTRY*	0.033	0.048
CDDISWT	-0.007	0.006	*CDDISWT*	-0.065	0.006***
Constant	-3.520	0.209***	Constant	-1.839	0.173***
WHCARD			*MHRISK*		
DEH1	1.896	0.072***	*DEH1*	0.216	0.062***
DEH2	2.285	0.080***	*DEH2*	0.331	0.063***
DEH3	1.756	0.072***	*DEH3*	0.188	0.061***
DEH4	1.092	0.069***	*DEH4*	0.110	0.058*
DEH5	0.627	0.071***	*DEH5*	0.105	0.055*
MIDEH	0.248	0.063***	*MIDEH*	0.105	0.041***
DEHMIS	0.739	0.064***	*DEHMIS*	0.134	0.055**
AGE	-0.005	0.008	*AGE*	0.068	0.007***

Table C.1 *Continued*

1			2		
	Coefficient	Standard Error		Coefficient	Standard Error
WHCARD			*MHRISK*		
AGE2	0.000	0.000	*AGE2*	-0.001	0.000***
MARRIED	-0.622	0.032***	*MARRIED*	-0.295	0.026***
WORKPT	0.684	0.040***	*WORKPT*	0.097	0.036***
UNEMPLYD	1.331	0.079***	*UNEMPLYD*	0.454	0.070***
NOTINLF	1.193	0.042**	*NOTINLF*	0.389	0.042***
SOMEDUC	0.291	0.049***	*SOMEDUC*	0.103	0.035***
NOEDUC	0.329	0.047***	*NOEDUC*	0.092	0.035***
FEMALE	0.000	0.033	*FEMALE*	0.086	0.026***
OTHCCON	0.243	0.033**	*OTHCCON*	0.341	0.026***
CITY	-0.114	0.037***	*CITY*	0.039	0.030
COUNTRY	0.031	0.048	*COUNTRY*	-0.036	0.040
CDDISWT	-0.065	0.006***	*CDDISWT*	-0.018	0.005**
Constant	-1.846	0.173***	Constant	-2.362	0.145***
			DPY1	0.114	0.066*
			DPY2	0.248	0.069***
			DPY3	0.418	0.067***
			DPY4	0.232	0.062***
			DPY5	0.135	0.058**
			MIDPY	0.071	0.041*
			DPYMIS	-0.068	0.064
ρ	0.199	0.028***	ρ	0.171	0.021***
Observations	15,290			15,290	
Likelihood-ratio test of ρ = 0 Chi^2 [a]		47.717***			65.293***

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] 5% significance level critical value $Chi^2(1) = 3.84$.
Omitted variable categories are: *HIDEH, WORKFT, HIEDUC, TOWN and HIDPY.*

Appendix D: Sensitivity tests

Female and male sub-samples

In addition to testing gender interaction terms on the income variables in the full sample of adults under pension age, which did not alter the model, gender sub-samples were estimated. Table D.1 shows the results for females and Table D.2 shows the results for males. The main results were slightly improved for the female sub-sample compared to the full sample of adults. The ρ variable was similar to results for the full sample previously discussed, and several of the coefficients on income were more precisely estimated. The female results were also consistent for the health card and no health card sub-samples compared to the main results previously discussed.

Table D.1: Estimation results from censored probit regressions for female sub-sample

	Full sample		With health card		Without health card	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
MHMEDS						
DEH1	-0.363	0.126***	0.151	0.569	-0.691	0.320**
DEH2	-0.264	0.129*	0.246	0.572	0.192	0.637
DEH3	-0.130	0.128	0.402	0.574	0.024	0.275
DEH4	-0.334	0.125**	0.254	0.572	-0.261	0.248
DEH5	-0.264	0.120**	0.525	0.588	-0.254	0.236
MIDEH	-0.211	0.091**	0.339	0.581	-0.130	0.216
DEHMIS	-0.175	0.121	0.298	0.571	-0.162	0.145
Constant	-0.213	0.724	-1.575	1.172	-1.090	3.280
MHRISK						
DPY1	0.000	0.087	-0.159	0.315	-0.012	0.105
DPY2	0.067	0.096	-0.063	0.306	-0.035	0.184
DPY3	0.344	0.090***	0.203	0.302	0.096	0.145
DPY4	0.168	0.083**	-0.126	0.302	0.236	0.151
DPY5	0.026	0.080	-0.258	0.300	0.008	0.134
MIDPY	-0.039	0.063	-0.477	0.294*	0.002	0.096
DPYMIS	-0.157	0.087	-0.640	0.355*	-0.063	0.152
Constant	-1.926	0.197***	-2.136	0.487***	-1.641	0.263***
ρ	-0.672		-0.658		-0.109	
Wald test [a]	0.013		0.032		0.944	
Total obs.	8,033		2,461		5,572	
Censored	6,028		1,527		4,501	
Uncensored	2,005		934		1,071	
Pred. Prob.	0.317		0.348		0.305	
Parameters	20		19		19	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Wald test of ρ = 0; p-value is shown. Omitted variables: *HIDEH, HIDPY*.

The male results generally performed less well compared to the main results for all adults under pension age and for the health card and no health card sub-samples. For the male full sample model, the ρ coefficient was not significant and several of the income variables in the medication equation were not statistically significant. Likewise, in the male health card sub-sample, ρ was not significant, and in the male sub-sample without a health card the model did not converge after many iterations.

Table D.2: Estimation results from censored probit regressions for male sub-sample

	Full sample		**With health card**	
	Coef.	Std. Err.	Coef.	Std. Err.
MHMEDS				
DEH1	-0.124	0.136	0.189	0.572
DEH2	-0.223	0.148	0.202	0.774
DEH3	-0.239	0.150	0.105	0.654
DEH4	-0.114	0.146	0.097	0.551
DEH5	0.055	0.163	0.884	0.724
MIDEH	-0.089	0.101	0.440	0.661
DEHMIS	-0.237	0.125*	0.092	0.547
Constant	1.119	1.270	-2.002	7.829
MHRISK				
DPY1	0.255	0.109**	0.283	0.365
DPY2	0.232	0.119**	0.409	0.420
DPY3	0.313	0.115***	0.430	0.354
DPY4	0.101	0.099	0.306	0.464
DPY5	0.192	0.085**	0.253	0.430
MIDPY	0.113	0.050**	0.045	0.257
DPYMIS	-0.066	0.093	-0.095	0.590
Constant	-2.879	0.232***	-3.247	0.471
ρ	-0.800		0.032	
Wald test [a]	0.112		0.991	
Total obs.	7,257		1,432	
Censored	5,914		841	
Uncensored	1,343		591	
Pred. Prob.	0.213		0.324	
Parameters	20		19	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Wald test of $\rho = 0$; p-value is shown. Omitted variables: *HIDEH, HIDPY.*

Omitted variables - country of birth and language

The main model and health card sub-sample results were tested for possible missing variables such as country of birth and if English was the main language spoken at home. Summary statistics for these variables in Table 4.3 do not reveal significant differences between those with and without mental health risk. As well, Table 4.4 shows no major differences between the country of birth variables by health card status. Table 4.4 shows, however, that there are slightly more people with English as the main language spoken at home in the no health card sub-sample. In the estimation results, some of the country of birth variables were negative and statistically significant in both mental health risk and mental health medication use, but overall the main findings were preserved, as shown in Table D.3.

Table D.3: Estimation results from censored probit regressions with country of birth and language variables

	Full sample		With health card		Without health card	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
MHMEDS						
DEH1	-0.184	0.105*	0.141	0.360	-0.119	0.137
DEH2	-0.166	0.109	0.164	0.364	-0.106	0.217
DEH3	-0.121	0.108	0.244	0.363	-0.099	0.120
DEH4	-0.233	0.107**	0.160	0.365	-0.186	0.090**
DEH5	-0.075	0.101	0.608	0.384	-0.178	0.076**
MIDEH	-0.109	0.077	0.331	0.370	-0.145	0.053***
DEHMIS	-0.124	0.092	0.200	0.364	-0.098	0.072
Constant	-0.782	0.809	-1.372	0.977	1.221	0.936
MHRISK						
DPY1	0.187	0.064***	0.025	0.196	0.088	0.065
DPY2	0.277	0.067***	0.139	0.192	-0.078	0.091
DPY3	0.464	0.063***	0.305	0.190	0.161	0.102
DPY4	0.266	0.059***	0.048	0.188	0.100	0.103
DPY5	0.165	0.056***	-0.072	0.192	0.059	0.057
MIDPY	0.099	0.039**	-0.219	0.183	0.036	0.041
DPYMIS	0.009	0.052	-0.437	0.212**	-0.064	0.058
Constant	-2.395	0.159***	-2.539	0.331***	-2.056	0.202***
ρ	-0.515		-0.531		-0.931	
Wald test [a]	0.050		0.054		0.102	
Total obs.	15,290		3,893		11,397	
Censored	11,942		2,368		9,574	
Uncensored	3,348		1,525		1,823	
Pred. Prob.	0.272		0.340		0.246	
Parameters	27		26		26	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Wald test of $\rho = 0$; p-value is shown. Omitted variables: *HIDEH, HIDPY*.

Excluding missing income observations

The effect of measurement error due to the high number of observations with missing income was tested by dropping observations with missing income. Table D.4 shows that overall the results are consistent with the main results, leading to the conclusion that including observations with missing income does not alter the main results. The table shows improved precision in the full sample model as a result of dropping observations without income. For the health card sub-sample, the low income variables remain positive but not statistically significant, which is consistent with the main findings previously discussed. The results for the sub-sample without a health card remain the same although identification is slightly improved, with more personal income variables in the mental health risk equation being positive and statistically significant.

Table D.4: Estimation results from censored probit regressions excluding missing income observations

	Full sample		**With health card**		**Without health card**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
MHMEDS						
DEH1	-0.280	0.103**	0.026	0.325	-0.201	0.129
DEH2	-0.242	0.108**	0.046	0.331	-0.155	0.195
DEH3	-0.177	0.106*	0.141	0.330	-0.108	0.119
DEH4	-0.267	0.101***	0.088	0.330	-0.204	0.088
DEH5	-0.124	0.096	0.451	0.354	-0.191	0.075**
MIDEH	-0.156	0.073**	0.204	0.337	-0.160	0.051***
Constant	-0.128	0.737	-0.418	0.928	1.543	0.733**
MHRISK						
DPY1	0.163	0.062***	0.159	0.155	0.117	0.059***
DPY2	0.260	0.066***	0.285	0.147	-0.005	0.088
DPY3	0.457	0.063***	0.445	0.146	0.207	0.101***
DPY4	0.249	0.059***	0.188	0.144	0.128	0.084**
DPY5	0.147	0.054***	0.054	0.145	0.080	0.054**
MIDPY	0.070	0.039*	-0.081	0.139	0.033	0.035**
Constant	-2.470	0.156***	-2.620	0.311***	-2.144	0.199***
ρ	-0.637		-0.735		-0.947	
Wald test [a]	0.017		0.011		0.110	
Total obs.	13,145		3,462		9,683	
Censored	10,203		2,082		8,121	
Uncensored	2,942		1,380		1,562	
Pred. Prob.	0.277		0.340		0.250	
Parameters	20		19		19	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Wald test of $\rho = 0$; p-value is shown. Omitted variables: *HIDEH, HIDPY*.

Heart medication use model

The censored probit model was also tested for its relevance in assessing possible income barriers to medication use for another chronic condition. The impact of household income on heart medication, *HARTMEDS*, taken for a heart condition, *HARTPROB*, was considered in the censored probit model with the same explanatory variables used in the mental health medication model. Table D.5 provides variable definitions and summary statistics for heart condition.[37] While 27.7 per cent of people with mental health risk take mental health medication (see Table 4.3), the share of people with heart condition taking heart medication is much higher at 58.3 per cent. A greater share of people with mental risk have a health card (39.9 per cent in Table 4.3) compared to 32.4 for people with a heart condition; but a higher share of people with a heart condition with a health card take heart medication, at 65.8 per cent, compared to 35.0 per cent taking mental health medication for those with mental health risk and health card (shown in Table 4.4).

Table D.5: Variable definition and summary statistics for heart condition

Variable name	Definition	Full sample [a]	Heart condition Sample	With health card	Without health card
HARTPROB	Ever been told by a doctor or nurse have heart or circulatory condition	0.189	1.000	0.324	0.676
HARTMEDS [b]	Taking medication for any heart or circulatory condition	0.110	0.583	0.658	0.547
Sample size (unweighted)		15,651	3,283	4,038	11,613

Note: The means in the table are weighted to represent the Australian population at the time of the survey.
[a] Full sample: all adults below pension age which is slightly larger than sample used for main results due to dropping observations taking mental health medication without mental health risk in the main results (see Table 5.2).
[b] Health card status is conditional on having a heart condition.

Results from the censored probit regressions are shown in Table D.6. In the full sample, household income is negatively associated with heart medication use, but many of the income variables are not statistically significant. The ρ coefficient is not statistically significant, which could mean there is no correlation between unobservable factors affecting both heart medication use and health disease in the full sample, or that some important variables are missing from the model. The sub-sample with a health card did not converge, which could be due to the high share of people with heart condition taking heart medication in the health card sub-sample

[37] Further details on heart conditions are available in National Health Survey: Users' Guide 2004 – 05 (ABS, 2006b, 43).

(65.8 per cent in the weighted sample results in Table D.5). The results for the sub-sample without a health card are similar to those for the full sample. Few of the coefficients for the personal income variables in the heart disease selection equation were statistically significant, indicating that income may not play the same role in medication use for heart disease as for mental health medication use for mental health risk.

Table D.6: Estimation results from censored probit regressions for adults below pension age using heart medication

	Full sample		**Without health card**	
	Coef.	Std. Err.	Coef.	Std. Err.
HARTMEDS	-0.298	0.115***	-0.313	0.143**
DEH1	-0.082	0.108	-0.086	0.203
DEH2	-0.149	0.108	-0.142	0.127
DEH3	-0.218	0.115*	-0.070	0.096
DEH4	-0.116	0.097	-0.113	0.077
DEH5	0.131	0.082	0.080	0.058
MIDEH	-0.178	0.085**	-0.148	0.064**
DEHMIS	-0.298	0.115***	-0.313	0.143**
Constant	-3.289	0.947***	-3.518	0.364***
HARTPROB				
DPY1	-0.005	0.068	0.065	0.070
DPY2	0.041	0.071	0.189	0.101*
DPY3	0.197	0.068***	0.145	0.100
DPY4	0.056	0.064	0.112	0.072
DPY5	0.059	0.058	0.039	0.056
MIDPY	0.076	0.041*	0.048	0.039
DPYMIS	-0.064	0.064	-0.030	0.061
Constant	-2.557	0.172***	-2.452	0.211***
ρ	0.551		0.925	
Wald test [a]	0.435		0.110	
Total obs.	15,651		11,613	
Censored	12,368		9,557	
Uncensored	3,283		2,056	
Pred. Prob.	0.430		0.419	
Parameters	21		20	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Wald test of $\rho = 0$; p-value is shown. Omitted variables: *HIDEH, HIDPY*.

Chapter 5

Income eligibility changes to the Commonwealth Seniors Health Card and the impact on mental health medication use

5.1 Introduction

Prior to January 1999, most self-funded seniors in Australia faced a significantly higher co-payment for medications than seniors receiving a pension[38]. A policy change effective in January 1999 nearly doubled the income eligibility for the Commonwealth Seniors Health Card. Having the Commonwealth Seniors Health Card (CSH Card) reduced the price of medication from $23.10 to $3.70 per prescription. (see Australia Parliamentary Library Bills Digest 1998-99).

In a Faculty seminar in January 2007, UNSW PhD Candidate, Peter Siminski, presented work in progress on the impact of this policy change on medication use for several chronic diseases including, heart and circulatory conditions, asthma and diabetes (Siminski, 2009, 2008a,b). Using difference-in-difference analysis, his preliminary results revealed no effect of the policy change on the increase in the number of medications for the conditions studied. This result seemed surprising given the significant increase in the pharmaceutical expenditure through the Pharmaceutical Benefits Scheme (PBS) over the same period, especially for concessional payees.

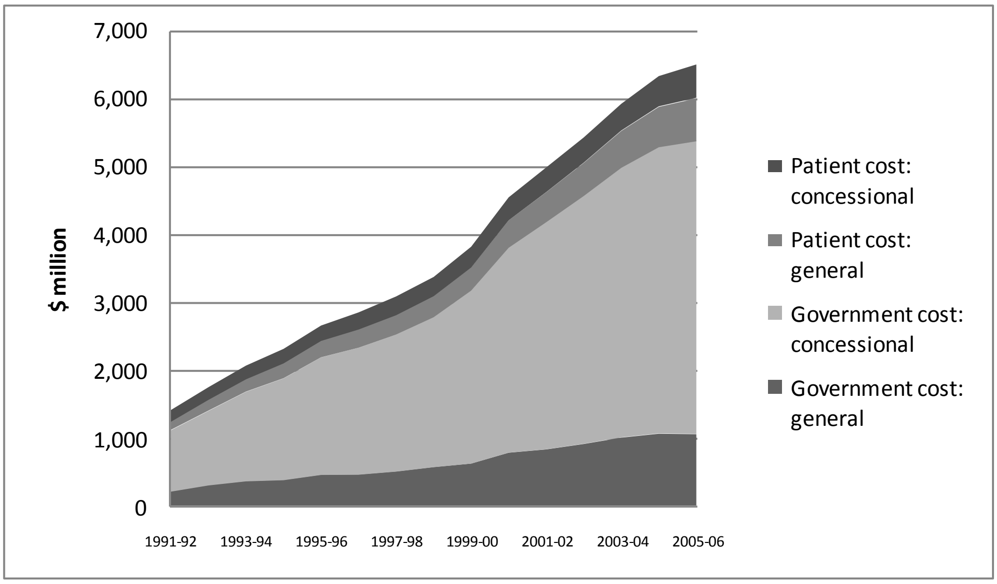
The PBS scheme subsidises the cost of prescription drugs in Australia above the co-payment amounts set for concessional patient and general patients. For example, in

[38] Self-funded seniors are above income eligibility cut-offs and therefore are not eligible for Government pension benefits.

2005-06, the government share of non-safety net PBS patient costs was 58.3 per cent for general patients compared to 86.5 per cent for concessional patients (Sweeney, 2007).

Figure 5.1 shows PBS expenditures for government and patients by patient type from 1991-2 to 2005-06. The figure shows the five-fold increase in total PBS costs from 1991-92 to 2005-06, and the increasing share of government expenditure for concessional patients (including CSH Card holders). While the increase is attributed to both the introduction of new drugs and continuing strong demand for drugs, Sweeny in his 2002 report, highlights the increasing use of drugs by seniors with concession cards as a driver of increasing PBS expenditure (Sweeny, 2002).

Figure 5.1: PBS costs for government and patients by patient type from 1991-92 to 2005-06, nominal $



Source: Sweeny, 2007.

Siminski's analysis excluded mental health medication, which has been a driver of PBS costs since the mid-1990s. According to Sweeny (2002), mental health medication is one of the three top categories of drugs that account for about two thirds of the total cost of the PBS[39]. The aim of this paper is to examine the effect of the 1999 increase in income eligibility for the CHS Card on the uptake of mental health medication. While Siminski's analysis explored the effect of the policy change

[39] PBS top selling drugs are in three major drug categories: alimentary tract and metabolism, cardiovascular, and nervous system (Sweeney, 2002, 19).

on the number of medications taken, my focus is on the expansion of treatment for mental illness. This involves investigating the effect of the policy on the share of people taking mental health medication.

My approach involves identification of a treatment group – those seniors that qualify for the CSH card after the 1999 policy but who that didn't qualify for the CSH Card before the 1999 policy. There are a number of interesting potential control groups - those seniors that were eligible for the CSH Card before and after the 1999 policy change and those that were never eligible.

Taking advantage of three National Health Surveys (NHS), one before the policy change, 1995, and two after the policy change, NHSs from 2001 and 2004-05, difference-in-difference estimation enables an assessment of the initial policy impact as well as any lagged effect. Testing the results with two different control groups and extending the analysis with an instrumental variable approach as well as a pooled sample model with the 2004-05 NHS, my results are consistent with findings by Siminski. Including models with control variables and interactions with treatment effects provides additional information on the factors that impact mental health medication use. The lack of significant results suggests a number of possible conclusions. First, the policy change was non-distorting for the intended population, or second, omitted factors not available in the data may have accounted for the results. For example, differences in severity of mental health disorders or treatment preferences between the intended group and the control groups could have impacted the results.

5.2 Background and previous studies

The Commonwealth Seniors Health Card was introduced in 1994, with eligibility based on having reached pension age, satisfaction of an income test and not in receipt of a social security pension. The main benefits of the CSH Card are related to health care including concession prices for pharmaceuticals, access to bulk-billed GP appointments, and a reduction in the cost of out-of-hospital medical expenses above a concessional threshold. Additional benefits of the CSH Card include: national rail service discounts and health, household, transport, education and recreation concessions offered by State or Territory, local governments and private providers).[40]

The stated aim of the 1999 budget measure was two-fold: to reduce the complexity of the income test and to extend the income limit to eligible recipients of the CSH Card. Greater access to pharmaceutical concessions by self-funded retirees was an expected outcome of the policy change. The budget document acknowledged that the policy change would result in a "fundamental shift in the recipient target group from low income earners to those with up to $40,000 for singles and $67,000 for couples" (Parliament of Australia, 1998, 6). Based on a take-up of 70 per cent following the policy change, the government estimated that this would affect up to 222,000 seniors, representing about 10 per cent of the senior population in 1999. Planning out at least four years, the financial cost (for PBS only) was estimated at over $100 million. This indicates that a large impact was expected by the policy change.

Table 5.1 shows the income eligibility changes associated with the Commonwealth Seniors Health Card. The primary policy change occurred in January 1999, with further income limit changes in September 2000, and another significant increase in the income limit for the CSH card occurring in September 2001.

Table 5.1: Income limits for the CSH Card for singles and couples, 1998 to 2001 ($)

	Dec 1998 ***a***	**Jan 1999** ***b***	**Sept 2000** ***c***	**Sept 2001** ***d***
Singles annual income	21,460.40	40,000.00	41,000.00	50,000.00
Single weekly income (annual/52)	412.70	769.23	788.46	961.54
Couples annual income	35,859.20	67,000.00	68,676.00	80,000.00
Couples weekly income (annual/52)	689.60	1,288.46	1,320.69	1,538.46

Source: Parliament of Australia. Bills Digest No. 18 2001-02. Family and Community Services and Veterans' Affairs Legislation Amendment: Further Assistance for Older Australians Bill 2001. Available from: http://www.aph.gov.au/LIBRARY/pubs/bd/2001-02/02bd018.htm

[40] The Centrelink website provides general information on the additional discounts available to CSH cardholders: http://www.centrelink.gov.au/internet/internet.nsf/payments/conc_cards_cshc.htm

Despite the increasing government expenditure on the PBS program, low levels of medical treatment remains an issue in the area of mental health. Mental health disorders are among the ten leading causes of disease burden in Australia, accounting for 13 per cent of the total burden. (Begg et al., 2007). While medically proven treatments exist for the main mental health disorders: anxiety and depression, alcohol abuse, and personality disorders, health experts are concerned that the disease burden persists (Andrews et al, 2000, 2001a, 2001b). Andrews and co-authors (2001b) point to evidence from the 1997 Survey of Mental Health and Well Being (MH&W) that an estimated 60% of mental health sufferers do not seek treatment (ABS 1998). However, limited analysis has been conducted in Australia on the factors that affect demand for mental health care.

As discussed in Chapter 2, Frank and McGuire attribute sub-optimal coverage of treatment for mental health in the US insurance market to problems of moral hazard and adverse selection. They point to evidence from the RAND Health Insurance Experiment that investigated the demand response for a subset of users of mental health treatment. The general finding from the RAND experiment for mental health was a greater elasticity compared to general health (see also Keeler et al. 1988). However, the RAND Experiment did not include seniors and was conducted prior to the increased availability of psychotropic drug treatments.

More recently, health economist Darrel Doessel and colleagues (2008) indicate a potential problem with ‘structural imbalance’ in Australia’s mental health sector. Their analysis of data from the 1997 Survey of Mental Health and Wellbeing, points to a mismatch between the rate of those treated without actual mental health need, and the rate of non-treatment for those with a reported mental health care need. According to their research, an estimated 4.4 per cent of those surveyed are in the first group and an estimated 11 per cent in the second group. Factors contributing to a possible imbalance in mental health treatment have not been investigated, although prices for mental health medication may be a factor. Low prices for prescription drugs such as those available to health card holders may contribute to the group that receives mental health treatment without actual mental health need, and a barrier to treatment may exist for those not eligible for the health card who face much higher prices for medication.

Studies of price responsiveness related to prescription drug utilisation among seniors generally find less price responsiveness compared to younger people due higher rates of chronic disease (see Rice and Matsuoka, 2004 for an overview of North American studies). A study of the impact of increases in drug copayments in 1990 and 1992 for Australia also found evidence of less price responsiveness for essential drugs taken for chronic conditions compared to less essential drugs taken for short term symptom relief (McManus et al, 1996). In addition, seniors with high income would likely be less responsive to a price change than their low income counterparts. For these reasons, the effect of the 1999 CSH Card policy may be negligible for the intended group of high income seniors.

My study contributes to the literature on demand responsiveness in mental health by examining the effect of lower prices for mental health medication for mid-high income seniors.[41] Using a natural experiment approach following the 1999 CSH Card policy that increased income limits for the health card, I am able to show that lower drugs prices available though Australia's PBS for those newly eligible CSH Card did not result in increased use of mental health medication. This result provides some evidence that this group of seniors may not be among those being treated for mental health disorders without actual mental health need as raised by Doessel and co-authors (2008).

5.3 Estimation approach

Natural experiments involving difference-in-difference estimation is a standard policy evaluation tool used to investigate the effect of a policy for a particular group (Blundell and Dias, 2000). The general approach is to compare the effect of a policy for a 'treated' group, with a 'control' group, a group similar to the treated group but

[41] Footnote 38 provides an explanation of high income used in this paper.

not a target of the policy. The idea is to establish a counterfactual, that is: how the treated group would have behaved in the absence of the policy in order to determine the effect of the policy. The assumption of a common trend between the treated and control group is central to the validity of the difference-in-difference approach. The following difference of means equation illustrates the approach:

$$\delta = (\bar{y}_{1,T} - \bar{y}_{1,C}) - (\bar{y}_{0,T} - \bar{y}_{0,C}) \tag{5.1}$$

where the policy impact, δ, is the difference in the mean value of an outcome variable, y, for the treated, T, and control group, C, before a policy change, noted by the subscript *0* and after, noted by subscript *1*. δ will equal zero if there is no impact of the policy.

Wooldridge (2003) outlines the following a regression approach or difference-in-difference estimator to estimate the treatment effect:

$$Y = \beta_0 + \delta_0 YR + \beta_1 T + \delta_1 YR * T + u \tag{5.2}$$

Consider T as the treated group, with T equal to one for those in the treated group and zero if they are in the control group, YR is a dummy variable that is equal to 1 for the post treatment time period, 0 for the pre-treatment year, and Y is mental health medication use and u represents the residual. The treatment effect is δ_1 on the interaction term. Without controlling for other characteristics, the treatment effect is equivalent to the difference-in-difference estimator shown in equation (5.1).

In my model of the impact of the 1999 income eligibility changes to the Commonwealth Seniors Health Card the dependent variable is binary: taking mental health medication or not. I therefore use the following probit estimation model which is analogous to the linear model in equation (5.2):

$$M_i^* = \alpha + \gamma' YR_i + \theta' T_i + \delta' YR_i * T_i + \beta' X_i + u_i \quad \begin{cases} M_i = 1 \text{ if } M_i^* > 0 \\ M_i = 0 \text{ otherwise} \end{cases} \tag{5.3}$$

where M_i* is a continuous and latent variable measuring the utility gain of mental health medication use for individual i and M_i is the observed mental health medication use. T_i is equal to 1 for observations in the treated group: those newly eligible for the CSH Card due to the higher income limits and equal to 0 for those in the control group. Using National Health Surveys, one conducted before the policy change, the 1995 NHS, and one conducted after the policy change, the 2001 NHS, YR_i is equal to 1 for observations in 2001 and equal to 0 for observation in 1995. X_i represents a vector of variables for socio-demographic characteristics such as marital status, gender, geographic location, employment status, and health status. The treatment effect is represented by δ, the coefficient on interaction term. In addition, α represents the constant term, γ, θ, are coefficients for year and treated, β, is a vector of coefficients for the X characteristics, and u_i represents the unobserved factors that influence the demand for mental health medication and is assumed to be normally distributed with a mean equal to 0 and variance equal to 1. u_i. is assumed to be independent of all explanatory variables including the treatment dummy variable. Probit regression estimates the predicted probability of using mental health medication. In using the probit model for the difference-in-difference estimation, I am assuming a linear trend for the underlying latent variable, the demand for mental health medication; not a linear trend in the predicted probability of mental health medication use.

As discussed, since take-up of the Commonwealth Seniors Health Card is voluntary for those eligible, the treatment effect needs to be considered as an 'intention to treat' in the difference-in-difference analysis. Having data from two surveys following the 1999 policy change, for 2001 and 2004-05, allows me to take into account a possible lagged treatment effect of the 1999 CSH Card income eligibility change. Therefore, in addition to the difference-in-difference, or double difference effect, which is a comparison of 1995 and 2001, I include a triple difference effect, which is a comparison of the policy effect between 1995 and 2004-05, after accounting for the policy effect between 1995 and 2001. My estimation model therefore involves two time variables, *YEAR1* represents observations in 2001, and *YEAR2* represents observations in 2004-05, and two treatment interactions terms, *TRXYR1* and

TRXYR2, with the coefficient on *TRXYR1* indicating the double difference effect and the coefficient on *TRXYR2* indicating the triple difference effect.

An alternative specification is considered to reflect the fact that the treatment effect in the difference-in-difference model has an impact on mental health medication use through the causal impact of having a health card and related price effect. A more direct approach that uses information on health card status would be to estimate a model of mental health medication use with health card status as an explanatory variable. However, having a health card may be endogenous with mental health medication use in the model. For example, people taking mental health medication are more likely to be in low income groups which make them eligible for other health cards. The NHS data does provide details on type of health card. One way to address problem of health card endogeneity is to utilise the exogenous information about the treatment effect to instrument for having a health card. The IV specification provides an indication of the importance of having a health card for the sample of seniors considered on the uptake of mental health medication, and advances the understanding of the impact of the 1999 CSH Card policy.

The IV probit model for mental health medication use is:

$$M_i^* = \alpha + \beta' X_i + \lambda G_i + u_i \qquad \begin{cases} M_i = 1 \text{ if } M_i^* > 0 \\ M_i = 0 \text{ otherwise} \end{cases} \tag{5.4}$$

where, G_i , having a health card, is instrumented using the treatment effect. The following latent variable model for having the health card is:

$$G_i^* = \alpha + \gamma' YR_i + \theta' T_i + \delta' YR_i * T_i + v_i \qquad \begin{cases} G_i = 1 \text{ if } G_i^* > 0 \\ G_i = 0 \text{ otherwise} \end{cases} \tag{5.5}$$

which includes the treatment effect variables discussed earlier plus v_i, indicating the unobserved factors influencing the demand for the health card.

Estimating the maximum likelihood function for equation (5.4) is complex as it involves a limited dependent variable model with a binary endogenous regressor.[42] Since no ready programming code exists for this operation, I adopt an alternative approach recommended by Angrist and Pischke (2009, 198), which is linear estimation with two stage least Squares (2SLS).[43]

To summarize, the modelling approach is as follows. First, double and triple difference analysis by straightforward difference of means is shown for the pooled sample of National Health Surveys for 1995, 2001, and 2004-05. These results are verified by probit estimation in Model 1, and extended to include control variables in Model 2. Further treatment interaction variables are tested in Model 3 to account for possible characteristic changes in the treatment group compared to the control group. The results from the instrumental variable specification are then presented. In advance of the results is the data section, which discusses construction of the treated and control groups and presents summary statistics of key variables.

5.4 Data

The analysis relies on data from three National Health Surveys (1995, 2001 and 2004-05) which is described in detail in Section 3.3 of Chapter 3. Utilising Confidential Unit Record Files (CURF) data through ABS's Remote Access Data Laboratory (RADL) provided access to an expanded set of variables for 2001 and 2004-05. What follows is a description of the variables used in the present analysis followed by a presentation of summary statistics. The section also discusses the issue of a common trend between the treated and control groups which is central to the validity of the natural experiment approach.

[42] Wooldridge (2002, 477-478) provides a detailed discussion on estimation of discrete response models with a binary endogenous explanatory variable.
[43] I estimate the instrumental variable specification, equation (5.4) with the Stata 10 code, *ivreg*.

5.4.1 Key variables

Mental health medication and mental health risk

Questions on mental health medication use, with some important differences, exist in the 3 surveys. The 1995 survey provides limited information on type of mental health medication while both 2001 and 2004-05 surveys provide detailed information on brand types. The 1995 survey asked about use of tranquillizers and anxiety medications, but has no specific question on other medications such as anti-depressants and mood stabilizers. Additional questions on type of mental health medication in the 2001 NHS reflect market changes and the increase in anti-depressants listed on the PBS. With available information it was possible to develop a definition of mental health medication used for all mental health conditions restricted to pharmaceutical products excluding sleeping pills. The share of the adult population using mental health medications increased significantly over the decade, from 3.6 per cent in 1995, 6.8 per cent in 2001 and 7.7 per cent in 2004-05.

With brand information it was possible to determine, from information on the PBS website, that the majority of the mental health medications included in the 2001 and 2004-05 National Health Surveys were listed on PBS and therefore subject to PBS prices: concession prices for health card holders and general prices for non-health card holders (PBS website). It is assumed that the majority of mental health medication available in 1995 were also included listed on PBS.[44]

The same approach of deriving mental health risk as outlined in Section 3.3 is utilised in this analysis. Relying on data from three questions, mental health risk is defined as having any one of the following attributes: a long term mental health condition, using mental health medication or a high level of current distress. Based on these data, the share of the population at risk for a mental health problem has also risen over the decade from 13.3 per cent in 1995, to 14.9 per cent in 2001 and 16.4 per cent in 2004-05, as shown previously in Table 3.1.

[44] I consulted a pharmaceutical research expert to confirm the reasonableness of this assumption.

Table 5.2 corresponds to Table 3.1 and shows mental health risk trends among the Australia's elderly population, defined as over 65 years of age. Table 5.2 shows that the elderly share of the adult population is stable at 16 per cent from 1995 to 2004-05. The share with mental health risk is similar between the elderly population and the population 18-64 years old, except for 1995 where the share with mental health risk is slightly higher compared to the younger group.

Table 5.2: Mental health risk trends for Australia's elderly population

	18-64 years	**65 years and over**	**18 years and over**
1995			
Share with mental health risk	0.129	0.147	0.133
Total population	11,234934	2,154,947	13,389,887
Share of total population	0.839	0.161	
2001			
Share with mental health risk	0.149	0.149	0.149
Total population	11,922,411	2,258,999	14,181,410
Share of total population	0.841	0.159	
2004-05			
Share with mental health risk	0.163	0.165	0.164
Total population	12,523,000	2,440,100	14,963,100
Share of total population	0.837	0.163	

Source: National Health Surveys 1995, 2001 and 2004-05
Notes: Numbers and means are weighted to reflect Australia's benchmark population at time of survey.

Age cohorts, treated and control groups

Key information on which to construct the treated group is provided in Table 5.1. The table shows the changes to the income limits for eligibility to the CSH Card. The difference-in-difference analysis focuses on the treated group that became newly entitled to the CSH Card due to the policy change. As the 2001 NHS was conducted between February and November 2001, most respondents would face the income limits in column c. Therefore the treated group constitutes singles of pension age and older with household income between $412.70 and $788.46, and couples of pension age and older with household income between $689.60 and $1,320.69 per week.

Pension age in my study is considered 65 years old for both men and women, although the pension age for women is slightly younger for women in Australia.[45]

There are two options for the control group. The first is to consider the same income band for the pre-pension age group – 55-64 years old. Since some women in this age group may be entitled to the CSH card, I excluded females between 60-64 years of age. A second possible control group is pension age seniors but in a lower income group. The second control group therefore includes all pension age people with incomes less than $412.70 for singles, and household income less than $ 689.60 for couples. Following Meyer's (1995) advice to use multiple control groups to verify findings, both control group options are considered in this analysis. I discuss the common trend assumption after reviewing the summary statistics for the treated and control groups.

Income

Income unit income was chosen as the comparable variable for all three years, as CSH Card eligibility is based on household income. In 1995, I converted 9 personal income bands to unit income with the income unit identifier. Respondents were assigned to treated and control groups according to income and age criteria above. In 2001, unit income is provided in 38 categories in the Expanded CURF data for file. These were matched to the same income and age criteria for treated and control groups in 1995. The NHS 2004-05 Expanded CURF data provides continuous personal and household income variables. Using the income unit identifier I converted personal income data to an income unit basis in order to be consistent with the earlier surveys. I also expanded the income band for the treated group in 2004-05 to reflect the policy change in September 2001 which increased the annual income

[45] Women have traditionally qualified for a pension at age 60. Changes were introduced in 1995 to gradually increase the pension age for women, whereby it will be 65 by 2014 (Australian Government, 2010). Due to the effect of women's birthday on pension age eligibility, women in 1999 needed to be 62 to qualify for pension age benefits, and by 2004 the pension eligible age for women became 63.

eligibility for the CSH Card to \$50,000 for singles and \$80,000 for couples, under column *d* in Table 5.1.[46]

The corresponding income bands for the treatment group in 1995 and 2001 are: couples in weekly unit income group \$689.0-\$1,320.69 and singles in weekly unit income \$412.70-\$788.46. Control group 1 corresponds to these same income groups in 1995 and 2001. In 2004-05, the income bands for the treatment and control group 1 are: couples in weekly unit income group \$689.0-\$1,538.46 and singles in weekly unit income group \$412.70-\$961.54. The income group for control group 3 in 1995, 2001 and 2004-05 corresponds to couples with weekly unit income less than \$689.0 and singles with weekly unit income less than \$412.70.

Missing income is an issue requiring reconciliation. In 1995, 14.7 per cent of the adult sample having missing unit income, in 2001, 18.72 per cent of the adult sample report missing unit income, and in 2004-05, over 13.2 per cent of adults report missing unit income. The usual option of assigning missing income to the mean value was first considered but due to the sensitivity of the income band of interest, an alternative method was determined more appropriate for the difference-in-difference analysis. For example, in 1995, the mean income was outside (lower than) the income band while in 2001, the mean income was within the band. Due to importance of the income limits for the CSH Card eligibility, I wanted to eliminate possible bias in the difference-in-difference estimation due to possible effects of unobservable characteristics for observations with missing income. Therefore, observations with missing income were dropped for all survey years. In the results section, I discuss the sensitivity of the results due to the dropped missing income observations.

To ease analysis, the sample was divided into 2 sub-samples. Sample 1 compares the treated group to control group 1, and sample 2 combines the treated group with control group 2. The sample totals are provided in the Table 5.3. In addition, analysis was done for 1995 and 2001 separately, and then pooled with all three survey years.

[46] Based on the income distribution of seniors in the sample in 1995, 2001, and 2004-05, those eligible for the CSH Card are in the top 20 percent of the distribution for all years. For this reason I refer to the seniors in the treated group as mid-high income seniors.

Table 5.3: Sample sizes for Sample 1 and Sample 2

Sample 1	**1995**	**2001**	**2004-05**	**Total**
Treated Group (T) *Pension age, mid-high income*	421 [a]	404 [a]	393 [c]	1,218
Control Group 1 (C1) *Pre-pension age, mid-high income*	687 [a]	579 [a]	844 [c]	2,110
Total	1,108	983	1,237	3,328
Sample 2				
Treated Group *Pension age, mid-high income*	421 [a]	404 [a]	393 [c]	1,218
Control Group 2 (C2) *Pension age, low income*	4,896 [b]	2,641 [b]	3,298 [b]	10,835
Total	5,317	3,045	3,691	12,053
Pooled sample total (T+ C1+C2)	6,004	3,624	4,535	14,163

[a] Pension age males and females; married in weekly unit income group $689.0-$1,320.69; singles in weekly unit income group $412.70-$788.46.
[b] Pension age males and females; married with weekly unit income less than $689.0; singles with weekly unit income less than $412.70.
[c] Pre-pension age males and females; married in weekly unit income group $689.0-$1,538.46; singles in weekly unit income group $412.70-$961.54.

Socio-demographic variables

Control variables are used in the estimation analysis to account for differences in the characteristics of the treated and control groups that may systematically vary across the years before and after the policy introduction. Second, control variables provide some general information on characteristics that would affect the probability of using mental health medication. Factors such as health status, employment status, geographic location and other demographic characteristics could be expected to play a role in the demand for mental health medication. All control variables are constructed as dummy variables.

As discussed in Chapter 2, endogeneity of some of the covariates with mental health disorders could possibly result in bias among the estimated coefficients. For instance, taking mental health medication indicates mental health risk. Depending on severity, having a mental health condition may negatively affect both health status and employment status, and may be positively related to having a having a health card.

Possible endogeneity due to the covariates and mental health medication use requires caution in interpreting a causal relationship for these variables.

Self-assessed health (SAH) status is established in the health economics literature as a reliable predictor of health morbidity and mortality (Crossley & Kennedy 2002). For this study, the top scores, 4 and 5, are grouped to define excellent health, 3 is good health, and scores 1 and 2 are poor health. Poor self-assessed health is likely an indication of having chronic conditions, including physical and mental health conditions that may necessitate use of mental health medication, while being in excellent health is expected to have a negative effect on use of mental health medication. The regressions compare excellent and poor health to the omitted category good health.

Being employed is associated with a higher opportunity cost of having a mental health condition, and would therefore increase the likelihood of mental health medication use. Not in the labour force may be positively or negatively related to mental health medication use. The positive association could be related to retirement from work, or, given a severe mental health disorder; this may contribute to being out of the labour force. The regressions compare working and not in the labour force to those unemployed.

While level of education would be important to include as a control variable the data does not allow inclusion of this variable. In the 1995 NHS only half of the sample was asked questions on highest level of educational attainment.

Gender and marital status are factors known to be related to mental health disorders. From previous analysis, females are more likely than men to report mental health disorders, while married people are less likely.

Geographic variables are included. However, it is inconclusive as to how they impact on mental health and related use of mental health medication. With treatment more likely to be available in the cities, the direction of causation may be indeterminate. City and country geographical designations are compared to residing in a town.

The IV probit specification includes the variable for having a health card. In the three National Health Surveys, having a health card includes having any of a number of government health cards, such as a Veterans' Affairs treatment entitlement care, a Pension Concession Card, a Health Care Card, and a CSH Card. It is not possible to distinguish the type of health card in the NHS.

5.4.2 Summary statistics

Summary statistics in Table 5.3 are presented in a way to allow for comparison of the characteristics of the treated group with control group 1 and control group 2 for 1995, 2001, and 2004-05.[47] The equality of means test in columns 3 and 4 indicates the degree of similarity between the groups. First, general differences in characteristics between the treated and control groups are discussed, and then the issue of a common trend in mental health medication use among treated and control groups is considered.

In comparing the treated group to control group 1 in Table 5.4, the main differences are with respect to the following attributes. In the pre-policy year, 1995, compared to the treated group, control group 1 had higher income, better health, a greater share working, and fewer female observations. In 2001, health status differences as well as married and female bias drop out. There are no significant differences with respect to geographic area of residence in either year. As expected, the pre-pension group is less likely to have a government health card and this is substantially different in the post policy survey. The differences between the treated group and control group 1 found in 1995 and 2001, are generally found in 2004-05, as well.

Also indicated in Table 5.4 are differences between the treated group and control group 2, with respect to the following. In the pre-policy year, 1995, control group 2 has lower income, lower shares working and in the labour force, fewer married, fewer residing the city and more in towns, and substantially more with a government health card. In the post-policy year, 2001, several of these differences remain, and in

[47] All means presented in Table 5.3 are based on unweighted data.

addition health status is worse for control group 2. Likewise, the differences between the treated group and control 2 are evident in 2004-5.

It is important to note the change in having a government health card following the policy change for the treated group (all potentially eligible for the CSH after 2001). The share having a government health card was 58.2 per cent in 1995, 73.5 per cent in 2001 and 74 per cent in 2004-05. This indicates that not all eligible seniors in the treated group took advantage of the CSH Card; and as a result may impact on the results of the analysis.

Factors affecting take-up of the CSH Card

A 2005 study by Dianna McAlister and co-authors of retirement decisions in Australia using *HILDA* data estimated a 70 per cent take-up rate for the CSH Card due to the ability of many eligible seniors to manage their finances in retirement (McAlister D. et al, 2005, 33). They estimate that 37 per cent take up the CSH Card upon eligibility, with another 25 per cent between the ages of 66 to 70. Take-up of the CSH Card comes later at older ages which they associate with retirees being able to manage their finances less well as they spend a longer period in retirement. An estimated seventeen per cent of CSH cardholders do not take up the card until they are over 75 years old.

Eligibility for the PBS safety net card or the Medicare Safety program could also impact the take-up of the CSH Card. For example, people with high prescription expenses associated with chronic conditions may be eligible for a PBS Safety Net card and people with high out-of-pocket out-of-hospital expenses may be eligible for concessions once thresholds are reached. But the take-up of these programs is estimated to be small and would not likely affect my overall results.[48]

[48] See footnote 34.

Table 5.4: Sample means of key variables for treated and control groups

	Treated (T)	**Control 1 (C1)**	**Control 2 (C2)**	**Compare T and C1 *t*-test**	**Compare T and C2 *t*-test**
1995					
Sample size	421 [a]	687 [a]	4,896 [b]		
Unit Income $/week	699	797	206	6.99	-80.381***
MHRISK	.185	.119	.147	-3.04***	-2.073**
MHMEDS	.076	.041	.061	-2.52**	-1.222
EXCELHE	.389	.536	.345	4.77***	-1.831*
GOODHE	.292	.292	.303	-0.243	0.154
POORHE	.311	.172	.352	-5.465***	1.682*
WORKING	.071	.788	.021	32.33***	-6.401***
UNEMPLYD	0	.018	.0002	2.855***	0.294
NOTINLF	.095	.191	.122	4.311***	1.656*
MARRIED	.668	.664	.645	-0.023	-1.412
FEMALE	.567	.387	.620	-5.948***	2.135**
CITY	.784	.803	.681	0.786	-4.378***
TOWN	.087	.090	.147	0.135	3.366***
COUNTRY	.128	.106	.171	-1.128	2.253**
WHCARD	.582	.163	.896	-16.076***	19.071***
2001					
Sample size	404 [a]	579 [a]	2,641 [b]		
Unit Income $/week	725	825	309	9.987	-51.834***
MHRISK	.128	.152	.141	1.034	0.679
MHMEDS	.104	.095	.107	-0.469	0.223
EXCELHE	.448	.472	.315	0.735	-5.328***
GOODHE	.312	.316	.338	0.143	1.044
POORHE	.240	.212	.347	-1.237	4.266***
WORKING	.218	.751	.042	19.621***	-13.434***
UNEMPLYD	0	.005	.002	1.448	0.787
NOTINLF	.787	.243	.957	-19.892***	13.182***
MARRIED	.495	.644	.471	4.716***	-0.905
FEMALE	.574	.561	.637	-0.404	2.436**
CITY	.691	.646	.604	-1.463	-3.327***
TOWN	.200	.211	.245	0.395	1.963**
COUNTRY	.109	.143	.150	1.584	2.200**
WHCARD	.735	.119	.966	-25.201***	8.521***

Table 5.4 *Continued*

	Treated (T)	Control 1 (C1)	Control 2 (C2)	Compare T and C1 *t*-test	Compare T and C2 *t*-test
2004-05					
Sample size	393 [c]	844 [c]	3,298 [b]		
Unit Income $/week	700	848	252	9.982	-70.556***
MHRISK	.158	.144	.178	-0.608	1.024
MHMEDS	.094	.079	.101	-0.871	0.444
EXCELHE	.506	.578	.341	2.371**	-6.517***
GOODHE	.280	.297	.319	0.630	1.577
POORHE	.213	.124	.341	-4.090***	5.080***
WORKING	.275	.880	.053	26.719***	-16.053***
UNEMPLYD	0	.002	.001	0.965	0.691
NOTINLF	.725	.009	.945	-26.945***	15.851***
MARRIED	.593	.560	.500	-1.601	-1.842**
FEMALE	.552	.460	.642	-3.037***	3.505***
CITY	.687	.645	.588	-1.426	-3.794***
TOWN	.201	.218	.244	0.679	1.904*
COUNTRY	.112	.136	.167	1.188	2.838***
WHCARD	.740	.0722	.956	-33.265***	16.945***

Notes: For details on variable descriptions see Table 3.3 in the previous chapter. ***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Pension age males and females; married in weekly unit income group $689.0-$1,320.69; singles in weekly unit income group $412.70-$788.46.
[b] Pension age males and females; married with weekly unit income less than $689.0; singles with weekly unit income less than $412.70.
[c] Pre-pension age males and females; married in weekly unit income group $689.0-$1,538.46; singles in weekly unit income group $412.70-$961.54.

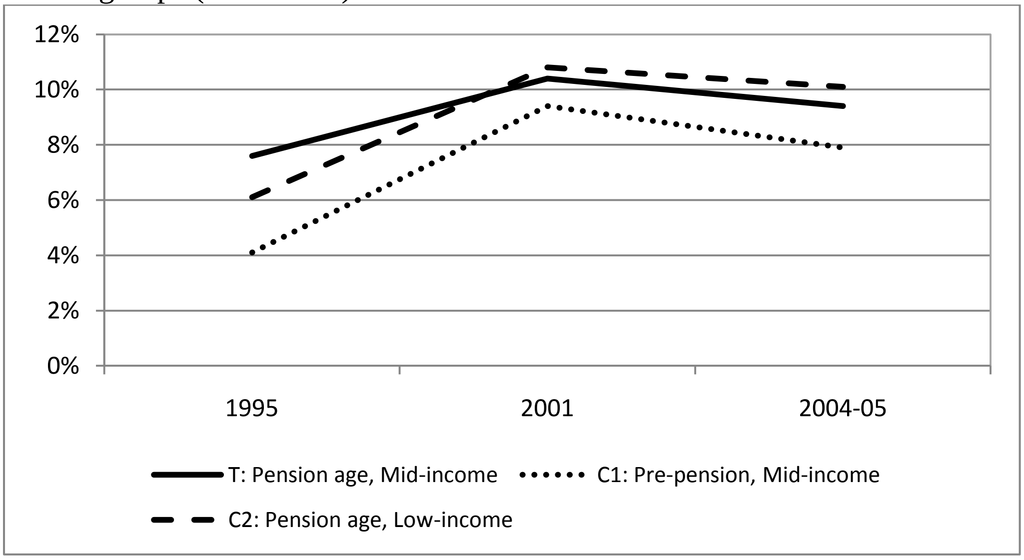
The common trend assumption

The validity of an estimated treatment effect in a natural experiment relies on an underlying common trend between the treated and control groups. According to Myer (1995) finding a suitable control group is a common difficulty for natural experiments due to the potential variability of factors over a given time period. For my analysis, the increased availability of new psychotropic treatments since the early 1990s is an important factor which resulted in the overall increased level of mental health medication use observed in the 2001 NHS, and in the subsequent survey in 2004-05. A varied response in the adoption of the new mental health treatments among different groups of people would be expected due to issues such as preferences, knowledge and access. For a valid natural experiment, one needs to assume that both treated and control groups responded similarly to the adoption of new psychotropic treatments.

The increased availability of new mental health treatments is apparent in NHS surveys. The 1995 NHS introduced additional responses for types of mental health medication compared to the 1989 NHS. Subsequent surveys in 2001 and 2004-05 included anti-depressants which were not included in the previous surveys. Clearly, this pronounced trend in the availability of new mental health medication adds to the complexity of the present difference-in-difference analysis.

Figure 5.2 shows the trends in mental health medication for the treated and control groups before the 1999 CSH Card policy, in 1995, and in the two survey years after the policy change, in 2001, and in 2004-05. A common trend for treated and control groups is more evident between 2001 to 2004-05 than from 1995 to 2001. Having data after 2004-05 would help to confirm a common trend. Testing comparisons of the treated and control groups in the earlier pre-treatment period, between 1989 and 1995 proved unreliable. The share of the seniors using mental health medication in the 1989 NHS was below 2 per cent. The issues of limited availability of psychotropic drugs at the time of the 1989 survey and somewhat different survey methods used are discussed in greater detail in Chapter 3.

Figure 5.2: Share using mental health medication for the treated group (T) and control groups (C1 and C2)



Source: National Health Surveys 1995, 2001 and 2004-05

Regression discontinuity is a technique to consider that would eliminate the need to compare data from two surveys. Regression discontinuity techniques could be applied to the NHS 2000, and would involve utilising detailed income and age data to compare those just eligible for the CSH Card to those just ineligible to determine the policy impact (Imbens and Lemieux, 2006).[49]

5.5 Results

5.5.1 Difference in means analysis

The first application of difference-in-difference estimation is a simple difference in means for the treated and control groups. These results are shown in Table 5.4. For the treated group compared to control group 1, the treatment effect is -2.5 per cent in the initial period between 1995 and 2001, as shown in column 3 of row 4. This implies that the 1999 CSH Card policy reduced uptake of mental health medication by 32 per cent compared to the 7.6 per cent level before the policy change. The first period treatment effect estimated with control group 2 is slightly less at -1.9 per cent, shown in column 5, row 4. Based on *t*-test results, the treatment effect estimated with control group 1 is statistically significant. The treatment effect in the next period, between 2001 and 2004-05 is small and not statistically significant for both comparisons, indicating that the treatment effect was most pronounced just following the 1999 policy. The triple difference is the lagged effect of the policy over the second time period, and is about -2.0 per cent for both control groups, as indicated in the last row of the table.

Although the 1999 policy increased income cut-offs for those eligible for the CSH Card, the policy seemed to have reduced, rather than increased the take-up of mental health medication, as expected from economic theory. It is apparent from Table 5.5 that both control groups increased mental health medication use from 1995 to 2001

[49] Access to the ABS RADL currently does not permit use of use graphics, bootstrapping and other code required for application of regression discontinuity methods.

by a greater amount than the treated group. The results in Table 5.5 also show that there was no significant lagged treatment effect. As such, the 1999 CSH policy did not have an impact on expanding access to mental health medication. Several possible explanations for this effect are presented in the results section, but first regression analysis results are discussed.

Table 5.5: Results of difference of means (|*t*|-test in bracket) [a]

	T: Treated Group	**C1: Control Group 1**	**Difference T - C1**	**C2: Control Group 2**	**Difference T-C2**
Mean mental health medication use in 1995	0.076	0.041	0.035*** (2.520)	0.061	0.015 (1.222)
Mean mental health medication use in 2001	0.104	0.095	0.010 (0.469)	0.108	-0.004 (0.223)
Mean mental health medication use in 2004-05	0.094	0.079	0.015 (0.871)	0.101	-0.007 (0.444)
Change in mean mental health medication use (2001-1995) Double difference *1*	0.028 (1.404)	0.053*** (3.904)	-0.025*** (2.048)	0.047*** (7.230)	-0.019 (1.251)
Change in mean mental health medication use (2004-05-2001) Double difference *2*	-0.010 (0.463)	-0.015 (1.033)	0.005 (1.054)	-0.007 (0.785)	-0.003 (0.429)
Change in mean mental health medication use (2004-05-1995) Triple difference (*1+2*)	0.018 (0.927)	0.038*** (3.124)	-0.020*** (2.073)	-0.040*** (6.702)	-0.022 (0.770)

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Significance level based on *t*-test.

5.5.2 Difference-in-difference estimation results

Probit estimation results shown in Tables 5.6 and 5.7 are based on pooled data from 1995, 2001 and 2004-05. Table 5.6 shows results for the treated group and control group 1 (pre-pension age with same income as the treated group) and Table 5.7

shows results for the treated group and control group 2 (pension age with lower income than the treated group). The dependent variable in all models is a binary variable indicating mental health medication use. All explanatory variables are dummy variables, with the following omitted groups for the categorical variables health status, labour status and geographic location: *GOODHE*, *UNEMPLYD* and *TOWN*. All models are estimated with robust standard errors to account for possible heteroskedasticity.

First consider the results for Model 1 in Tables 5.6 and 5.7. The *TREAT* variable represents the treated group and is positive but not significant in Table 5.5, and positive and significant in Table 5.7. The first year following the policy change, 2001 is represented by the variable *YEAR1* and *YEAR2,* indicates 2004-05. Both these year variables are positive and statistically significant, reflecting the increase in mental health medication use for both treated and control groups since 1995. These results are consistent for both control groups tested. The interaction variable *TXYEAR1* represents the treatment effect for the first period, the difference-in-difference, and *TXYEAR2* represents the triple difference, the treatment effect over and above the effect up to 2001. The interaction variables in Model 1 in both Tables 5.6 and 5.7 confirm a negative treatment effect found by difference of means in Table 5.5, e.g., that the control group increased mental health medication use from 1995 to 2001 by a greater amount than the treated group. However, the standard errors on these coefficients are not statistically significant.[50]

In addition to coefficients, standard errors and significance levels, marginal effects are included for Models 1 and 2 to allow for comparison with the difference of means results in Table 5.5. Bootstrapped standard errors are recommended for better precision of standard errors in difference-in-difference estimation (Bertrand et al, 2004). I was unable to estimate bootstrapped standard errors due to RADL programming restrictions.[51] The marginal effects from the probit regression are not

[50] In the case of a linear model, Meyer (1995, 155) explains that standard errors on the treatment effect calculated by OLS will differ from the standard errors calculated by the difference of means due to the residual term.

[51] ABS's Remote Access Data Laboratory does not allow bootstrapping code to obtain standard errors on coefficients or marginal effects.

expected to be identical to the difference of means calculations due to non-linear estimation with probit regression.

Using the probit estimation results, the marginal effects are computed for each observation at their observed value and averaged over the sample and are calculated to correspond to the results in Table 5.5. First consider the results for Model 1 in Table 5.6. The marginal effect of 0.041 for the constant term represents the predicted probability of mental health medication use for the control group in 1995, and corresponds to the results in Table 5.5, in the first row, column 2. For the variable *TREAT* the marginal effect of 0.035 compares the average difference in mental health medication use between the treated group and control group 1 in 1995, and corresponds to the result in Table 5.5, in the first row, column 3. The marginal effect on *YEAR1* of 0.059 compares the difference in mental health medication use between 1995 and 2001 for both treated and control groups. The marginal effect for the variable *TRXYR1* is -0.026 which is the treatment effect or double difference for the initial period following the policy change, and roughly corresponds to the difference-in-difference calculation in Table 5.5. The marginal effect on *YEAR2* is the difference in mental health medication use between 2004-05 and 1995 for both treated and control groups, and the marginal effect of -0.020 on *TRXYR2* is the triple difference or lagged treatment effect between 2004-05 and 1995, which also corresponds to the calculation in Table 5.5.

Model 2 in both tables includes a set of control variables with the parameter estimates indicating how these factors affect mental health medication use for people in either treated or control group.[52] There are several characteristics that are consistent across both samples in Table 5.6 and Table 5.7. The traits that are negatively associated with mental health medication use are: being in excellent health, working and married. Traits likely to predispose mental health medication use are: being in poor health and female. Not in the labour force was positively associated with mental health medication use compared to being unemployed, while working was negatively associated with mental health medication use. For the

[52] Marginal effects for the categorical variables: health status, labour status and geographic location are computed to compare to the missing category: *GOODHE, UNEMPLYD, TOWN.*

geographic variables, *CITY* was positive compared to *TOWN* in Table 5.6. In Table 5.7 both *CITY* and *COUNTRY* were negatively associated with mental health medication use compared to *TOWN*.

Model 3 in Table 5.6 includes a set of treatment interaction variables from the statistically significant characteristics in Model 2 – health status, married and female – and the treated group to determine if these factors are significantly associated with the treated group and the treatment effect. Only estimation coefficients and standard errors are shown, not marginal effects. The results show that the coefficient on the interaction term for married, *TRXY1XMR,* is negative and significant, indicating that the treatment effect may have been more concentrated among married people. The treatment interaction variables were tested for joint significance to reveal systematic differences among these characteristics between the treated group and control group 1. The result of the Wald test in the second last row of the table indicates there is no systematic difference.

Model 3 in Table 5.7 includes treatment interaction variables for health status, geographic location and female. None of these treatment interaction terms are significant. Likewise, based on the Wald test of joint significance, there is no systematic difference among these characteristics between the treated group and control group 2.

Table 5.6: Estimation results for Sample 1: Treated Group (Pension Age, Mid-Income) and Control Group 1 (Pre-Pension Age; Mid-Income)

Dependent variable mental health medication: *MHMEDS*								
	1			**2**			**3**	
	Coeff.	Stand. Error	Marg. Effect	Coeff.	Stand. Error	Marg. Effect	Coeff.	Stand. Error
TREAT	0.310	0.125**	0.035	-0.008	0.216	-0.001	-0.200	0.319
YEAR1	0.431	0.112***	0.059	0.419	0.120***	0.049	0.477	0.242**
TRXYR1	-0.258	0.167	-0.026	-0.225	0.244	-0.033	-0.282	0.444
YEAR2	0.333	0.107***	0.042	0.469	0.116***	0.057	0.457	0.117***
TRXYR2	-0.216	0.165	-0.020	-0.322	0.245*	-0.047	-0.312	0.249
EXCELHE				-0.314	0.083***	-0.034	-0.319	0.126**
POORHE				0.508	0.085***	0.095	0.453	0.142***
WORKING				-0.258	0.225	-0.032	-0.242	0.234
NOTINLF				0.148	0.222	0.024	0.173	0.231
MARRIED				-0.236	0.074***	-0.031	-0.305	0.110***
FEMALE				0.176	0.072***	0.023	0.210	0.115*
CITY				0.148	0.095*	0.018	0.139	0.095
COUNTRY				0.138	0.128	0.023	0.132	0.129
TRXEH							0.085	0.208
Y1XEH							-0.220	0.233
TRXY1XEH							0.397	0.371
TRXPH							0.074	0.213
Y1XPH							0.012	0.229
TRXY1XPH							0.275	0.363
TRXMR							0.458	0.198**
Y1XMR							0.060	0.193
TRXY1XMR							-0.811	0.319**
TRXFE							-0.057	0.192
Y1XFE							-0.011	0.196
TRXY1XFE							0.148	0.319
Constant	-1.742	0.086***	0.041	-1.711	0.252***	0.052	-1.680	0.278***
Sample size	3,328			3,328			3,328	
Pseudo R^2	0.012			0.104			0.112	
Wald test: Chi^2 (p- value) [a]							16.52 (0.169)	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.

[a] Null hypothesis that all interaction coefficients in Model 3 are jointly zero; 5% critical value $Chi^2(12) = 21.03$

Table 5.7: Estimation results for Sample 2: Treated Group (Pension Age, Mid-Income) and Control Group 2 (Pension Age; Low-Income)

Dependent variable mental health medication: *MHMEDS*								
	1			**2**			**3**	
	Coeff.	Stand. Error	Marg. Effect	Coeff.	Stand. Error	Marg. Effect	Coeff.	Stand. Error
TREAT	0.113	0.095	0.015	0.167	0.099	-0.001	-0.323	0.281
YEAR1	0.306	0.043***	0.046	0.237	0.080***	0.049	0.386	0.135***
TRXYR1	-0.133	0.131	-0.018	-0.076	0.135	-0.033	0.000	0.406
YEAR2	0.272	0.041***	0.040	0.207	0.078**	0.057	0.206	0.079***
TRXYR2	-0.155	0.132	-0.022	-0.069	0.137	-0.047	0.002	0.139
EXCELHE				-0.291	0.047***	-0.034	-0.303	0.059***
POORHE				0.387	0.040***	0.095	0.381	0.049***
WORKING				-0.059	0.108	-0.032	-0.047	0.109
NOTINLF				0.075	0.077	0.024	0.079	0.078
MARRIED				-0.034	0.036	-0.031	-0.037	0.036
FEMALE				0.274	0.038***	0.023	0.288	0.048***
CITY				-0.098	0.042**	-0.018	-0.066	0.054
COUNTRY				-0.091	0.056*	-0.023	-0.066	0.070
TRXEH							0.034	0.178
Y1XEH							0.017	0.109
TRXY1XEH							0.164	0.304
TRXPH							0.136	0.170
Y1XPH							-0.047	0.091
TRXY1XPH							0.318	0.291
TRXCI							0.552	0.226**
Y1XCI							-0.175	0.094*
TRXY1XCI							-0.374	0.325
TRXCR							0.584	0.280**
Y1XCR							-0.137	0.129
TRXY1XCR							-0.471	0.443
TRXFE							-0.016	0.087
Y1XFE							-0.178	0.140
TRXY1XFE							0.252	0.245
Constant	-1.546	0.028***	0.061	-1.731	0.065***	0.065	-1.759	0.077***
Sample size	12,053			12,053			12,053	
Pseudo R^2	0.010			0.059			0.061	
Wald test: Chi^2 (p- value) [a]							18.30 (0.247)	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.

[a] Wald test for null hypothesis that all interaction coefficients in Model 3 are jointly zero; 5% critical value $Chi^2(15)$= 25.00.

Table 5.8 provides test of model validity by comparing the probit results for Model 2 with linear difference-in-difference, as recommended by Angrist and Pischke (2009). Marginal effects for the probit model are shown with standard errors from the coefficient estimates.[53] Correct standard errors for the probit marginal effects are needed for direct comparison; however, the marginal effects from the probit model are very similar to the coefficient estimates for the linear specification. The year variables, *YEAR1* and *YEAR2*, are significant, but the treatment effect variable for the first period, *TRXYR1* is not significant in either probit or OLS models

Table 5.8: Estimation results for Model 2: probit compared to linear regression

	Treated & Control Group 1				**Treated & Control Group 2**			
	Probit		OLS		Probit		OLS	
	Marg. Effect	Stand. Error	Coeff.	Stand. Error	Marg. Effect	Stand. Error	Coeff.	Stand. Error
TREAT	-0.001	0.216	-0.010	0.028	-0.001	0.099	0.022	0.013
YEAR1	0.049	0.120 ***	0.043	0.014 ***	0.049	0.080***	0.037	0.012 ***
TRXYR1	-0.033	0.244	-0.021	0.034	-0.033	0.135	-0.007	0.021
YEAR2	0.057	0.116 ***	0.047	0.012 ***	0.057	0.078**	0.032	0.011 **
TRXYR2	-0.047	0.245 *	-0.033	0.033	-0.047	0.137	-0.007	0.020
EXCELHE	-0.034	0.083 ***	-0.034	0.010 ***	-0.034	0.047***	-0.033	0.005 ***
POORHE	0.095	0.085 ***	0.101	0.017 ***	0.095	0.040***	0.068	0.007 ***
WORKING	-0.032	0.225	-0.023	0.029	-0.032	0.108	-0.013	0.013
NOTINLF	0.024	0.222	0.035	0.031	0.024	0.077	0.007	0.011
MARRIED	-0.031	0.074 ***	-0.029	0.010 ***	-0.031	0.036	-0.004	0.005
FEMALE	0.023	0.072 ***	0.022	0.010 ***	0.023	0.038***	0.039	0.005 ***
CITY	0.018	0.095 *	0.017	0.012	-0.018	0.042**	-0.016	0.007 **
COUNTRY	0.023	0.128	0.016	0.016	-0.023	0.056*	-0.015	0.009
Constant	0.052	0.252 ***	0.049	0.032	0.065	0.065***	0.040	0.009 ***
Sample size	3,328		3,328		12,053		12,053	
R^2 [a]	0.104		0.061		0.059		0.034	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Pseudo R^2 is shown for probit models.

Table 5.9 provides predicted probabilities of mental health medication use based on Model 2 for Samples 1 and 2. The predicted probabilities are computed at their observed value for each observation and averaged across the sample. These results are close to the sample means provided in Table 5.5, and provide a basis for

[53] The ABS Remote Data Access Laboratory does not allow programming commands such as the delta method (Greene, 2000) or bootstrapping methods, that would enable me to construct correct standard errors for the marginal effects.

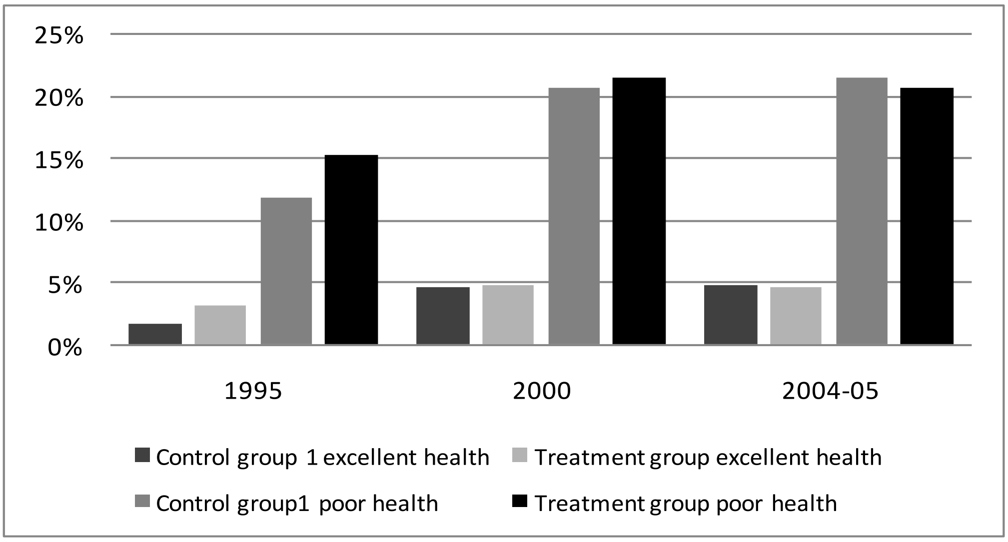
comparing the predicted probabilities of mental health medication use for people in excellent and poor health shown in the Figure 5.3.

Table 5.9: Predicted probability values for mental health medication use for treated and control groups, Model 2

	Treated & Control Group 1		**Treated & Control Group 2**	
	Treated	Control	Treated	Control
1995	0.078	0.040	0.076	0.061
2000	0.104	0.094	0.103	0.107
2004-05	0.094	0.079	0.093	0.101

Comparisons of predicted mental health medication use by health status, shown Figure 5.3, provide an indication of the importance of this characteristic for mental health medication use and for the treatment effect. First consider those with poor health status in both treated and control groups in 2001 and 2004-05. Their average rate of mental health mediation use was nearly 20 per cent compared to 4 per cent for those with excellent health. The figure also shows the increase in mental health medication use for both treated and control groups for both groups – those with excellent health and those in poor health status between 1995 and 2001. It is important to note, however, that the rate of increase for the control group with poor health status was nearly 3 percentage points greater than for those with poor health status in the treated group. This higher rate of increase in mental health medication use for the control group is a key contributing factor to the negligible treatment effect. One possible explanation is that newly available drug treatments were attractive to the younger control group, despite the fact that only 12 per cent of control 1 in 2001 had health card. Further investigation of other factors, besides the health card would be important to consider regarding take-up of mental health medication over this period, including factors such as severity of illness, availability of new mental health treatments, changes in provider behaviours, or changes in cultural attitudes such as stigma toward treatment for mental illness.

Figure 5.3: Predicted probabilities of mental health medication use for those with excellent and poor health in treated and control group 1, Model 2



As previously mentioned, missing income variables were dropped from the sample due to the importance of the income bands for designation of treated and control groups in the difference-in-difference estimation. A sensitivity test on the results was conducted by including the missing income observations. Including the missing income observations at the mean income value for each survey year, resulted in a larger negative treatment effects for both samples. Although the results did not qualitatively change the results, it confirmed the sensitivity of the income bands in the difference-in-difference estimation. The results for Model 1 are included in the Appendix.

5.5.3 IV estimation results

The alternative specification to difference-in-difference estimation, discussed in the methodology section, focuses on the effect of having a health card on mental health medication use, using the treatment effect as an instrument for having a health card, as outlined in equations (5.4) and (5.5).

The results for the two stage least squares (2SLS) model and OLS are provided in Table 5.10. The sample for the analysis combines the treated group and both control groups for a total of 14,163 observations. The results 2SLS model in Table 5.9

indicates that the health card variable is not a significant factor for mental health medication use after controlling for other factors such as health status and other characteristics. The table also includes the results of the Hausman test of exogeneity, which indicates that health card is not an endogenous variable in the mental health medication model.[54]

Table 5.10: Estimation results for Two Stage Least Squares and OLS

Dependent variable: MHMEDS				
	Two Stage Least Squares		OLS	
	Coefficient	Standard Error	Coefficient	Standard Error
EXCELHE	-0.032	0.005***	-0.031	0.005***
POORHE	0.068	0.007***	0.065	0.007***
WORKING	0.046	0.028	0.043	0.029
NOTINLF	0.040	0.005***	0.038	0.006***
MARRIED	-0.010	0.005*	-0.010	0.006*
FEMALE	0.032	0.005***	0.031	0.005***
CITY	-0.012	0.006*	-0.011	0.007*
COUNTRY	-0.014	0.008*	-0.013	0.008**
WHCARD	0.038	0.039	0.036	0.038
Constant	0.120	0.038***	0.188	0.020***
First stage results: WHCARD				
EXCELHE	-0.040	0.006***		
POORHE	0.039	0.006***		
WORKING	-0.762	0.010***		
NOTINLF	-0.083	0.010***		
MARRIED	-0.058	0.005***		
FEMALE	0.009	0.005		
CITY	-0.024	0.007***		
COUNTRY	0.013	0.009		
TREAT	-0.272	0.015***		
YEAR1	0.096	0.010***		
TRXYR1	0.233	0.022***		
YEAR2	0.097	0.010***		
TRXYR2	0.269	0.022***		
Constant	0.953	0.010***		
Sample size	14,163		14,163	
R^2	0.453		0.444	
Hausman test: F (p-value) [a]		0.14 (0.707)		

Note: ***Significant at 1% level, ** significant at 5% level, * significant at 10% level.
[a] Hausman test of endogeneity is the null hypothesis that *WHCARD* is endogenous in *MHMEDS* model; 5% critical value F(1, 14,153) = 3.84.

[54] Further details on the test of exogeneity are provided in Wooldridge (2003, 506).

The OLS results are consistent with the 2SLS results, indicating that *WHCARD* is not significantly associated with mental health medication use in this specification. The previous chapter revealed a complex relationship between mental health risk and mental health medication which required a selection estimation approach.

The aim of the IV approach was to model the effect of the CSH Card policy change in 1999 on mental health medication use. The results from the IV model are somewhat consistent with the difference-in-difference estimation results. [55] The 2SLS results shows a negligible effect of the health card on mental health medication use for this group of pensioners and pre-pensioners in the sample, while the difference-in-difference model found that there was no increased use of mental health medication use as a result of the 1999 CSH Card policy. The consistency of the results provides some indication of the robustness of the difference-in-difference estimation results.

5.5.4. Threats to validity

The finding that the 1999 CSH Card policy which expanded access to concession prices for pharmaceuticals had no significant impact on uptake of mental health medication indicates that the seniors eligible for the CSH Card were not responsive to the lower price for mental health medication. This result is consistent with Siminski's study of the effect of CSH Card policy on the take-up of medications for a range of physical ailments (Siminski, 2008a). He concludes that due to their high income, the seniors eligible for the CSH Card do not need concessions. Yet, it is important to consider possible problems with the natural experiment approach itself, which may threaten the validity of the results. Meyer (1995) provides a useful list of threats to the validity of inferences associated with natural experiments, including: omitted variables, selection and mismeasurement.

[55] Angrist and Pischke (2009, 163) point out that the results from the two approaches are not directly comparable. Difference-in-difference estimates an 'intention to treat' and the IV approach estimates the 'local average treatment effect' based on the assumption of heterogeneous effects.. The two results from the two approaches would be comparable if the take-up rate for the CSH Card was close to 100 percent. As previously stated, the take-up rate for the CSH Card is estimated at 70 per cent so the two approaches may not be directly comparable.

There are several omitted variable problems related to voluntary take-up of the CSH Card. First, voluntary take-up affects the extent of the policy shock, which could be small if many people do not take advantage of the policy. I attempted to take into account a lagged treatment effect by including a treatment effect in the second period. However, the lagged treatment effect was small (0.5%) and statistically insignificant.

Second, omitted variable problems could affect the outcome due the heterogeneity of the sample. This relates to the problem of sample selection bias. It could be the case that people without mental health problems or less severe mental health conditions could have been more inclined to take-up of the card due to the other benefits associated with the card (discounts on other health, household, transport, education and recreation concessions) and therefore have less need for mental health medication.

It was possible to restrict the sample to those with stated mental health risk in order to determine if this resulted in a significant treatment effect. The conditional models resulted in a positive treatment effect for the first period, but it was not statistically significant. The results for Model 1 for both Samples are included in the Appendix.

Cultural attitudes regarding mental health medication use could also be an important missing variable. The 1990s was a period of increasing availability of new treatments for mental health, including new psychotropic drugs. The pre-pension age control group and the low income control group both increased their use of the mental health medication between 1995 and 2001 to a greater extent than the treatment group. It is plausible the younger group were more culturally favourable to the new technology and perhaps had less stigma associated with mental health problems and related treatments. In addition, amongst the low income pensioners severity of mental health problems could have led to greater demand for mental health medication. However, without data on cultural attitudes and severity it is difficult to verify these claims.

There are several issues related to mismeasurement that were highlighted in the data description section. While the 1995 and 2001 NHS surveys provide appropriate periods to analyse the impact of the policy change, data inconsistency between the two years, as well as adjustment for age and categorical income data could affect the results of the analysis. One area of concern with this study is the differences between the 1995 and 2001 surveys especially with regard to defining mental health medication. Although, I carefully attempted to create comparable definitions for these variables, using data from different series is likely to affect the results. The issue of consistency in the National Health Surveys is discussed in more detail in Chapter 3 of my thesis.

Issues of omitted variables, selection and measurement all contribute in some way to the most important problem in conducting natural experiments: a lack of common trend between the treated and control group. Matching techniques can be used to achieve a closer correspondence between the two groups.[56] Alternatively, regression discontinuity is another technique to consider in future research. This involves utilising detailed income and age data to compare those just eligible for the CSH Card to those just ineligible (Imbens and Lemieux, 2006). Both matching and regression discontinuity would be a worthwhile directions to consider in further research. In addition, data from the recently 2007-08 NHS would be useful in verifying the common trend assumption.

5.6 Conclusion

This paper examined the effect of the increase in income eligibility limits for the CHS Card in 1999 on the uptake of medications for mental health problems. Taking advantage of three National Health Surveys, one before the policy change, 1995, and two after the policy change, 2001 and 2004-05, difference-in-difference estimation was used to assess of the policy impact. Using two different control groups and extending the analysis with an instrumental variable specification, the results are consistent with findings by Siminski (2008a). Including models with control variables and interactions with treatment effects provided additional information on

[56] Blundell and Dias (2000) provide a good overview of the matching method and its use in difference-indifference estimation.

the factors that impact mental health medication use. Extending the analysis to consider the impact of having a health card on mental health medication use revealed that after controlling for health status and other characteristics, having a health card for the sample for pensioners and pre-pensioners in the sample was not significantly related to mental health medication use.

The finding that the policy change to expand access to concession prices for pharmaceuticals had a negligible impact on uptake of mental health medication is somewhat surprising given previous literature on the greater demand response associated with mental health treatment compared to general medical treatment. Siminski's explanation, however, that high income older people do not need concessions is plausible, and may extend to mental health medication for this group of seniors.

Omitted variables and mismeasurement were identified as possible factors affecting the validity of the results. The issue of voluntary take-up of the CHS Card created omitted variable problems. The determinants of having a CHS Card needs to be addressed in future work on the topic.

Other problems related to mismeasurement of key variables between the two surveys are a concern. The significant increase in use of anti-depressants in the 2001 and 2004-05 surveys compared to 1995 is a matter that needs to be reconciled in the model.

In general, a model using longitudinal data may help to provide more precise estimates of the impact of the policy than pooled-cross section data. However, Australia has limited longitudinal health surveys, which would make it difficult to find one that would match the income, age and timeframe criteria needed for this study.[57]

[57] The Australian Longitudinal Study of Women's Health has conducted 4 waves over the past 2 decades but their older age cohort does not match that required for this study (see: http://www.alswh.org.au/surveys.html).

Appendix A: Sensitivity tests

Including missing income observations

My main results excluded observations with missing income due to the importance of the income band for CSH Card eligibility. I also tested the results by including observations with missing income. The approach used was to assign the sample mean value of income unit income to the missing income observations for each survey year. While the number of observations increased for both Samples 1 and 2, the results are very similar to my main results.

Table A.1: Estimation results with missing income observations, Model 1

Dependent variable mental health medication: *MHMEDS*				
	Sample 1 (Treated and Control Group 1)		Sample 2 (Treated and Control Group 2)	
	Coefficient	Standard Error	Coefficient	Standard Error
TREAT	0.330	0.155**	0.115	0.105
YEAR1	0.467	0.100***	0.344	0.056***
TRXYR1	-0.321	0.189	-0.172	0.188
YEAR2	0.335	0.147***	0.293	0.049***
TRXYR2	-0.289	0.187	-0.175	0.166
Constant	-1.924	0.093***	-1.836	0.033***
Sample size	3,727		13,499	
Pseudo R^2	0.012		0.050	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Mental health medication use conditional on having mental health risk

My main results investigate the effect of the 1999 CSH Card policy on the uptake of mental health medication for seniors eligible for the CSH Card. It is possible to test the results for the sub-sample with mental health risk, with roughly 15 per cent of the sample compared to the sample used for main results. The results are similar to main findings, with the treatment effect, *TRXYR1*, not statistically significant; yet in the results for the sample conditional on mental health risk the coefficient is positive.

Table A.2: Estimation results conditional on mental health risk, Model 1

Dependent variable mental health medication: *MHMEDS*				
	Sample 1 (Treated and Control Group 1)		Sample 1 (Treated and Control Group 2)	
	Coefficient	Standard Error	Coefficient	Standard Error
TREAT	0.182	0.202	-0.008	0.151
YEAR1	0.727	0.197***	0.929	0.085***
TRXYR1	0.369	0.316	0.167	0.260
YEAR2	0.532	0.183***	0.387	0.070***
TRXYR2	-0.060	0.283	0.085	0.227
Constant	-0.408	0.142***	-0.218	0.046
Sample size	484		1,877	
Pseudo R^2	0.057		0.057	

***Significant at 1% level, ** significant at 5% level, * significant at 10% level.

Chapter 6

Conclusion

6.1 Overview

Accounting for 24 per cent of total disability in Australia, mental health disorders result in significant social and economic costs. Health care costs alone amounted to $4.1 billion in 2004-05. Additional costs related to lost productivity and disability support payments necessitate the importance of further economic research in mental health. Australia's health care system aims to provide equitable access to mental health care, but more research is needed to quantify that this aim is met. This thesis has investigated several of the equity and efficiency issues raised in mental health care financing in Australia, and makes a critical contribution to the dearth of existing economic research on mental health in Australia.

Chapter 2 provided an overview on economic issues in mental health as a context for the analytical papers that followed. The chapter discussed how ensuring adequate access to mental health care is more challenging than for other health conditions. Health financing issues related to moral hazard, externalities and adverse selection are more prominent for mental health than for general health, according to Frank and McGuire (2002). In addition, mental disorders can hamper rational demand decisions (Ettner and Schoenbaum, 2006). Investigating income and price barriers to mental health treatment requires attention to issues of endogeneity and measurement.

Chapter 2 also discussed how the expansion of psychotropic treatments for mental health since the 1980s changed the focus of treatment toward ambulatory care and community care in Australia and other developed countries, while lessening hospital-based mental health care. Australian mental health research provides evidence of equitable access to health care, although more rigorous analysis is needed. Other research has raised the problem of low treatment rates generally for mental health compared to other chronic conditions. Structural imbalance raised by health economist Darrel Doessel and colleagues (2008) points to a problem of operational inefficiency involving evidence of treatment for a significant share of people with no identified mental health condition and a significant level of non-treatment for people with a mental health condition. Mental health experts Harvey Whiteford and William Buckingham (2005) indicate that recent mental health sector reforms involving greater funding and availability of ambulatory care now require investigation on the effectiveness of these investments.

Chapter 2 also provided an overview of data available to conduct mental health economic research in Australia. Population based surveys, two Surveys of Mental Health and Well-being for 1997 and 2007, and the ongoing National Health Survey, are the main source of data to conduct mental health economic research. Few longitudinal surveys are available in Australia which provide detailed information on mental health disorders and related health actions; although both the Australian Longitudinal Study of Women's Health and the labour-focused HILDA Survey provide some information on mental health. Administrative data sources relevant for mental health research such as data from Medicare and PBS were also discussed

Chapter 3 investigated data from four National Health Surveys to provide a more in-depth examination of mental health trends in Australia, which previously has been unavailable. My analysis showed that the share of the adult population reporting mental health risk in the National Health Survey nearly doubled from 8.9 per cent in 1989 to 14.4 per cent in 2004-05, and that the share of those with mental health risk using mental health medication also rose significantly from 26.6 per cent to 47.2 per cent over the period. The results from decomposition analysis showed that socio-demographic characteristics accounted for only a small amount of the growth in both the increase in mental risk and mental health medication use between 1989 and 2004-05.

The findings of Chapter 3 also showed a concentration of people with mental health risk using mental health medication in low income groups, which points to the importance of concession prices available through the health card for the purchase of mental health medication. My analysis also provided some evidence that the negative income gradient for mental health risk exists for other chronic conditions including health problems, diabetes, and cancer. Asthma was an exception. Similar income trends were also observed for medication use for mental health risk, diabetes and heart conditions.

Chapter 4 examined in greater depth the effect of income on mental health medication use in 2004-05. Selection methods were used to separate the effect of income on medication use from the effect of income on mental health risk. I utilised a novel approach to identify the model by using only household income in the outcome equation for mental health medication use. By estimating mental health medication use separately for those with and without the health card, I determined that having the health card improves access to mental health medication use and that a positive income gradient for mental health medication use exists only for those without the health card.

Chapter 5 used a natural experiment approach to determine the price responsiveness of seniors to the demand for mental health medication following income eligibility increases in 1999 for the Commonwealth Seniors Health Card. The results indicated that after controlling for health status no significant change in mental health medication use occurred following the policy for this group of mid-high income seniors, thus confirming the greater importance of the health card for mental health sufferers in low income groups.

The results from my analytical chapters have important policy implications. Policy changes aimed at addressing low treatment rates for mental health in Australia need to consider access issues for those just above thresholds for the health card in low-middle income groups. In addition, policy changes to increase copayments for pharmaceuticals need to take into account the importance of concession prices for those with mental health disorders. My research shows that these concessions are more important for people with low income compared to seniors in the mid-high income groups, suggesting that targeted income interventions may be more effective.

My thesis contributes to the field of health economics and specifically to the area of mental health in Australia by providing empirical evidence on the demand responsiveness in the area of mental health. My research provides some evidence that concession prices for prescription drugs are important in supporting access to treatment for mental health in Australia, but much more economic research is needed on mental health issues. The dearth of economic studies on mental health in Australia generally, as outlined by Williams and Doessel (2008, 2006), has been discussed in Chapter 2. The remainder of this chapter will therefore focus on the topics covered in my thesis and the areas where additional research would extend understanding.

6.2 Future research

The recent release of the 2007-08 NHS provides an opportunity to update and verify the mental health trends established in Chapter 3 of my thesis. Likewise, the addition of another NHS provides opportunities to conduct further decomposition analysis of the increase in mental health risk and mental health medication and on the trends in the association between income and mental health risk and related medication use. The findings of Chapter 3 on the importance of the health card for accessing medication for chronic conditions in addition to mental health disorders in Australia can be further investigated with the latest NHS.

Investigation of other data sources is needed, though, to provide further information on important behavioural factors that were associated with mental health trends. The National Health Survey does not collect data on out-of-pocket expenses, health care attitudes, and preferences, nor does it include information on providers’ behaviours and other supply side factors that were likely contributors to increased mental health medication use since 1989. In addition, the gap identified by Williams and Doessel (2008), and confirmed in the NHS data in Chapter 3, between ‘need’ and use of mental health medication points both to the need for improvements in survey measurement methods in mental health and the need for more research on the determinants of mental health treatment.

The findings of Chapter 4 which confirmed the importance of the health card for mental health medication use and showed that a positive income gradient exists for mental health medication use for those without the health card suggests that further investigation of the impact of income thresholds for the health card on mental health medication use would be beneficial. Regression discontinuity estimation methods utilising continuous income data in the 2004-05 and 2007-08 National Health Surveys could assist in this regard.

Further research can build on selection methods used in Chapter 4 to separate the effects of income on mental health risk from the effect of income on mental health medication use. New selection bias, however, was introduced when the sample was split into having a health card and not having a health card as there may be endogeneity of mental health risk with having a health card. A possible extension to consider in future research is maximum likelihood estimation involving three stages – mental health medication, mental health risk and health card status.

The natural experiment approach used in Chapter 5 could be improved with matching techniques to achieve a closer correspondence between the treated and control group. Regression discontinuity is another approach to consider. In addition, data from the 2007-08 NHS would be useful in verifying the common trend assumption. Both areas would be worthwhile to consider in further research.

The policy implications stemming from my results signal the need for more investigation on the design of targeted policy assistance in mental health in Australia. The possible distortion on mental health medication use due to the discontinuous threshold of health card eligibility is an area that requires attention. In addition, the negligible effect of income eligibility changes for the Commonwealth Seniors Health Card on mental health medication use after the 1999 policy supports the need to consider redirecting health card benefits from mid-high income seniors to low-middle income groups currently above health card thresholds. Given that the government cannot provide concession prices on prescription drugs to everyone, it may be possible to design a targeted assistance policy based on a continuous or gradual assistance schedule. The empirical analysis in my thesis on the demand for mental health treatment provides an important first step for future research on improvements to health card benefits and mental health policy development in Australia.

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