THE DEMAND FOR HOSPITAL CARE AND PRIVATE HEALTH INSURANCE IN A MIXED PUBLIC AND PRIVATE HEALTH CARE SYSTEM: THEORETICAL AND EMPIRICAL ANALYSIS FOR THE CASE OF AUSTRALIA

TERENCE CHAI KIET CHENG

2010

A thesis submitted for the degree of Doctor of Philosophy
of the Australian National University

To my family

Declaration

The work in this thesis is my own except where otherwise stated.

Terence Chai Kiet Cheng

Acknowledgements

This thesis would not be possible in its present form without the valuable guidance and support of the following individuals and organisations:

To my supervisors, Professor Jim Butler, Professor Farshid Vahid and Dr Alexandra Sidorenko. I would like to express my utmost gratitude for their advice, guidance and encouragement throughout the journey of writing this thesis. I have benefited immensely from their expertise, experience and their invaluable comments on the draft versions of this manuscript.

To the academics, administrative staff and fellow students at the Australian Centre for Economic Research on Health and the National Centre for Epidemiology and Population Health. My heartiest appreciation to Dr Ian Mcrae, Dr Yuhua Shi, Mr Michael Palmer, Dr Vasoontara Yieng, Dr Masha Somi and Dr Julie Smith for their encouragement, friendship and support.

Special thanks to the generous financial support provided by the Australian Centre for Economic Research on Health throughout my student candidature as well as the Melbourne Institute of Applied Economics and Social Research for providing me with the resources to complete the thesis.

My sincere appreciation to Ms Wenli Khoo and Dr Michael Chua for their invaluable assistance in proof reading this thesis.

To my parents I sincerely thank for the opportunities and for providing the fundaments for this work.

Finally, I would like to express my heartfelt gratitude to my wife Janice for her love, patience and encouragement and for being the source of strength and comfort throughout this journey. For raising together our three children Timothy, Joan and Joen who can now finally see what their father have been busy with for the last few years. To my family, I dedicate this thesis.

Abstract

This thesis examines the processes that underlie how individuals seek hospital care and purchase private health insurance in a mixed public and private hospital system such as that of Australia. To achieve this objective, a theoretical model with explicit functional forms is first developed to analyse the determinants of the intensity of hospital care use, the choice to seek public or private hospital care and the decision to purchase insurance. The key areas of interest are how direct and indirect 'prices' for hospital care, viz-á-viz waiting times and private health insurance, influence the decisions to seek either public or private care and the intensity of care. A key result from the analysis is that individuals with more severe medical conditions are expected to have a higher probability of seeking treatment from the public sector because the duration of wait for public care is shorter due to priority setting in the public sector. In addition, the availability of private hospital insurance reduces the effective price of private hospital care and increases both the probability that individuals seek private treatment and the intensity at which private hospital care is utilised.

A simultaneous equation econometric model that is based on the structure of the theoretical framework is developed. The econometric model accommodates count and binary outcomes variables as well as endogenous binary regressors. The model is estimated using data from the 2004-05 National Health Survey to conduct two empirical analyses. The first analysis examines the determinants of the intensity of hospital admissions and the decision to purchase private health insurance. A key result is that having private hospital insurance increases the expected number of hospital admissions each year by 19 percentage points. In addition to insurance status, the intensity of hospital admission is also influenced by age, gender, employment status, health status and locality.

The second empirical analysis examines the determinants of the intensity of hospital care use and the decisions to seek public or private hospital care and purchase private health insurance using a simultaneous framework. The results indicate that individuals with private hospital insurance are 81 percentage points more likely to seek hospital care as a private patient. Age, household income, private sector employment and the presence of dependent children are factors that increase the probability that individuals obtain private care. On length of stay, the results show that the expected length of hospital stay by private patients is on average 1.11 nights shorter than that of public patients which suggests that systematic differences exist in the types of medical conditions for which individuals seek public or private treatment. Contrary to existing evidence, this study does not find any significant moral hazard effect amongst patients who sought hospital care as a private patient.

From a policy perspective, the results suggest that the effectiveness of government initiatives in Australia to encourage the purchase of private hospital insurance is likely to be limited to reducing public hospital waiting lists and lowering waiting times for public treatment.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Health care is one of the key policy concerns among governments in many developed countries. The rapid growth in public expenditure on health and long-term care from the late 1990s has placed tremendous fiscal pressures on government budgets. Average public expenditure on health and long-term care in developed countries from the Organisation for Economic Cooperation and Development (OECD) is projected to roughly double from 6.7% of Gross Domestic Product (GDP) in 2005 to 10-13% by 2050 (Organisation for Economic Cooperation and Development 2006). For Australia, this is projected to rise from 5.6% in 2005 to between 9.9%-12.6% in 2050. Population aging and longevity, technological advancement and increasing relative prices of health services have been identified as the key drivers of the growth in health care spending. As fiscal pressures mount, governments have sought to identify and implement alternative mechanisms to finance the health care demands of their populace. Policy makers in countries where the public sector plays a significant role in paying for health care have looked to private health insurance markets as an additional source of funding to complement public financing. Private health insurance also perform the role as a policy instrument to help governments achieve their health policy goals such as reducing pressures on the public health care system, promoting individual choice and improving efficiency (Colombo and Tapay 2004).

Australia adopts a mixed public and private approach in the financing and provision of hospital care. The country's tax financed national health insurance program, Medicare, ensures free and universal access for public patients in public hospitals. Patients may elect to seek private care in both public and private hospitals where they are given the freedom to choose their treating doctor, access to private rooms and avoid significant waiting times for elective treatment in public hospitals. The charges associated with private treatment are either borne by individuals as out-of-pocket expenditures or by other insurers (e.g. private health funds, Department of Veterans' Affairs). In Australia, private health insurance provides duplicate insurance coverage for hospital services that are included under the public insurance scheme Medicare. Individuals are allowed to utilise the public system and obtain free hospital care regardless of their private health insurance status.

Against the background of steadily declining private health insurance membership after the Australia's national health insurance program Medicare was introduced in 1984, the Australian government introduced a series of policy changes between 1997 to 2000 aimed at encouraging the purchase of private health insurance. These policies included a combination of tax subsidies, tax penalties and a modification of the community rating regulations. The then prevailing policy stance clearly supported a balanced public and private involvement in the delivery of health care to ensure both universal access and choice and the declining private health insurance membership was regarded as threatening the financial viability of the private hospital sector, which could eventually lead to greater burden on the public hospital system (Commonwealth Department of Health and Aged Care 1999). The implementation of the policies resulted in a dramatic increase in private health insurance coverage, from a low of 30.1% in December 1999 to 45.7% in September 2000 (Butler 2002).[1]

Whilst it is clear that the series of policy changes have been effective in reversing the declining trend in health insurance coverage, the effectiveness of these policies in relieving the burden on the public hospital system is less conclusive. The available evidence in the literature suggest that while utilisation of private hospital care increased following the expansion of private health insurance coverage in 2000, a significant fraction of this increase was attributed to admissions for elective surgical and medical procedures (Sundararajan et al. 2004). Furthermore, patients suffering from severe medical conditions are more likely to seek public as opposed to private hospital care, which leads to the public hospital system being increasingly burdened by patients with complicated, and potentially expensive medical needs (Hopkins and Frech 2001). Evidence on the effect of

[1]Although coverage began to drift downwards again after September 2000, by mid 2004 it had stabilised at 43%. Since then, coverage has begun to increase slightly with 44.7% of the population having hospital coverage at 31 December 2009 (PHIAC 2010).

the increase in private hospital activity on public hospital waiting lists has also been inconclusive. Hanning (2002) observed that the length of waiting lists in Victorian public hospitals shortened following the dramatic increase in the proportion of Victorian population with private health insurance although a major contributor was the decrease in additions to waiting lists rather than the increase in the number of admissions from lists. Duckett (2005) on the other hand found that waiting times in Australia were negatively associated with the proportion of public hospital separations and argues that financing the provision of elective surgery directly through the public system is likely to be more effective in decreasing public hospital waiting times.

A precursor to any investigation on the feasibility and effectiveness of private health insurance as a policy tool requires first a thorough understanding of the processes that underlie how individuals seek hospital care and purchase private health insurance in a mixed public and private hospital system such as that of Australia. And the latter is the main motivation of this thesis. This thesis contributes to the body of literature on the demand for hospital care and private health insurance in a mixed public and private health care system. Following a review of the existing literature in Chapter 2, Chapter 3 examines the relationship between the intensity in the utilisation of hospital care, the decision to seek public or private hospital care and the choice to purchase private health insurance through a theoretical model with explicit functional forms. The data that is employed for the empirical analysis is described in Chapter 4. A novel simultaneous equation econometric model that accommodates count and binary outcomes as well as endogenous binary regressors is discussed in Chapter 5. The framework for the econometric model is based on the theoretical model presented in Chapter 3. In Chapter 6, the econometric model is estimated empirically to examine the determinants of the demand for hospital admissions and private health insurance. In Chapter 7, the determinants on the demand for hospital stay, the decision to seek public or private care and the choice to purchase private health insurance are investigated. Chapter 8 concludes with a summary of the main findings in this thesis.

Chapter 2

Institutional Setting & Literature Review

2.1 Introduction

This chapter describes the institutional setting of hospital care financing in Australia and reviews the literature on the relationship between private health insurance and the demand for hospital care in a mixed public and private health care system. The chapter is organised in four sections. The discussion begins with a description on how hospital care is financed in Australia in Section 2.2. In Section 2.3, the literature on the determinants of demand for public and private health care is discussed. Section 2.4 reviews the literature on the relationship between medical care use and insurance and Section 2.5 discusses the determinants of demand for private health insurance.

2.2 Institutional Setting in Australia

In Australia, individuals can choose to be admitted as public or Medicare patients in public hospitals and receive free treatment from doctors and health practitioners nominated by hospitals as well as free hospital accommodations and meals. Public hospital care is financed through Medicare, a compulsory tax-funded universal health insurance scheme which subsidies both outpatient and inpatient medical services and technologies according to a schedule of fees referred to as the Medicare Benefit Schedule (MBS). An alternative to choosing hospital care as a publicly funded patient is private care, which can be obtained in either private or public hospitals. Individuals who choose private care are entitled to their choice of treatment doctor, better amenities such as private hospital rooms, and faster access to treatment (for elective surgeries). Private patients are charged fees for the professional services rendered by doctors, although they can claim a portion amounting to 75% of the MBS fees from Medicare. Private patients are also billed by hospitals for accommodations, theatres fees, diagnostic tests and medical supplies (such as medications, dressings and other consumables). The private hospital charges, as well as the portion of the difference between the fees that doctors charge and the Medicare subsidy (known as a 'gap fee'), is afforded either by private health insurance or as out-of-pocket expenditures.

There are two types of private health insurance cover in Australia and these types can be defined by its role in relation to the public insurance program Medicare. The first type is private hospital coverage which provides *duplicate* coverage for hospital services already included under Medicare as well as *complementary* coverage towards the gap fees or copayments on private hospital expenditures. It is important to highlight that individuals are not allowed to opt out of Medicare hence private health insurance neither exempts nor excludes individuals from contributing or utilising the public system. The second type is ancillary or extra coverage (also referred to as general treatment policies) which performs a *supplementary* role in covering expenditures on services such as dental care, allied health and items such as eye glasses which are not covered under Medicare. Individuals can choose either hospital, ancillary or combined cover. The health plans within each type of cover can vary in the amount of annual excess or deductibles, copayment rates, as well as the comprehensiveness in terms of the menu of services covered.[1] Policies may cover solely individuals (e.g. singles) or as a family unit (e.g. couple, single parent family, family). Children under the 21 years of age and full-time students below 25 years may be covered under their parents' policy without additional cost.

A key feature of the regulatory structure on the private health insurance market in Australia is the community rating requirement on premiums, which stipulates that insurers must charge the same price for a particular insurance plan regardless of individuals' age, gender, health status, utilisation and claims history. Premiums are allowed to vary by states and may be different across

[1]The information on the details of individuals' private health insurance plans are not available in the data used for the empirical analysis in this paper.

policies and insurers. The requirement on community rated premiums was widely believed to have contributed to the dramatic decline in the proportion of the Australian population with private health insurance, which fell from roughly 50% when Medicare was introduced in 1984, to 32% in 1997 (Industry Comission 1997; Hall et al. 1999; Barrett and Conlon 2003). The contraction in private health insurance membership invoked active public debate on the appropriate role of public and private health insurance and the declining membership was regarded as threatening to the financial viability of the private hospital sector, which could eventually lead to greater burden on the public hospital system (Commonwealth Department of Health and Aged Care 1999). Between 1997 and 2000, three policy changes were implemented in the private health insurance market in Australia. These changes followed The first of three policies was the Private Health Insurance Incentive Scheme (PHIIS) introduced in July 1997. The scheme involved using tax subsidies to encourage the purchase of private health insurance amongst lower income individuals and tax penalties for individuals without insurance. On the latter, single individuals and families whose annual household income is above $50,000 or $100,000 respectively, and are without private health insurance cover, are liable for a tax penalty amounting to 1% of their annual income. In early 1998, the subsidy component of the PHIIS was replaced a non means-tested 30% rebate on health insurance premiums, with the tax penalty on high income earners remained in place. The third policy introduced in July 2000 is the Lifetime Community Rating (LCR) which involved a modification of the community rating regulations. Individuals above 30 years of age when joining an insurance fund are required to pay a higher premium over the remainder of their lifetime. The premium increase is calculated at 2% per year for each year of age above 30 years at the time of entry. The implementation of the policies resulted in a dramatic increase in private health insurance coverage, from a low of 30.1% in December 1999 to 45.7% in September 2000 (Butler 2002). Coverage began to drift downwards again after September 2000 but have since stabilised. At the end of 2005, roughly 43% of the population have private hospital insurance coverage

2.3 The Demand for Public and Private Health Care

In countries where the public sector plays a dominant role in the financing of medical services and where services are provided free at the point of use, waiting lists feature predominantly as allocation mechanisms to control the access to publicly financed health care. Often, a private market coexists alongside the public sector which delivers private medical care financed either through direct payments by consumers or private health insurance. The following sections review the literature on the demand for health care in a health care system where health care is delivered at zero monetary cost through the public sector but rationed through the use of waiting lists. Individuals can choose to avoid waiting on public sector waiting lists by seeking private treatment that is provided at a positive price. The review begins with a discussion in Section 2.3.1 on how waiting on waiting lists performs a rationing role for public care where explicit monetary prices are absent. Section 2.3.2 reviews a selection of studies that have empirically estimated the cost of waiting on waiting lists. The literature on the demand for public and private health care is reviewed in Section 2.3.3. The main interest here is empirical studies that have examined how 'prices' for public and private medical care, viz-á-viz waiting times and private insurance, influence the demand for public and private care.

2.3.1 Waiting as Rationing

In health care markets where monetary prices are either minimal or absent, queues and waiting lists play a central, albeit different, role as allocation mechanisms to control access to and distribution of health care resources. Queueing, through the act of waiting in person, imposes a waiting cost on individuals undertaking the wait. The cost of waiting emerges in the form of the opportunity cost of time individuals spent physically waiting which can be channeled to labour market or leisure activities (Barzel 1974).[2] Individuals join the queue if the benefits of obtaining the good exceeds the cost of waiting plus the price of the good. For

[2] There are a variety of situations where queues have been noted to emerge. In the goods market, queues may arise as a result of uncertainty in demand and supply and where prices do not instantaneously adjust to clear the market (Arthur 1976). In a non-random environment, queues may occur if prices do not adjust the disequilibrium in demand or supply (See Culyer and Cullis (1976), p. 240). This discussion will focus on the latter.

the marginal queuers, the cost of waiting is equal to the benefit of the good if the price of the good is zero.

Waiting on waiting lists to access health care differs from physical queuing in that individuals on waiting lists are able to pursue labour or leisure activities in the duration of the wait. Hence, the opportunity cost of time that is associated with physical queuing does not fully apply. The absence of an opportunity cost of time however does not imply that waiting on waiting lists imposes no cost on individuals. Individuals waiting on waiting lists may be perceived as paying a price through the pain, suffering, inconvenience and uncertainty in waiting (Culyer and Cullis 1976).[3] Waiting can be a source of disutility given that individuals on waiting lists are in poorer health than they would otherwise and because waiting may be associated with anxiety arising from the uncertainty surrounding the length of time individuals have to wait as well as the eventual outcomes of medical treatments (Propper 1995).

Rather than directly inflicting a cost on individuals, Lindsay and Feigenbaum (1984) argue that waiting on waiting lists performs a rationing role because the value of medical care diminishes when care delivered with a delay. The benefits from medical care depends on both the expected duration individuals are required to wait as well as the rate at which the value of care diminishes.[4] The latter is referred to as the decay rate which is influenced by the characteristics of medical conditions that individuals suffer from. For instance, illness conditions that are self-correcting in nature if left untreated, and for which alternative treatments are available have a higher decay rate than otherwise.[5] According to the model, individuals join waiting lists if the expected present value of the benefits of treatment exceeds the cost of joining, where the latter includes all costs associated

[3]A necessary condition for the validity of the proposition that individuals pay a time-price in the form of the non-pecuniary cost associated with waiting is that these costs may be avoided if individuals choose not to join the waiting lists. In this regard, the authors remarked that their proposition is theoretically weak given that the non-monetary cost of pain, suffering and uncertainty incurred while waiting cannot be avoided if individuals choose not to join the waiting list.

[4]Formally, the present value of medical care may be denoted by $V \cdot e^{-g\hat{t}}$, where V denotes the value of medical care, g a decay rate and $\hat{t}$ the expected duration of wait.

[5]In Lindsay and Feigenbaum (1984), the decay rate g is a combination of two effects. The first component in g is the intertemporal discount rate. The second component is a decay factor that is dependent on characteristics of medical conditions. Variations in g across individuals arise from differences in the decay rates as opposed to the discount rate as the magnitude of the former is expected to be considerably larger relative to the latter. This is because waiting times in practice are seldom long enough for the effect of intertemporal discounting to be significant (Lindsay and Feigenbaum 1984, p.407).

with qualifying to be placed on the waiting list such as expenditure on medical examinations, consultations and referrals, and non medical related expenditures such as transportation costs and market information.

An implicit result of the studies discussed above is that all else being equal, a shorter duration of wait will always be preferred to a lengthier one. Johannesson et al. (1998) argue the contrary and showed that individuals can actually be worse off when the waiting time for medical care is reduced. This is because there are both positive and negative discounting effects that arise which may increase or decrease individuals' expected present value utility from health and consumption when medical treatment is brought forward. Hence, it is not necessarily the case that individuals' willingness to pay for a shorter wait is always non-negative (p.643). The positive estimates of the willingness to pay for a one month reduction in waiting times obtained by the authors suggest that one would expect that individuals are on average better off from a short duration of wait than otherwise.[6]

2.3.2 Empirical Estimates on the Cost of Waiting

Studies have sought to estimate the cost of waiting on hospital waiting lists. The available literature on this subject differs in terms of the *perspective* or *viewpoint* (patients, caregivers and/or health systems) adopted in the analysis and the methodological approaches that were employed to calculate or elicit the estimates of the cost of waiting. The discussion here focuses on a selection of studies that have attempted to estimate the cost of waiting from the perspective of patients who are the demanders of hospital care.[7] Using the framework proposed by Lindsay and Feigenbaum (1984), Cullis and Jones (1986) argue that the cost of waiting may be approximated by the price of private medical care where available. Individuals can avoid waiting for public hospital care by paying a positive price for treatment in the private sector where the expected duration of wait is zero. Individuals are indifferent between waiting for public care and the private alternative if the net present value of public hospital care is equal to the net benefit of private treatment.[8] Hence, the average price of private medical care

[6]The empirical estimates obtained in this paper are discussed in Section 2.3.2 below.

[7]See Centre for Spatial Economics (2008) who estimated the cost of waiting from a societal perspective for the case of Canada.

[8]The net present value of benefits of public hospital care is $V \cdot e^{-gt} - C$, where C is the expenditure associated with medical examinations, diagnosis and referral by a general practitioner and the remaining variables are defined above. The net benefit of private treatment is given by $(V - C) - P$ where P is the price of private care.

provides an upper bound estimate on the cost of waiting and the lower bound is zero. Based on this argument, the authors estimated that the total cost of waiting in the United Kingdom (UK) National Health Survey (NHS) ranges between £1,205 million to £2,155 million (in 1984 dollars), or 9.1% to 16.2% of the total government expenditure on the NHS (Cullis and Jones 1986, p. 253). Based on these estimates, the cost of one month's wait ranges from £110 to £220.[9] Propper (1995) estimated the monetary values of the disutility of waiting on UK hospital waiting list using contingent valuation.[10] The estimates of the value of waiting time were found to vary by income. For individuals whose income is below £350 per week, the value of time ranges from £26.7 to £30.1 per month of wait (1987 dollars). The value of time for individuals whose weekly income is above £350 is higher than the former, ranging from £37.7 to £39.5 per month of wait. Johannesson et al. (1998) derived estimates on the value of time on waiting lists by considering individuals' willingness-to-pay for private insurance to reduce the length of waiting time based on data collected through interviews with a sample of Swedes. The estimate of the willingness-to-pay for a reduction in one month's wait, factoring the exchange rate between the Swedish Kroner and the British pound, ranges between £95 to £110 in 1991 prices.[11] As a first inter-country study on the cost of waiting times, Bishai and Lang (2000) estimated the monetary value of willingness to pay for a one month reduction in waiting time for cataract surgery using data collected from patients who underwent surgery in Canada, Denmark and Spain. The authors estimated that the average willingness to pay to reduce waiting times ranges from $24 in Denmark, $33 in Canada and $107 in Spain (1992 dollars).[12] These estimates suggest that the "hidden" cost of cataract surgery waiting time comprised 10% – 25% of the pecuniary cost of the surgical procedure.

Although the estimates on the value of waiting times from the selected studies reviewed above are broadly comparable, it is not unexpected that the estimates

[9] In 1985 dollars. See Propper (1995), p.695.

[10] A separate objective of the paper was to investigate if the value of waiting time is influenced by uncertainty surrounding duration individuals are required to wait for care. In this regard, the author obtained estimates of the value of the uncertainty.

[11] This result is broadly consistent with that obtained in Propper (1995), where the total willingness-to-pay for a reduction in one month's wait is approximately £80 in 1991 dollars (Johannesson et al. 1998, p.641).

[12] These results are consistent with the authors' hypothesis that the actual waiting times for surgery would be the shortest in the country with the highest willingness to pay to reduce the length of wait (Bishai and Lang 2000, p. 228)

should differ given that considerable differences exist in the way the studies are designed in terms of the medical conditions of interest, the methodological approaches to elicit the willingness to pay measures as well as the country of focus.[13]

2.3.3 Theoretical and Empirical Studies: Demand for Public & Private Medical Care

In countries where health services are provided free at the point of delivery, waiting lists feature predominantly as resource allocation mechanisms to control the access to health care. Here, the cost of waiting on waiting lists performs the rationing role that market prices traditionally play and the expected duration of wait influences individuals' decisions to join waiting lists (Lindsay and Feigenbaum 1984). When a private alternative to public care is available, individuals weigh the cost of waiting on waiting lists against the price of private treatment in formulating their choices (Cullis and Jones 1986). The utilisation decisions of individuals influence the aggregate demands of public and private health care which in turn affect the respective market prices. The public provision of private goods, which include health care and education, can also play a role in the redistribution of income from the rich to the poor (Besley and Coate 1991).

Within the framework briefly outlined above, individuals' decision making on the demand for public and private health care is succinctly described in Martin and Smith (1999). In their model, individuals face the choice of either receiving public or private treatment or alternatively choosing to forgo treatment altogether. Private treatment that is undertaken immediately confers the maximum health benefit to individuals at a positive price. Free public treatment that is delivered after a duration of wait produces a smaller health gain as compared to private treatment. Individuals incur a fixed cost of seeking care regardless of the type of care which is avoided only if individuals forgo treatment. Individuals decide between the three treatment strategies by choosing the option that produces the largest net benefits.

The interaction between the public and private markets for hospital care is the

[13] For example, the estimates of the cost of waiting are considerably higher in Cullis and Jones (1986) compared with those in Propper (1995) which may be attributable to methodological differences where the analysis in the former is based on medical conditions with varying decay rates g whereas the latter explicitly considers only conditions with zero decay rates (Propper 1995, p.695).

subject of interest in Goddard et al. (1995). The authors developed a theoretical general equilibrium demand and supply model of public and private hospital treatments that incorporates attributes of the demand side models in Lindsay and Feigenbaum (1984) and Cullis and Jones (1986).[14] Waiting times in the public sector and the price of private treatment are endogenously determined and adjust to clear the public and private markets for hospital treatments. From Goddard et al.'s model, expectations of an increase in public sector waiting times decrease the demand for public care and increase the demand for private care. Correspondingly, a decrease in the private treatment price increases the proportion of individuals seeking public treatment. An increase in the decay rate has two effects. Firstly, it reduces the demand for private care by inducing individuals to shift away from private into public care. Secondly, individuals shift away from using the public hospital sector and seek non-hospital alternatives. Consequently, the effect on an increase in g on the demand for public care is indeterminate as it depends on the relative magnitude of the two shifts (Goddard et al. 1995, p. 44).

Iversen (1997) analysed the effect on public hospital waiting times in the presence of a private sector emphasising the supply side institutional features of the public and private hospital care sectors. If waiting list admissions are not rationed, the effect of a private sector on public hospital waiting times is indeterminate unless the elasticity of public hospital care with regards to waiting times is sufficiently high, in which case the presence of a private sector will increase public sector waiting times (Iversen 1997, p.389). If admissions to waiting lists are rationed, and where hospital consultants work in both sectors, the introduction of a private sector increases the length of wait for public hospital treatments. The presence of a private sector does not affect public hospital waiting times if consultants do not dual practice and work in separate sectors (p. 391).

A variety of studies have empirically investigated the relationship between utilisation, prices and costs to the users of public and private medical care. McAvinchey and Yannopoulos (1993) investigates the demand for public and

[14]The interpretation of the decay rate in Goddard et al. (1995) differs from Lindsay and Feigenbaum's model in two aspects. Firstly, the authors make a distinction between the intertemporal discount rate δ and the decay rate g and both variables enter the utility function separately. Here, the discount rate is represented by the interest rate which affects the present value of income and consumption. Secondly, while the interpretations of g in Goddard et al. (1995) and Lindsay and Feigenbaum (1984) are similar insofar that they both represent the rate at which illness conditions improve or deteriorate over time, the increase in g in Goddard et al.'s model is motivated by improvements in the efficacy of non-hospital treatment.

private acute care in the UK using an interrelated expenditure share model with aggregate data from 1955 to 1987. Expenditures on the following three commodities are considered: (1) NHS acute care obtained through waiting on NHS waiting lists, (2) private acute care with access through insurance and (3) general consumption. The price of NHS care is represented by a weighted average of the time spent waiting on NHS waiting lists for eight medical specialties.[15] The average medical insurance premium across all insurance types[16] is used as a proxy for the price of private medical care while the retail price index acts as the price for general consumption. The interrelated share model was specified as a translog cost function and the estimated coefficients were used to compute the short and long-run own-price, cross-price and income elasticities of the three commodities. The authors estimated that the price elasticity of public care with respect to waiting times ranges from between -0.30 to -0.68. Estimates for the price elasticity of private acute care is relatively higher (-0.78 to -0.85) and is considerably less volatile across time than the elasticity estimates for public care. Cross-price elasticity estimates suggest that while the relationship between public and private care varies over time, public and private care are generally considered as substitutes. This evidence suggests that the increase in NHS waiting times may be associated with relatively higher expenditures on private care, while a reduction in the price of private medical insurance leads to lower public expenditures.

Martin and Smith (1999) examined the determinants of the demand and supply for elective surgery in the U.K. NHS using ward level data in 1991-92.[17] The utilisation of public hospital services is measured by the ratio of the actual against the expected number of admissions to the NHS for elective surgery in a given ward.[18] A standarised index of public hospital waiting times is constructed by calculating the ratio of the actual waiting times for the routine surgery specialty

[15]The eight medical specialties considered in the study include General Surgery; Orthopaedic; Ear Nose and Throat; Ophthalmology; Urology; Oral Surgery and Oral Medicine; Surgical Paediatrics and Gynaecology. Waiting time for each specialty is computed as a ratio of the number of people on NHS waiting lists and the total deaths and discharges from hospital in any given year.

[16]The three categories of insurance plans are individual, corporate and group.

[17]The unit of observation in the study is the 'synthetic ward' which provides an indication of the area an individual resides. The average population size of a ward is roughly 10,000 with a total of 4,985 wards covering the whole of England (Martin and Smith (1999), p. 148)

[18]The expected number of admissions in a given ward is calculated by first calculating the national NHS utilisation rates by age and sex groups. Thereafter, the utilisation rates are applied to age and sex profile of the population within a given ward.

against a measure of expected waiting times.[19] Further measures that influence the demand for public care include the number of family practitioners which acts as an alternative to hospital care and the accessibility of private inpatient treatment, represented by the availability of private hospital beds. The supply model is based on managerial models of supply and is influenced by waiting times, and the number of public sector beds. Demand and supply are estimated separately using two-stage least squares to address the problem of endogeneity in waiting times to both demand and supply. The authors found that the demand elasticity of NHS elective surgery with respect to NHS waiting times is -0.21. The accessibility to private care, measured by the availability of private hospital beds, does not have a significant impact on the demand for public elective care. Utilisation of NHS surgery is negatively associated with the available of family practitioner care (coefficient estimate is -0.08) which suggests that family practitioner care may perform as a weak substitute for public inpatient care. The degree of substitutability between the family practitioner care for inpatient care is synonymous to the definition of the decay rate g in Goddard et al. (1995) and hence the negative relationship between family practitioner care and the demand for NHS care is consistent with Goddard et al.'s theoretical results.

Using the 2004-05 Australian National Health Survey, Srivastava and Zhao (2008) examined the determinants of individuals' choice between public and private hospital services. The key explanatory variable of interest is the role of private health insurance. The authors estimated a recursive trivariate probit system of equation model that accounts for partial observability given that individuals' choice between public and private care is only observed for those who have visited a hospital. The econometric model also allows for the endogeneity of the insurance binary variable in the public/private choice equation. In addition to covariates such as age, educational attainment, employment status and occupation and household income, indicators of the quality of public health care were included (e.g. average waiting time and the proportion of individuals who waited more than a year for elective surgery, the public hospital bed-to-population density and the number of full time equivalent public hospital doctors). The results showed that the availability of private health insurance is the most important determinant of private heath care use. Individuals with private cover are 76 percentage points more likely to seek private hospital care relative to public care.

[19] The expected waiting times are derived using national average waiting times by age and sex.

The quality indicators of public hospital care are not significantly associated with both the choice to purchase private health insurance and to receive public or private care.

Propper (2000) examined the demand for public (NHS) and private health care for the case of the UK. The author exploited the individual level longitudinal data feature of the British Household Panel Survey (BHPS) to account for individual heterogeneity on utilisation choices and to examine if past utilisation decisions can predict current choices of providers. The number of individuals waiting under and over 12 months on NHS waiting lists and an availability index for dental services are chosen as indicators of NHS quality. Individual occupations were used as proxies for employment linked private health insurance coverage given that information on private medical insurance is not captured in the survey. Contrary to previous studies, Propper found that individuals' decisions to seek private care are not significantly influenced by waiting times in the NHS. It was also observed that while movement between the public and private sectors occurred frequently and individuals do not obtain care only from a particular sector, individuals' choices tend to persist over time. The estimated probability that previous use of a given sector is followed by current use of the same sector (termed as the *same sector effect*) is higher than the probability that current use is of a different sector (cross sector effect). Socioeconomic characteristics such as income and employment are significantly associated with the choice to receive care from a particular sector. The author found that political attitudes significantly influence the choice of between public or private care in that more users of public care supported the principles of the NHS as compared to those who use private care.

Gertler and Roland (1997) investigated how the demand for public and private medical care is affected by private medical insurance using survey data from Jamaica. For the case of preventive care, the authors found that the availability of insurance shifted individuals from public to private providers and increased the overall demand for preventive visits. More specifically, insurance is associated to a 28% reduction in the number of visits to public providers and a 114% increase in the visits to private providers. Overall, the number of public and private care visits increased by 48%. In the case of curative care, insurance reduces the number of visits to public providers by 45% and increases the private care visits by 37%. The overall number of curative care visits however does not increase significantly.

2.4 Insurance, Moral Hazard and Medical Care Use

In his seminal article, Arrow (1963) emphasised the presence of uncertainty and asymmetric information in the market for medical care that result in the absence of markets providing medical insurance coverage for certain types of health risks.[20] The failure of the market for insurance was argued as a justification for governments to intervene and insure against risks for which insurance policies would fail to materialise if left to the markets (Arrow 1963, p.961). As Arrow points out, an important consideration here is the incentive effect of insurance known as the problem of moral hazard. There are two types of moral hazards that are associated with medical insurance. The first refers to *ex ante* moral hazard which occurs prior to the onset of illness, where the availability of insurance increases the likelihood of illness and the expected expenditure on medical care (Ehrlich and Becker 1972). The second is *ex post* moral hazard which occurs after the incidence of illness. Here, insurance lowers the effective price of medical care to individuals, and hence increasing utilisation and medical expenditures (Pauly 1986).[21]

Cutler and Zeckhauser (2000) describes the structure and design of health insurance and discusses the role of agency problems and moral hazard. Within the literature, there is substantial empirical evidence that individuals use more medical care when the generosity of insurance increases. Studies in the literature on this subject is divided into three types: randomised experiments of insurance, natural (or quasi) experiments and observational studies (Zweifel and Manning 2000). Randomised experiments are specially designed studies where study participants or 'subjects' are randomly assigned to receive different interventions or 'treatments'. For random experiments involving insurance, the main objective would be to examine how the utilisation of medical care varies across individuals randomly assigned to insurance plans with different levels of cost sharing. Random experiments avoid the self-selection problem and the estimates obtained from these studies can be regarded as reflecting the causal effects of insurance on medical care. The second type of empirical study is natural experiment which

[20]See McGuire (2000) for a comprehensive review of the related literature.

[21]The classical theory of moral hazard applies to the case of a single good. Goldman and Philipson (2007) shows that the classic moral hazard results may not apply for the case of multiple goods which are either complements or substitutes.

typically relies on observational data. Natural experiments in insurance exploit changes in the regulatory and policy environment in insurance markets to analyse how medical care utilisation patterns vary across individuals who were or were not affected by the changes. These studies are referred to as natural or quasi-experiments given that the policy changes are external to individuals and individuals can be thought of as being randomly assigned to different 'treatments' depending on whether or not they are affected. The third type of empirical study involves the use of observational data to compare how medical care utilisation behaviour of individuals varies with the generosity of insurance. In such studies, considerable attention is devoted to addressing the problem that the insurance explanatory variable is endogenous.

The remainder of this section will be devoted to reviewing the literature on the relationship between insurance and the utilisation of medical care. The review begins in Section 2.4.1 with a brief discussion of the key findings from the RAND Health Insurance Experiment which is often regarded as the 'gold standard' of studies on health insurance given the randomised feature of the study. Section 2.4.2 reviews the literature on empirical studies that have used observational data to examine the impact of insurance on medical care use. The main interest here is in empirical studies that have examined the effects of supplementary insurance on the demand for medical care within the context of a health care system where the public sector plays a dominant role in the provision and financing of health services and where individuals can purchase supplementary health insurance for services not covered under the public program. This institutional feature is consistent with the health care system in Australia. Studies using natural experiments, which is the second of the three types of empirical study, will not be discussed here and readers can refer to Zweifel and Manning (2000) for an excellent review.[22] Finally, Section 2.4.3 concludes with a review of the methodological issues and complexities that frequently arise in using observational data for insurance studies and discusses the strategies that have been adopted to address them.

2.4.1 Randomised Experiment in Insurance

The RAND Health Insurance Experiment (HIE) was a randomised trial of health insurance conducted in the United States between 1974 and 1977. The main

[22] Section 5.2.1, pp. 429-433.

objective of the HIE was to examine the impact of insurance cost sharing on the demand for health care, the financial risk from health expenditures and on health status (Newhouse and the Insurance Experiment Group 1993). The random assignment of insurance plans is important to control for confounding effects that could substantially bias the estimates of the price elasticity of medical care. An example where this can happen is if individuals who are in poorer health and expect to use more medical care purchase insurance with more generous coverage. Failing to account for this adverse self-selection implies that the observed insurance effect on medical care use is likely be biased upwards. Adverse selection into insurance is likely to occur if insurance premiums are not risk-adjusted due to incomplete information on individuals' risk or constraints as a result of government regulations (Rothschild and Stiglitz 1976).

In the HIE, study participants were randomly assigned to 14 different fee-for-service insurance plans with different levels of costing sharing. 12 of the 14 insurance plans differ according to four coinsurance rates (0, 25, 50 or 95 percent) and three stop-loss levels (5, 10, 15 percent of family income) on out-of-pocket expenses up to a limit of $1000. All expenses incurred beyond the stop-loss were fully reimbursed. Two remaining plans have different coinsurance rates for different types of medical services.[23] The results obtained from the HIE showed that the demand for medical care is responsive to insurance cost sharing for a broad range of medical services (Manning et al. 1987). For example, moving from an insurance plan with zero patient copayment to that with a 95 percent coinsurance reduces the average number of doctor visits from 4.55 to 2.73, hospital admissions rates from 12.8 percent to 9.9 percent and outpatient expenses from $340 to $203 (1984 dollars).[24] Of the total of eight utilisation measures examined in the study, only inpatient expenditures do not vary significantly across insurance plans. However, this result is observed either because inpatient care is less responsive to price or because inpatient expenditures have a higher probability of exceeding the stop-loss as the size of inpatient expenditures are higher compared to outpatient expenditures. The price elasticity or the pure price response on medical care were found to vary by service type and prices (Newhouse and the Insurance Experiment Group 1993). The price elasticity of total medical care

[23]The first plan had a 25 percent coinsurance rate for inpatient and ambulatory medical services and a 50 percent coinsurance rate for dental and ambulatory mental health service. The second plan had a 95 percent coinsurance rate for outpatient services, with a $150 ($450) annual limit on out-of-pocket expenses per participant (family).

[24]See Table 2, p. 259 in Manning et al. (1987) for a summary of all the results.

demand is -0.17 at the low coinsurance rates of 0-25 percent and -0.22 at the high coinsurance rates of 25-95 percent. The price elasticity for total outpatient care is higher than that of hospital care (-0.31 vs. -0.14) for the high coinsurance rates but similar (-0.17) at the low coinsurance levels.

The results from the HIE showed that the demand for medical care is responsive to insurance cost sharing. The magnitude of the price response of demand was also found to be smaller in the HIE as compared to other nonexperimental studies conducted in the United States (Zweifel and Manning 2000). This is consistent with the view that the estimates of the insurance response from observational studies of insurance are biased due to non-random self-selection into insurance. However, Manning et al. (1987) indicated that comparability between the HIE and nonexperimental studies is difficult because of differences in study designs. One difference is that the insurance policies in the HIE had a two dimensional cost sharing mechanism consisting of coinsurance rates and stop-loss provisions while most nonexperimental studies adopted only a constant coinsurance rate.

2.4.2 Empirical Studies Using Observational Data

This section reviews the literature on empirical studies that have used observational data to examine the impact of supplementary health insurance on medical care use. The review focuses on studies conducted in countries where the public sector plays a dominant role in financing and provision of medical services. Individuals can opt to purchase supplementary private health insurance to finance expenditures on health services that are not covered under the public program or otherwise choose to afford these expenditures as out-of-pocket payments.

Cameron et al. (1988) examined the effect of having private health insurance on the utilisation of seven health care measures within the context of a universal public health insurance program using data from the 1977-1978 Australian Bureau of Statistics (ABS) Health Survey.[25] The seven measures were visits to (1) doctors/specialists and (2) non-doctor health professionals; (3) the number of hospital admissions and (4) hospital days and the number of (5) prescribed, (6)

[25]The universal public health insurance system that prevailed at that time was the Medibank program which provided free public hospital care. The Medibank program was financed through an income-based levy. Individuals could choose to opt out of the Medibank program and avoid paying the levy by purchasing private health insurance which, in addition to the benefits provided under the Medibank program, covers the fees charged to privately admitted patients. Unlike publicly admitted patients, private patients are allowed to be treated by doctors of their choice and received better quality services.

non-prescribed and (7) total medications used. Two different regression models were estimated. The first model was a negative binomial regression model that accommodates the count data (non-negative integer) feature of the dependent variable. The second model was an instrumental variable regression model, which unlike the negative binomial regression, accounts for self-selection into insurance and to isolate the incentive effects of insurance. Individual specific characteristics such as sex, age, income and measures of individuals' health status were included as exogenous regressors that influence the use of medical care. The latter included binary variables indicating the presence of limiting and non-limiting chronic conditions; the number of chronic conditions and illnesses and the number of reduced activity days due to illness and injury. The authors found that individuals with supplementary insurance utilised more doctor visits and prescribed medications and the insurance effects persisted after controlling for self-selection.[26] Insurance does not have any significant effect on the number of hospital admissions and hospital days. Measures of individuals' health status such as the presence of chronic conditions and the number of illnesses reported was found to affect medical care use to a larger extent as compared to individuals' insurance status and income.

Also using Australian data from the 1998-1990 National Health Survey, Savage and Wright (2003) investigated if moral hazard effects are present in the utilisation of private hospital services. In contrast with Cameron et al. (1988) who did not make the distinction between public or private medical care use, Savage and Wright (2003) examined if the duration of private hospital stay is longer for individuals with private hospital insurance as compared to the uninsured. The intensity of private hospital stay is modeled as a hazard function and the binary insurance regressor is instrumented using the estimated probability of having insurance coverage which was estimated separately. Other exogenous regressors included in the hospital duration equation are gender, age, income of household head and spouse and the reasons for hospitalisation. The selection and moral hazard effects were found to vary by income unit types. Adverse selection effects were observed for income units consisting of young singles, young couples, couples

[26]This result pertains to individuals from the *rich sample* where the estimates on the insurance binary variable is the difference in the intensity of medical care use between individuals with supplementary private hospital insurance (LEVYPLUS) and those covered under the public health insurance program (LEVY) (See Table VIII, p. 104). The predictions from a reduced-form logit regression where insurance status is the dependent variable were used as instruments for the endogenous insurance binary variable. The squared-age and activity days variables were not included as regressors in the insurance equation but were included in the utilisation equation.

with dependents and old couples but not for old singles. Significant moral hazard effects were found for individuals in income units consisting of couples with dependents and old couples, where the expected length of private hospital stay by insured individuals exceeded that of uninsured individuals by a factor of 1.9 to 3.2. The authors also found that income has a negative relationship with the duration of hospitalisation which may be because individuals with higher income face a higher opportunity cost of time.

Riphahn et al. (2003) exploited the panel data feature of the German Socioeconomic Panel (GSOEP) to investigate the presence of adverse selection and moral hazard in individuals with add-on insurance. The authors estimated a bivariate Poisson lognormal model of doctor and hospital visits that allows for the unobservables in both utilisation equations to correlate. Without controlling for self-selection effects, the authors' findings suggest that add-on insurance increases the expected number of hospital visits by between 22% to 55%. Evidence suggestive of adverse selection was observed in the case of hospital visits but not for doctor visits.[27] Based on the estimated effects of both the add-on insurance and the public insurance binary variables, the authors concluded that neither hospital nor doctor visits are significantly influenced by insurance status. Contrary to the findings by Riphahn et al. (2003), Harmon and Nolan (2001) found for the case of Ireland that the probability of having a hospital inpatient stay is 5.8% higher for individuals with private health insurance. The magnitude of the insurance effect on the probability of hospital use doubled from 3.1% to 5.8% when the endogeneity of insurance was accounted for which is consistent with advantageous selection as opposed to adverse selection into private health insurance.

Using Spanish data from the Catalonia Health Survey, Vera-Hernández (1999) examined the utilisation of specialist services by individuals with and without duplicate private insurance coverage.[28] The dependent variable of interest is the number of specialists visits in the 12 months prior to the survey. The negative

[27] The authors estimated a linear instrumental variable model of medical care utilisation where predictions of add-on insurance status were used as instruments for the endogenous insurance regressor. The Hausman test was used to test for the endogeneity of the insurance variable.

[28] Individuals who purchase private medical insurance have *duplicate* coverage as they are eligible to receive public medical care under the Spanish National Health Service as well as their entitlements under the private health insurance contracts. In addition to public providers, privately insured individuals can choose to seek medical care from private providers designated by the insurers (known as in-catalogue providers) where the expenditure on these services are covered under private health insurance. If individuals choose to visit private providers that are not designated by private insurers (out of catalogue providers), individuals will have to pay for these expenses out-of-pocket.

binomial model was employed to model the count data nature of doctor visits and the insurance status was instrumented using the predicted probability of insurance estimated from logit equation of insurance coverage. Estimation was conducted using the General Methods of Moments (GMM). The authors found no significant moral hazard effects after accounting for the endogeneity of insurance in a subsample of consisting only of household heads. There is however evidence of moral hazard for the subsample of non-household heads.

In contrast to the studies discussed above where the endogeneity of insurance status was addressed using instrumental variable techniques, Barros et al. (2008) adopted the strategy of focusing on a subsample of insured individuals where the insurance status may be regarded as exogeneous and uncorrelated to the health status of beneficiaries. The authors compared how the utilisation of medical care differs between civil servants and their dependents in Portugal with additional insurance coverage under the employer-based insurance scheme with individuals just covered under the Portuguese National Health Service. The propensity matching estimator was used to assign individuals to the treatment and control group, where the former consist of individuals with the supplementary insurance. The authors found significant moral hazard effects in the number of blood and urine examinations by individuals covered under the civil servant insurance program. No evidence of moral hazard effects was observed for doctor visits and the probability of visiting the dentist.

Of the studies reviewed above, the only study that distinguished between the utilisation of public versus private medical care is that by Savage and Wright (2003). For studies where this information was not available, the authors relied on the relationship between having supplementary medical insurance and the utilisation of both public and private medical care to investigate the issues of adverse selection and moral hazard. However, in the context of health systems where publicly financed health care is provided free at the point of use and where supplementary medical insurance serves to reduce the price of private medical services, moral hazard effects can only be identified from the relationship between having supplementary insurance and the utilisation of private medical services (Savage and Wright 2003).

2.4.3 Methodological Issues in Using Observational Data for Insurance Studies

Studies that attempt to empirically estimate the price or incentive effects of insurance on the utilisation of medical care with the use of observational data are faced with two main methodological complexities. The first issue concerns the nature of medical care utilisation measures. Outcome measures of 'events' or 'episodes' such as the number of doctor visits or the number of hospital admissions are characterised as non-negative integer value counts.[29] The infrequency of utilisation or occurrence also implies that the outcome variable can contain a large proportion of zero observations. The second issue concerns the simultaneity of both insurance and intensity of medical care use. This problem arises because selection into insurance is usually non-random and is influenced by individuals' health or other socioeconomic factors. As elaborated in Section 2.4, suppose self selection into insurance occurs in that individuals who are in poorer health are more likely to purchase insurance or enrol into insurance plans with more generous coverage. In the context of a regression model, the estimated incremental effect of insurance on the intensity of medical care use is biased upwards as it reflects both the price effects of insurance (moral hazard) and the effects of (adverse) self selection. In designing or selecting an appropriate econometric model, special considerations should be given towards accommodating the count data nature of the utilisation measures and addressing the endogeneity problem of insurance.

A thorough treatment of the regression methods for analysis of count data is given by Cameron and Trivedi (1998). The simplest model for regression analysis of count data is the Poisson Regression Model (PRM). The PRM is derived from the Poisson distribution where the intensity factor is allowed to vary by a set of exogenous covariates. A major disadvantage in the use of the PRM is that it requires the restrictive assumption of equidispersion where the conditional mean of the data equals the conditional variance. This assumption however is often violated in many empirical applications where overdispersion - in which the conditional variance is larger than the conditional mean - is more frequently

[29]Medical care utilisation measures are not limited to non-negative integer values and can occur in the form of a continuous outcome (e.g. expenditure on medical care measured in dollars) or a binary outcome (e.g. whether an individual visits a general practitioner in the last two weeks). A wide variety of different statistical methods and econometric models exists and its application depends on the nature of the data and the specification of the research problem. See Jones (2000) for a review of the econometric methods applied to the analysis of health care data.

observed. Overdispersion is a result of unobserved heterogeneity which can arise in many ways. One consequence of unobserved heterogeneity is the problem of observing an excessive number of zeros in the data. As briefly mentioned in the preceding paragraph, the problem of excess zeros is common in data on health care utilisation due to the infrequency of use. For such data, the Poisson distribution is not suitable as it often under-predicts the realisation of zero value counts.

Mixed Poisson models have been developed to accommodate unobserved heterogeneity and overcome the restrictive assumption of equidispersion in the Poisson model. In Poisson mixture models, a heteorogeneity term is typically introduced in the form of a random variable into the conditional mean equation. Different assumptions on the distribution of the random variable hence produces different mixture models. One mixture model is the Negative Binomial (NB) model. The negative binomial model may be motivated in a variety of different ways, of which its representation as a Poisson-gamma mixture has been most common (Cameron and Trivedi 1986). Unlike the Poisson model, the NB model accommodates overdispersion by allowing the variance to be either a linear or quadratic function of the mean. These models are referred to as the NB1 and NB2 models respectively. An attractive feature of NB regression, in addition to the flexibility over the PRM, is that the model is computationally simple and readily estimated using maximum likelihood. A second mixture model is the Poisson lognormal model which assumes that the logarithm of the heterogeneity term is distributed normal. Unlike the NB regression, the Poisson lognormal regression cannot be estimated using conventional maximum likelihood methods as the likelihood function based on Poisson lognormal density does not have a closed form solution. As such, numerical integration techniques such as quadrature or simulation-based estimation are required.

A variety of methods have been developed for the analysis of count data models with endogenous regressors. Mullahy (1997) and Windmeijer and Santos Silva (1997) proposed a generalised methods of moments (GMM) approach using instrumental variables. The former applied the model to examine cigarette smoking behaviour in which the measure of smoking habit is endogenous whereas the latter examined the determinants of doctors visits where individuals' self-reported health is an endogenous regressor. Terza (1998) proposed a full information maximum likelihood (FIML) and a two-step estimation approach for count data and an endogenous treatment binary variable. In the two-step approach, the first step involves estimating a reduced-form regression where the dependent variable is the binary treatment variable. In the second step, the residuals obtained from the regression in the first step are included as a regressor alongside the endogenous treatment variable and the remaining exogenous covariates in a Poisson regression model. Like the GMM approach, the two-step estimation also requires that valid instruments are available. An alternative two-step approach that is common in the empirical literature is the nonlinear analogue of the two-stage least square. Unlike the two-step residual approach mentioned above, the second step involves substituting the endogenous regressor by the predicted values obtained from the first step regression. This was applied by Savage and Wright (2003) who modeled the length of stay in private hospitals using a duration model in which the insurance status is an endogenous regressor. In terms of this approach, Terza et al. (2008) compared the two-stage residual inclusion (2SRI) method and the two-stage predictor substitution (2SPS) method and found that the estimates from the 2SPS are substantially biased and recommends in favour of the 2SRI for nonlinear regression with endogenous regressors.

Poisson mixture models can be extended to accommodate endogenous regressors. Greene (2007) proposed a sample selectivity count data model based on a simultaneous equation model consisting of a Poisson lognormal and a probit regression dictating the selection process. Selectivity is incorporated by allowing the heterogeneity term in the Poisson lognormal to correlate with the error term in the probit selection equation. The likelihood function of the model does not have a closed-form solution and can be estimated using quadratures or simulation based methods. Deb and Trivedi (2006) developed a count data model with endogenous multinomial treatment outcomes using a NB and multinomial mixed logit mixture with latent factors. The model was applied to examine the effect of insurance on the utilisation of medical care where individuals were enrolled in insurance plans offered by health maintenance organisations (HMO) or two other non-HMO plans. The model was estimated using maximum simulated likelihood.

2.5 The Demand for Private Health Insurance

Health insurance plays an important role in the financing of health care in many countries around the world. Health insurance may be defined as a way to distribute the financial risk arising from the unpredictability of individuals' health care expenditure by pooling cost across time and over individuals (Colombo and Tapay 2004). Individuals buy health insurance for a variety of reasons. Risk averse individuals generally prefer certainty to risk and are willing to afford regular insurance premium payments to have their medical expenses covered rather than face the prospect of potentially large financial outlays when they are ill (Von Neumann and Morgenstern 1944, Friedman and Savage 1948). Insurance also provides individuals with access to expensive medical care that would otherwise be unaffordable (Nyman 1999). In health systems where the public sector is a dominant provider of health services, individuals typically can purchase supplementary private health insurance to finance expenditure on private health care services not covered under the public program.

This section reviews the theoretical and empirical literature on the demand for private health insurance. The review focuses on studies that have examined the demand for supplementary private health insurance in health systems where the public sector is the dominant provider of health care. This institutional setting is consistent with that of Australia, where individuals may purchase private health insurance to finance private hospital services which are not covered under the public health insurance programme Medicare. The main objective here is not to comprehensively review the literature on insurance but rather focusing on the determinants of the decision to purchase private hospital insurance.

A key theme of the discussion in Section 2.4 is that the demand for medical services is influenced by the availability of health insurance. The decision to purchase insurance by individuals and households will depend, amongst others, on the expected future utilisation of health services. This interdependence of the demand for health care and health insurance is emphasised in Cameron et al. (1988). The authors developed a theoretical model to analyse the determinants of the intensity of medical care use as well as the decision to purchase insurance. Individuals first decide on the optimum levels of consumption and health expenditure with each insurance strategy conditional on the realised health state and thereafter choose the insurance strategy that produces the highest expected utility. Savage and Wright (2003) considered the decision to seek public or private hospital services in addition to the insurance choice. Within the framework of a three-period model, individuals can either choose to seek private hospital care in the second period, or wait on public hospital waiting lists and receive free public hospital care in the third period. The insurance decision is undertaken in the first period. The choice between public and private care depends, amongst others, on the net prices for private hospital services which varies with different insurance strategies. The optimal choice between public and private care conditional on the insurance strategy and health status is the care type that confers the largest indirect utility.

Empirical evidence from Australian, British and European studies suggest that demographic and socioeconomic characteristics such as age, gender and income are the main drivers of the decision to purchase private supplementary health insurance. Using data from the 1977-78 and 1983 Australian Health Surveys, Cameron and Trivedi (1991) examined the determinants of the choice to purchase insurance for individuals for different household compositions and income groups. Single females are shown to have higher propensity of purchasing insurance as compared to their male counterparts. Household and individual incomes have a strong positive effect on the probability of having insurance. Age was observed to have a positive quadratic effect on having insurance in all subsamples except for low income individuals in the 1977-78 sample and the 1983 family sample. For the family sample, evidence on the relationship between the number of dependents and the probability of having insurance is weak. Educational attainment was found to have a strong positive association with the propensity to insure. The effect on the insurance status is also influenced by occupations where individuals in Professional, Clerical and Farmer categories are more likely to have insurance as compared to Miners, Tradesmen and Service categories. Measures of previous health service use do not significantly influence the propensity to insure. Instead, individuals who consulted a specialist in the three months preceding the survey are more likely to be insured. In terms of the effect on individuals' health on insurance status, the authors found no evidence that health status influence the decision to insure. Among the health status measures examined were the type and length of illnesses that individuals experienced and the prevalence of limiting and non-limiting chronic conditions. In a related study, Savage and Wright (2003) found that the minor chronic medical conditions are more likely to be significant predictors of insurance status compared to major medical conditions. The authors findings were based on the 1989-1990 National Health Survey and the results were broadly consistent with that in Cameron and Trivedi (1991).

Monetary and non-monetary prices of public and private health services and the cost of insurance in the form of premium payments are expected to influence the decision to purchase insurance. Studies as that described above that rely solely on the Australian National Health Survey to analyse the demand for private health insurance suffer from an important data limitation in that the survey does not collect any information on the price of insurance, viz-á-viz, the insurance premiums that individuals pay. Butler (1999) used published data on the premiums revenues received and benefit payments made by insurance companies to construct estimates of insurance premiums which were combined with data from the 1995 National Health Survey to estimate the price and income elasticities of private health insurance in Australia. Hospital and ancillary insurance were found to be price inelastic, and the elasticity estimates are -0.50 and -0.35 respectively. Estimates of income elasticities are 0.24 for hospital insurance and 0.20 ancillary insurance. Non-monetary prices of publicly provided health care and the relative quality differential between public and private health services were also found to influence the decision to purchase private health insurance. For the case of the United Kingdom, Besley, Hall, and Preston (1999) investigated if variations in the quality of the public National Health Service (NHS) care measured by the long-term waiting lists in NHS hospitals, NHS staffing numbers and public spending levels across different regions and through time explain differences in the number of individuals holding private health insurance. Using independent cross-sectional data from 5 waves of the British Social Attitudes Survey, the authors found that long term waiting lists have a significant positive impact on the demand for private health insurance. Similarly, Costa and Garcia (2003) found that individuals' perceptions of the quality gap between private and public health care influenced the decision to purchase private health insurance for the case of Spain. The decision to insure may also be influenced by the perceived value of insurance. Using contingent valuation methods, Johannesson et al. (1998) found that individuals who perceived themselves as having a greater probability of using private health insurance are willing to pay a higher premium to purchase insurance.

Political attitudes and beliefs on whether the provision of health care should be the responsibility of the public sector can be expected to influence whether individuals choose to purchase private health insurance. Propper (1993) hypothesised that the decision to purchase private medical insurance is a two-stage process where individuals either considers private medical insurance as within or out of their choice sets and conditional on the former, whether individuals actually buy insurance. Using data from the UK, the author found that individuals who are more receptive to having a private sector coexisting with the UK NHS are more likely to consider buying private medical insurance. Age, income, self-employment and housing tenure were also found to significantly influence whether one considers insurance as a option. On the other hand, the probability of purchasing insurance is associated with age, income and individuals' attitudes towards the risk of affording private health expenditures out-of-pocket.

2.6 Summary

As articulated in the introduction in Chapter 1, the main objective of this thesis is to conduct a thorough examination of the processes that underlie how individuals seek hospital care and purchase private health insurance in a mixed public and private hospital system such as that of Australia. The theoretical analysis undertaken by Cameron et al. (1988) and Savage and Wright (2003) that have been reviewed in Section 2.5 allow us to understand the determinants of the demand for health care and health insurance in a mixed system. However, neither of these papers adopted explicit functional forms which enable one to conduct comparative statics to study how the solutions from the theoretical models change as the model parameters and specifications are changed. A separate question of interest is how the interplay between illness severity and waiting times in public hospital waiting lists influence individuals' decisions to seek public or private hospital care. Neither of the above two papers, nor any of the studies reviewed in Section 2.3 addressed this issue.

Of the empirical papers reviewed in Sections 2.3 and 2.4, none of these studies have empirically examined the demand for health insurance, the choice to seek public or private care and the intensity of care in a simultaneous framework. This approach enables one to isolate and identify the intertwining factors that motivate the three decisions surrounding the use of hospital care. From the perspective of econometric modeling and its applications, the development of a simultaneous equation econometric model to achieve this objective would make an interesting and important contribution to the literature reviewed in Section 2.4.2 on empirical methods to analyse count data with endogenous regressors.

Chapter 3

Economic Model

3.1 Introduction

This chapter contributes to the literature on the demand for hospital care and private health insurance in a health system where public care is available at zero monetary price through a National Health Service but rationed through the use of waiting lists. A private market coexists alongside the public sector which delivers medical care financed either through direct payments or private health insurance. As reviewed in Chapter 2.5, Cameron et al. (1988) examined the interdependence between health care utilisation and health insurance but does not make the distinction between public and private use. On the other hand, Savage and Wright (2003) analysed the choice between public and private hospital care and the decision to purchase health insurance but employed a general model that does not allow for comparative statics to identify how the utilisation and insurance decisions are influenced by the parameters of the model. The relationship between health status and the decision to seek public or private care is examined by Savage and Wright (2003) and Goddard et al. (1995) but neither papers modeled the interactions between the severity of individuals' illness and public hospitals waiting times. Illness severity is important because whether individuals are accepted into hospital waiting lists and the expected duration of wait conditional on being waitlisted will depend on the urgency of individuals medical conditions.

The aim of this chapter is to examine the determinants of the intensity of hospital care use, the choice to seek public or private hospital care and the decision to purchase insurance. To this end, a theoretical model with explicit functional forms is developed. The relationship between illness severity and waiting times is explicitly incorporated into the model. The model is used to examine how non-monetary and monetary prices of public and private care, viz-á-viz waiting times and private health insurance influence the intensity of hospital care use and the choice between public and private care. The effects of illness severity on the choice between public and private and decision to insure is also investigated. The chapter is organised as follows: Section 3.2 describes the specification of the model and the consumer resource allocation problem. Section 3.3 presents the expressions for the optimal use of hospital care and examines the factors that influence the intensity of care. Sections 3.4 and 3.5 present the decision rules for the choice between public and private hospital care and the decision to purchase private hospital insurance respectively. Section 3.5.1 further examines the factors that influence the demand for private hospital insurance with the use of a simple case study. The chapter concludes with a summary of the findings in Section 3.6.

3.2 Model Specification

Consider a representative individual with a utility function of the following general form

$$U = U(C, h; s)$$

where C denotes the level of consumption and h is the health status of the individual. The state of nature or health state is given by s, where $s = 0, 1, \ldots, N$. The probability of the health state s is denoted by $\pi(s)$. A specific functional form for U is given as

$$U = C^{\gamma} \cdot h(s) \tag{3.1}$$

where $0 < \gamma < 1$. The parameter γ captures the individual's attitudes towards risk.[1] $h(s)$ is the individual's health status which is influenced by the incidence of

[1] A conventional approach to incorporate risk aversion in the model is to specify $U = (C \cdot h)^{\gamma}$ where the individual is said to be risk averse in both C and h. In addition to the conventional formulation, risk aversion has been modeled in different ways. For instance, the specification of the utility function in Cameron et al. (1988) is $U = C \cdot h^{\gamma}$. The implicit assumption of the utility function in (3.1) is that risk aversion applies directly to the level of consumption, but indirectly to health status through resource allocation of income Y to consumption and medical services.

illness associated with state of nature s. The utility accruing from consumption C depends on the individual's health status. For any given level of C, the benefits derived from consumption will be lower for smaller values of $h(s)$.

The individual's health status $h(s)$ has the following functional form

$$h(s) = \frac{m + \beta q}{m + \beta q + \delta s} \tag{3.2}$$

where $0 < \delta < 1$ and $\beta \geq 0$. m denotes the intensity of hospital care that the individual chooses to obtain. Measures of hospital care intensity include the number of hospitalisation episodes over a predetermined duration of time and the number of nights in hospital. The measures typically assume non-negative integer values. q is a composite index function that describes the quality of hospital care. The quality attributes of hospital care include the level of amenity associated with the hospital such as private hospital accommodation and the choice of one's treatment doctor. δs is an illness variable that reflects the degree of reduction in the individual's health in state s. Health state $s = 0$ corresponds to the situation where the individual is well or in perfect health. In this instance, the individual's health status $h(s)$ assumes a value of 1. Illness occurs in states $s = 1, \ldots, N$. The degree of reduction in health δs due to illness is increasing in s. It can be interpreted that $s = 1, \ldots, N$ represent health states that are associated with the incidence of progressively more serious medical conditions. When illness occur, the individual's health status $h(s)$ decreases given that $\delta s > 0$. The individual can mitigate the reduction in health by using hospital care at intensity m and quality q. A property of the health production function $h(s)$ is that $0 < \frac{m+\beta q}{m+\beta q+\delta s} \leq 1$. Hence, it follows that the individual's health cannot be fully restored to its full value of 1 for m and q less than infinity in the presence of illness, that is $s > 0$.[2] It is also the case that the individual's utility from consumption is always lower in the presence of illness relative to perfect health.

The properties of the health production function $h(s)$ are given as follows

$$\frac{\partial h(s)}{\partial s} = -\frac{(m + \beta q)\delta}{(m + \beta q + \delta s)^2} \quad (\leq 0) \tag{3.3}$$

[2]From the perspective of a static analysis, the utility function can be perceived as measuring the net present value (NPV) of utility accruing from consumption and health over a stipulated period. The incidence of illness within the period would reduce the NPV of utility given that the individual will have a level of health status which is less than that of full health over the duration of illness. Hence the NPV of utility in the presence of illness is always less than that of perfect health.

$$\frac{\partial^2 h(s)}{\partial s^2} = \frac{2(m+\beta q)\delta^2}{(m+\beta q+\delta s)^3} \quad (\geq 0) \tag{3.4}$$

$$\frac{\partial h(s)}{\partial m} = \frac{\delta s}{(m+\beta q+\delta s)^2} \quad (\geq 0) \tag{3.5}$$

$$\frac{\partial^2 h(s)}{\partial m^2} = -\frac{2\delta s}{(m+\beta q+\delta s)^3} \quad (\leq 0) \tag{3.6}$$

$$\frac{\partial h(s)}{\partial q} = \frac{\beta\delta s}{(m+\beta q+\delta s)^2} \quad (\geq 0) \tag{3.7}$$

$$\frac{\partial^2 h(s)}{\partial q^2} = -\frac{2\beta\delta s}{(m+\beta q+\delta s)^3} \quad (\leq 0) \tag{3.8}$$

From the above equations, we can observe that the individual's health status is decreasing in s (3.3). For health states $s > 0$, the health production function $h(s)$ is increasing in both m and q (3.5 & 3.7) and exhibits decreasing returns (3.6 & 3.8).

The individual may choose to seek publicly (Medicare) funded hospital care or obtain care as a private paying patient. Public hospital care is provided at zero monetary price but rationed through the use of waiting lists. To access public hospital care, the individual is required to wait on public hospital waiting lists. Ex ante, the duration of wait is uncertain. However, the individual forms an expectation of the wait duration with information on the severity of the medical condition. The expected duration of wait is denoted as $t^e(s)$ and is assumed to be decreasing in the severity of illness, that is $\frac{\partial t^e(s)}{\partial s} < 0$. The relationship between illness severity and the expected duration of wait on public hospital waiting list well describes how elective hospital care in public hospitals in Australia is rationed. Patients seeking elective surgery in public hospitals are first assigned one of three clinical urgency categories by their treating specialist prior to being placed on hospital waiting lists.[3] From these categories, patients can estimate

[3] In public hospitals in Australia, patients seeking elective hospital care are assigned to one of three clinical urgency categories (Australian Institute of Health and Welfare 2003). Urgent medical conditions are those which have the potential to deteriorate quickly into an emergency. Semi-urgent conditions are those which may be the cause of some degree of pain, dysfunction or disability but are unlikely to deteriorate quickly. Non-urgent conditions are those causing minimal or no pain, dysfunction and disability and are unlikely to deteriorate quickly and have a very low probability of becoming an emergency. At the time this manuscript is prepared, the national standard for urgent, semi-urgent and non-urgent cases is for treatment to be

the maximum length of time they will be expected to wait for treatment. For publicly funded hospital care, in addition to being required to wait on waiting lists, the individual is not entitled to private hospital accommodation and does not have the choice of treating doctor. As such, given the characteristics of public hospital care, the quality level of public care is denoted by a fixed value $q = 0$.

The individual may choose to avoid waiting on public hospital waiting lists, or obtain higher quality care, by choosing hospital care as a private patient. It is assumed that private hospital care is competitively supplied at a unit price of p^m. It is further assumed that the quality of private hospital care is given by a fixed value $q = 1$.[4] The unit price of quality is denoted by p^q, and applies to each unit of hospital care m that the individual obtains. Hence, the total expenditure on private hospital care is expressed as $(p^m + p^q)m$. This includes the charges for hospital and medical services such as hospital accommodation, theatre fees, surgical procedures, medications as well as doctors' fees. As a patient receiving private hospital care in Australia, Medicare covers 75% of the Medicare Benefit Schedule fee for eligible in-hospital professional services provided by doctors. The Medicare subsidy is incorporated into the model through the parameter η which is applied to the price of medical care p^m. The total private hospitalisation expenditure net of the Medicare subsidy is given as $(\eta p^m + p^q)m$, $0 \leq \eta \leq 1$. Suppose prior to the realisation of the health state s, the individual can decide to purchase private hospital insurance at a premium P $(P > 0)$which reduces the expenditure on private hospital care to $\alpha(\eta p^m + p^q)m$, where $0 \leq \alpha < 1$. The fraction α is the cost sharing parameter which denotes the proportion of the total private hospital expenses the individual is required to pay. The amount that is borne by private health insurer is $(1 - \alpha)(\eta p^m + p^q)m$. Given that the individual either decides to purchase insurance at premium P or not to purchase insurance, the individual's choice is a binary one and is represented by the indicator variable d which takes the value of 1 when insurance is purchased. Finally, it is assumed that private hospital care is available to the individual without any time delay, that is $t^e(s) = 0$.

The individual is assumed to receive income Y from both labour and non-

administered within 30, 90 and 365 days respectively.

[4]It is assumed that the function q, which represents the quality of hospital care, takes only two values, namely 0 for public care and 1 for private care. This assumption is imposed to make the theoretical model consistent with the empirical framework given that the quality measure adopted in the empirical analysis is a binary variable of whether hospitals are public or private in nature.

labour sources. Labour earnings arises from devoting a pre-determined number of hours L to employment at a wage rate w. The individual allocates a proportion of this income to consumption and to meet hospital expenditures if required. Although the monetary price for publicly funded hospital care is zero, the individual incurs a time cost which comprises of two components. The first component of time cost involved in seeking public hospital care is the monetary value of the expected duration the individual is required to wait on hospital waiting lists. The cost of waiting is expressed as $T_l \cdot t^e(s)$, where T_l is the cost per unit of waiting time. Waiting confers a cost to the individual in two ways. Firstly, the value of hospital treatment decays with time (Lindsay and Feigenbaum 1984). Secondly, disutility arises from waiting because individuals on hospital waiting lists can be expected to be in less than perfect health (Propper 1995). In addition, the uncertainty surrounding the actual duration of wait and the outcome of the hospital treatment result in anxiety and imposes a cost on individuals waiting on hospital waiting lists. It is assumed that the cost of waiting enters into the utility function and reduces the utility the individual derives from consumption.[5] Hence, the utility function in (3.1) is modified accordingly as

$$U = [C - T_l \cdot t^e(s)]^\gamma \cdot h(s) \tag{3.9}$$

While waiting on public hospital waiting lists does not impose an opportunity cost of time because individuals on waiting lists are able to pursue market or leisure activities in the duration of the wait, individuals who seek hospital care incur an opportunity cost in terms of the time spent in obtaining hospital treatment which would otherwise be devoted to employment. This opportunity cost of time applies regardless if the type of hospital care obtained is public or private. This time-cost is applied at a rate of T_m for every unit of hospital care m obtained. The value of T_m depends on the availability of sick leave provisions in employment contracts. In the case of self employed individuals or paid employees who are not remunerated when they are absent from work, the time cost T_m may

[5] Johannesson et al. (1998) argues that individuals can actually be worse off when the waiting time for medical care is reduced and hence it is not necessarily the case that individuals' willingness to pay (WTP) for a shorter wait is always non-negative (p.643). This is because there are both positive and negative discounting effects that arise which may increase or decrease individuals' expected present value utility from health and consumption when medical treatment is brought forward. The authors' found that the WTP to reduce the length of waiting time by one month is estimated to lie between £95 and £110. This empirical finding suggest that a reduction in waiting times would on average make individuals better off.

be set equal to the wage rate w. It is assumed that T_l and T_m are ≥ 0. The price of the consumption good is normalised to 1.

With the above assumptions, the individual faces a budget constraint that is dependent on the choices to purchase insurance and to obtain public or private hospital care. The relevant budget constraints of the individual who does not purchase private hospital insurance and who seeks public and private hospital care respectively are

$$Y - T_m m = C \tag{3.10}$$

$$Y - T_m m = C + (\eta p^m + p^q)m \tag{3.11}$$

The budget constraints of the individual with private hospital insurance and who seeks public and private hospital care respectively are

$$Y - T_m m = C + P \tag{3.12}$$

$$Y - T_m m = C + P + \alpha(\eta p^m + p^q)m \tag{3.13}$$

The budget constraints (3.10) to (3.13) may be collapsed into

$$Y - T_m m = C + Pd + (1-d)q(\eta p^m + p^q)m + dq\alpha(\eta p^m + p^q)m \tag{3.14}$$

Assuming that the individual is an expected utility maximiser, the individual solves the following allocation problem

$$\max_{m,q,d} \sum_s \pi(s)\big\{[C - T_l \cdot t^e(s)]^\gamma \cdot h(s)\big\} \tag{3.15}$$

such that

$$h(s) = \frac{m + \beta q}{m + \beta q + \delta s}$$

with budget constraint in (3.14)

3.3 Optimal Intensity of Hospital Care

The solutions on the optimal intensity of hospital care m^* is obtained for each insurance strategy and choice of public or private hospital care conditional on health state s. These are derived by substituting (3.2) and the relevant budget constraint into (3.15) and differentiating the result with respect to m. In terms of notation, let the optimal values of m, conditional on health state s, be denoted by $m^*_{d,q}$ where $d = 0, 1$ denotes the non-purchase and purchase of insurance respectively, and $q = 0, 1$ denotes public and private hospital care respectively. Consider $m^*_{0,0}(s)$, the optimal intensity of public hospital care by an individual without private hospital insurance in health state s.[6] The first order condition for an optimal value of $m_{0,0}(s)$ is

$$\gamma\bar{C}^{\gamma-1}\left[\frac{m}{m+\delta s}\right] = \frac{\bar{C}^{\gamma}}{T_m}\left[\frac{\delta s}{(m+\delta s)^2}\right] \tag{3.16}$$

where $\bar{C}$ is the level of consumption net of waiting cost, that is $C - T_l \cdot t^e(s)$. The expression on the LHS of equation (3.16) is equivalent to taking the derivative of the utility function in (3.9) with respect to $\bar{C}$, that is $\frac{\partial U}{\partial \bar{C}}$ and dividing the result by the price of consumption which has been normalised to 1. Correspondingly, the RHS of (3.16) is equivalent to $\frac{\partial U}{\partial h} \cdot \frac{\partial h}{\partial m(s)}$ and further dividing the result by the time price T_m for public hospital care. Hence, the first order condition is interpreted as follows: conditional on health state s, the intensity of public hospital care that maximises the utility of the individual occurs where the utility gain per dollar from a unit increment in the use of public hospital care equals the loss of utility in decreasing consumption by one dollar.

As presented in Section A of the appendix, the expressions for the optimal intensity of public hospital care in health state s by insurance status are

$$m^*_{0,0}(s) = \sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right) \tag{3.17}$$

$$m^*_{1,0}(s) = \sqrt{\frac{\delta s}{\gamma T_m}\left[Y - P - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right) \tag{3.18}$$

[6] The derivations are presented in Section A of the appendix.

Correspondingly, the solutions to the optimal intensity of private hospital care are

$$m_{0,1}^*(s) = \sqrt{\frac{\delta s}{\gamma}\left[\frac{Y}{(\eta p^m + p^q) + T_m}\right] + \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right]^2} - \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right] \tag{3.19}$$

$$m_{1,1}^*(s) = \sqrt{\frac{\delta s}{\gamma}\left[\frac{Y - P}{\alpha(\eta p^m + p^q) + T_m}\right] + \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right]^2} - \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right] \tag{3.20}$$

Equations (3.17) to (3.20) are a subset of the full set of solutions presented in Section A of the appendix as further assumptions are required to ensure that the solutions are defined.[7] In addition, it can be observed that $m_{d,q}^*(s)$ assumes both positive and negative values. Given the requirement that the optimal intensity of hospital care can take only non-negative values, it is further assumed that

$$Y - T_l t^e(s), Y - P - T_l t^e(s) \geq 0 \tag{3.21}$$

and

$$\frac{Y}{\alpha(\eta p^m + p^q)}, \frac{Y - P}{\alpha(\eta p^m + p^q)} \geq 0 \tag{3.22}$$

where (3.21) requires that the individual's income net of the monetary cost of waiting and the insurance premium must be greater or equal to zero.[8] The set of assumptions in (3.22) is reasonable given that the budget constraint will always be non-negative.

[7] The first part of the solutions in equations (A.5), (A.7), (A.9) and (A.10) of Section A contains a square root function. Hence, the terms under the square root have to be greater than or equal to zero for $m_{d,q}^*$ to be defined.

[8] Whether or not these assumptions are reasonable is an empirical question. Propper (1995) estimated that monetary value of waiting list time and the value of the uncertainty for individuals waiting on hospital waiting lists in the British National Health Service and found that the estimates vary by the individuals' income. For individuals whose income are below £350 per week, the estimated value of waiting list time and the value of uncertainty varies between £26.7 to £32.4 per month of waiting and £13.4 to £27.3 respectively. For individuals whose income are above £350 per week, the estimates ranges from £37.7 to £39.5 per month of waiting and £11.3 to £28.5 for the uncertainty. Although there have not been similar studies done for the case of Australia, the results in Propper (1995) strongly suggest that the cost of waiting can be expected to be considerably low relative to income.

3.3.1 Comparative Statics: Intensity of Hospital Care

The results in equations (3.17) to (3.20) provide insights on how the optimal intensity of public and private hospital care varies with the assumptions in the model. In terms of the relationship between the utilisation of hospital care and the severity of illness, the use of hospital care, regardless of care type, is zero when the individual is in perfect health. This occurs when $s = 0$. Also, the intensity of care demanded by the individual is non-decreasing in the severity of illness.[9] Individuals demand a greater intensity of hospital care to mitigate the larger reduction in health associated with more severe medical conditions. Moving on to the role of monetary prices, private hospital care use is decreasing in the effective unit price $(\eta p^m + p^q)$, which is defined as the market price less the subsidy provided through the Medicare Benefits Schedule. Here, the intensity of private care decreases as the unit prices for care p^m and care quality p^q increases. Also, the demand for care is increasing in the amount of subsidy η. On the influence of hospital insurance on the demand for hospital care, the availability of private hospital insurance increases the intensity in the use of private hospital services. This result is observed from equation (3.20), where a reduction in the degree of cost sharing through a smaller α parameter reduces the out-of-pocket expenses required on the part of the patient. The presence of private hospital insurance and variations in the effective price for hospital care do not affect the intensity of public hospital care given that the individual faces zero monetary prices.

Even in the absence of monetary prices, the utilisation of hospital care is constrained by the indirect cost of hospital care in the form of the opportunity cost of time, denoted as $T_m m$, involved in obtaining care which would otherwise be channeled into labour market activities.[10] This is the case with public hospital care where direct monetary prices are zero or in the context of private hospital care where patients have private health insurance policies with zero patient cost sharing. Where the intensity of hospital care is measured by the number of days in hospital, the opportunity cost per unit of time may be proxied by the earnings

[9] The proof is shown in Section A of the appendix.

[10] Conversely, the individual may tradeoff leisure time or time devoted to other utility producing activities to obtain hospital care. For example in Becker (1965), individuals face a constraint on the total time available which is allocated to labour market activities to purchase market goods. The market goods are combined with time inputs to produce basic commodities which enter directly into individuals' utility function.

forgone with every additional day in hospital. As discussed earlier, the time cost T_m may be set equal to the wage rate w. Depending on the availability of sick leave provisions in employment contracts, individuals receiving higher wage rates face a higher indirect cost of hospital care and correspondingly demand a lower intensity of care.

Waiting on public hospital waiting lists imposes a cost on the individual through the disutility of the illness as well as the uncertainty of the actual length of wait required. One can observe from equations (3.17) and (3.18) that the demand for public hospital care is decreasing in the length of time the individual is expected to wait for any given level of illness severity s. The demand for public hospital care use is also decreasing in the unit waiting cost T_l. As described in the introductory sections, T_l can be interpreted as the individual's valuation of the physiological and emotional pain and suffering associated with each unit of time the individual waits for care on hospital waiting lists.

3.4 Decision Rule: Hospitalisation as a Public or Private Patient

The solutions to the optimal intensity of hospital care presented in equations (3.17) to (3.20) is used to characterise the decision rule on the choice of admission into hospital as a public or private patient. Conditional on health state s, the expression for the indirect utility function for an individual without private hospital insurance who chooses public hospital care is derived by substituting $m^*_{0,0}(s)$ into the utility function (3.9) and the budget constraint (3.10). The indirect utility function $V_{0,0}(s)$ is given as

$$V_{0,0}(s) = [Y - T_m m^*_{0,0}(s) - T_l t^e(s)]^\gamma \cdot \frac{m^*_{0,0}(s)}{m^*_{0,0}(s) + \delta s} \tag{3.23}$$

Correspondingly, the indirect utility function for an uninsured individual who chooses private hospital care is given as

$$V_{0,1}(s) = [Y - (\eta p^m + p^q + T_m)m^*_{0,1}(s)]^\gamma \cdot \frac{m^*_{0,1}(s) + \beta}{m^*_{0,1}(s) + \beta + \delta s} \tag{3.24}$$

Using equations (3.23) and (3.24), the decision rule on the choice between public and private hospital care for an uninsured individual is characterised as follows: conditional on health state s, an individual without private health insurance will choose to be admitted as a public patient if

$$V_{0,0}(s) > V_{0,1}(s) \tag{3.25}$$

Alternatively, the individual will choose to seek private hospital care if

$$V_{0,0}(s) < V_{0,1}(s) \tag{3.26}$$

With the availability of private hospital insurance, the insured individual will choose public hospital care if

$$V_{1,0}(s) > V_{1,1}(s) \tag{3.27}$$

in which

$$V_{1,0}(s) = [Y - P - T_m m^*_{1,0}(s) - T_l t^e(s)]^\gamma \cdot \frac{m^*_{1,0}(s)}{m^*_{1,0}(s) + \delta s} \tag{3.28}$$

$$V_{1,1}(s) = [Y - P - \alpha(\eta p^m + p^q)m^*_{1,1}(s) + T_m m^*_{1,1}(s)]^\gamma \cdot \frac{m^*_{1,1}(s) + \beta}{m^*_{1,1}(s) + \beta + \delta s} \tag{3.29}$$

Correspondingly, the insured individual will choose private hospital care if the equality is reversed. More generally, the decision rule on the optimal choice of admission in hospital as a public or private patient is characterised as follows:

conditional on health state s and insurance status d, the optimal patient type choice $q^* = [0, 1]$ is such that

$$V_{d,q^*}(s) = max\Big[V_{d,0}(s), V_{d,1}(s)\Big] \tag{3.30}$$

where $q = 0$ and $q = 1$ denotes public and private hospital care respectively.

3.4.1 Comparative Statics: Public & Private Choice

In this section, I examine how the decision to obtain public or private hospital care is influenced by changes in the parameters in the model. The first question of interest is how the choice between obtaining public or private hospital care varies with the severity of illness. Let us examine this for the case of an uninsured individual.[11] This can be explored by examining how the indirect utility functions $V_{0,0}(s)$ and $V_{0,1}(s)$ changes as s increases. For the former,

$$\frac{\Delta V_{0,0}(s)}{\Delta s} = \underbrace{\gamma\Big[Y - T_m m^*_{0,0}(s) - T_l t^e(s)\Big]^{\gamma-1}}_{\geq 0}\Big[-T_m \frac{\Delta m^*_{0,0}(s)}{\Delta s} - T_l \frac{\Delta t^e(s)}{\Delta s}\Big]\underbrace{\Big[\frac{m^*_{0,0}(s)}{m^*_{0,0}(s) + \delta s}\Big]}_{\geq 0}$$

$$+ \underbrace{\Big[Y - T_m m^*_{0,0}(s) - T_l t^e(s)\Big]^{\gamma}}_{\geq 0}\underbrace{\Big[\frac{\delta(s\frac{\Delta m^*_{0,0}(s)}{\Delta s} - m^*_{0,0}(s))}{(m^*_{0,0}(s) + \delta s)^2}\Big]}_{\leq 0} \tag{3.31}$$

where the terms in the last bracket is less than or equal to 0 given that $s\frac{\Delta m^*_{0,0}(s)}{\Delta s} - m^*_{0,0}(s) \leq 0$.[12] Using (3.31), $\frac{\Delta V_{0,0}(s)}{\Delta s} \geq 0$ if

[11] The application of the analysis, and consequently the analytical results, are similar and straightforward for the case of an insured individual.

[12] See Section A for proof.

$$T_l\frac{\Delta t^e}{\Delta s} \leq -T_m\frac{\Delta m^*_{0,0}(s)}{\Delta s} + \frac{\delta}{\gamma}\left[Y - T_m m^*_{0,0}(s) - T_l t^e\right]\left[\frac{s\frac{\Delta m^*_{0,0}(s)}{\Delta s} - m^*_{0,0}(s)}{m^*_{0,0}(s)(m^*_{0,0}(s)+\delta s)}\right] \tag{3.32}$$

where $T_l\frac{\Delta t^e}{\Delta s}$ on the LHS of equation (3.32) is the reduction in waiting cost for public hospital care resulting from an incremental change in s. On the RHS, $T_m\frac{\Delta m^*_{0,0}(s)}{\Delta s}$ is the incremental opportunity cost of time associated with a higher optimal use of public hospital care given a unit increase in s. The expression in the first bracket on the RHS is the level of consumption C and the expression in the second bracket represents the rate of reduction in health resulting from a unit increment in s, which is denoted as $\frac{\Delta h}{h}/\Delta s$. On the contrary, the indirect utility function $V_{0,1}(s)$ is non-increasing in s. This is because

$$\frac{\Delta V_{0,1}(s)}{\Delta s} = \underbrace{\gamma\left[Y - \tilde{p}m^*_{0,1}(s)\right]^{\gamma-1}\left[-\tilde{p}\frac{\Delta m^*_{0,1}(s)}{\Delta s}\right]\left[\frac{m^*_{0,1}(s)+\beta}{m^*_{0,1}(s)\beta+\delta s}\right]}_{\leq 0}$$

$$+\underbrace{\left[Y - \tilde{p}m^*_{0,1}(s)\right]^{\gamma}\left[\frac{\delta(s\frac{\Delta m^*_{0,1}(s)}{\Delta s} - m^*_{0,1}(s) - \beta)}{(m^*_{0,1}(s)+\beta+\delta s)^2}\right]}_{\leq 0} \tag{3.33}$$

where $\tilde{p} = \eta p^m + p^q + T_m$. The first set of terms on the RHS of (3.33) represents the decrease in utility that arises from the reduction in consumption as a result of increasing the intensity of hospital care given an increase in the illness severity. The second set of terms captures the decrease in utility of the individual arising from a reduction in the individual's health given a unit increment in s. Given that both sets of terms are less than or equal to zero, therefore $\frac{\Delta V_{0,1}(s)}{\Delta s} \leq 0$. If $\frac{V_{0,0}(s)}{\Delta s} \geq 0$,

$$\frac{\Delta}{\Delta s}\Big[V_{0,0}(s) - V_{0,1}(s)\Big] \geq 0 \tag{3.34}$$

The key insight that can be drawn from the results in equation (3.34) on the decision making between the choice of to seek public or private hospital care is that the propensity to seek public hospital care is increasing in the severity of illness. For more severe medical conditions, public hospital care becomes comparatively more attractive than private hospital care given that waiting times for public hospital services are lower.

The influence of private hospital insurance on the choice between public and private hospital care can be investigated by examining how $V_{d,q}(s)$ varies with the extent of insurance cost sharing, given by the parameter α. First and foremost, given that public hospital care is provided at zero monetary price, changes in the cost sharing parameter have no effect on the indirect utility functions that correspond to the case of public hospital care, regardless of insurance status. In other words, $\frac{\partial V_{d,0}}{\partial \alpha} = 0$. The effect of a unit change in α on $V_{1,1}(s)$[13], or $\frac{\partial V_{1,1}(s)}{\partial \alpha}$, is ≤ 0 given that

$$\frac{\partial V_{1,1}(s)}{\partial \alpha} = \underbrace{\gamma\Big[Y - P - (\alpha p' + T_m)m^*_{1,1}(s)\Big]^{\gamma-1}}_{\geq 0}\underbrace{\Big[-p' m^*_{1,1}(s) - (\alpha p' + T_m)\frac{\partial m^*_{1,1}(s)}{\partial \alpha}\Big]}_{\leq 0}$$

$$\underbrace{\Big[\frac{m^*_{1,1}(s)+\beta}{m^*_{1,1}(s)+\beta+\delta s}\Big]}_{\geq 0} + \underbrace{\Big[Y - P - (\alpha p' + T_m)m^*_{1,1}(s)\Big]^{\gamma}\Big[\frac{\delta s\frac{\partial m^*_{1,1}(s)}{\partial \alpha}}{(m^*_{1,1}(s)+\beta+\delta s)^2}\Big]}_{\leq 0} \tag{3.35}$$

where $p' = \eta p^m + p^q$ and $\frac{\partial m^*_{1,1}}{\partial \alpha} \leq 0$. In (3.35), it can be easily shown that

[13]For the case of $V_{0,1}(s)$, this is equivalent to setting $\alpha = 1$ and $P = 0$ in $V_{1,1}(s)$

$$p' m_{1,1}^* \geq (\alpha p' + T_m)\frac{\partial m_{1,1}^*}{\partial \alpha} \tag{3.36}$$

In equation (3.36), $p' m_{1,1}^*$ represents the decrease in consumption associated with a unit increase in α. Given that α is expressed in the form of a percentage which takes value between 0 and 1, $p' m_{1,1}^*$ denotes reduction in consumption given one percent increase in patient's cost sharing. $(\alpha p' + T_m)\frac{\partial m_{1,1}^*}{\partial \alpha}$ on the other hand is the increase in consumption arising from the reduction in the optimal intensity of private hospital care demanded as a result of one percent increase in patient's cost sharing. Given that $\frac{\partial V_{1,0}(s)}{\partial \alpha} = 0$ and $\frac{\partial V_{1,1}(s)}{\partial \alpha} \leq 0$,

$$\frac{\partial}{\partial \alpha}\Big[V_{1,0}(s) - V_{1,1}(s)\Big] \leq 0 \tag{3.37}$$

Equation (3.37) indicates that a decrease in the fraction of private hospital expenses borne by the individual, given a reduction in cost sharing, increases the propensity to obtain private hospital care. More generally, the availability of insurance reduces the effective monetary price for private hospital care and increases the probability that the individual seeks private relative to public hospital care.

An increase in the parameter β, which is interpreted as the individual's preference for the quality attributes of private hospital care, increases the propensity for the individual to seek private as opposed to public hospital care. This result is observed when one examines how $V_{d,1}$ varies with β. Let us examine this for the case of an uninsured individual.[14] The change in $V_{0,1}(s)$ for a change in β is given by

[14] Again, the application of the algebra and the results are similar for the case of an individual with private hospital insurance

$$\frac{\partial V_{0,1}(s)}{\partial \beta} = \underbrace{\gamma\left[Y - \tilde{p}m^*_{0,1}\right]^{\gamma-1}\left[-\tilde{p}\frac{\partial m^*_{0,1}}{\partial \beta}\right]\left[\frac{m^*_{0,1}+\beta}{m^*_{0,1}+\beta+\delta s}\right]}_{\geq 0} + \underbrace{\left[Y - \tilde{p}m^*_{0,1}\right]^{\gamma}\left[\frac{(\frac{\partial m^*_{0,1}}{\partial \beta}+1)+\delta s}{(m^*_{0,1}+\beta+\delta s)^2}\right]}_{\geq 0} \tag{3.38}$$

given that $-1 \leq \frac{\partial m^*_{0,1}}{\partial \beta} \leq 0$.[15] Hence,

$$\frac{\partial}{\partial \beta}\Big[V_{0,0}(s) - V_{0,1}(s)\Big] \leq 0 \tag{3.39}$$

An increase in the unit cost of waiting T_l decreases the propensity to seek public hospital care. This can be seen by examining the change in $V_{d,0}$ for a given change in T_l. For the case of an individual without private hospital insurance, $\frac{\partial V_{0,0}(s)}{\partial T_l}$ is given as

$$\frac{\partial V_{0,0}(s)}{\partial T_l} = \underbrace{\gamma\left[Y - T_m m^*_{0,0} - T_l t^e(s)\right]^{\gamma-1}}_{\geq 0}\left[-T_m\frac{\partial m^*_{0,0}}{\partial T_l} - t^e(s)\right]\underbrace{\left[\frac{m^*_{0,0}}{m^*_{0,0}+\delta s}\right]}_{\geq 0}$$

$$+\underbrace{\left[Y - T_m m^*_{0,0} - T_l t^e(s)\right]^{\gamma}}_{\geq 0}\underbrace{\left[\frac{\frac{\partial m^*_{0,0}}{\partial T_l}(\delta s)}{(m^*_{0,0}+\delta s)^2}\right]}_{\leq 0} \tag{3.40}$$

where $\frac{\partial m^*_{0,0}}{\partial T_l} \leq 0$. From (3.40), $\frac{\partial V_{0,0}(s)}{\partial T_l} \leq 0$ if

$$T_m\frac{\partial m^*_{0,0}}{\partial T_l} \leq t^e(s) \tag{3.41}$$

where the LHS of equation (3.41) is the reduction in the opportunity cost of time associated with decrease in the optimal intensity of hospital care arising from an incremental change in T_l and $t^e(s)$ is the length of time the individual is expected

[15] The derivations are presented in Section A

to wait on hospital waiting lists in health state s. Given that $\frac{\partial V_{0,1}(s)}{\partial T_l} = 0$,

$$\frac{\partial}{\partial T_l}\Big[V_{0,0}(s) - V_{0,1}(s)\Big] \leq 0 \tag{3.42}$$

3.5 Decision Rule: The Purchase of Private Hospital Insurance

The solutions on the optimal choice between public and private hospital care presented in Section 3.4 can be used to characterise the decision rule on whether to purchase private hospital insurance. Given the assumption specified in Section 3.2 that the individual is an expected utility maximiser, the expected utility associated with the purchase of insurance is given as

$$EV_1 = \sum_s \pi(s)\Big[V_{0,q*}(s)\Big] \tag{3.43}$$

where $V_{0,q*}(s)$ is the indirect utility function associated with the optimal choice of public or private hospital care in each state s as specified in (3.30). Correspondingly, the expected utility associated with not purchasing private hospital insurance is

$$EV_0 = \sum_s \pi(s)\Big[V_{1,q*}(s)\Big] \tag{3.44}$$

Hence, the individual will choose to purchase private hospital insurance if

$$EV_1 > EV_0 \tag{3.45}$$

and not to purchase insurance if the equality is reversed.

3.5.1 Demand for Hospital Insurance: A Case Study with 3 Health States

In this section, I examine the factors that influence the demand for private hospital insurance using a simple case study. First and foremost, suppose that there are only three possible health states, $s = 0, 1, 2$ where the probability of occurrence of the respective states are given as $\pi(0)$, $\pi(1)$ and $\pi(2)$ and $\sum_{s=0}^{2} \pi(s) = 1$. As before, $s = 0$ corresponds to the state of perfect health or the absence of illness. Health states $s = 1$ and $s = 2$ correspond to the incidence of mild and severe illness conditions respectively. Suppose the mild medical conditions that occur in state $s = 1$ are conditions that are non-urgent in nature for which access to treatment from the public hospital system involves a non-zero duration of wait which is denoted by $t^e(1) = t$. Also, suppose that the medical conditions that occur in state $s = 2$ are urgent in nature and require immediate medical attention. For these conditions, it is assumed that the expected duration of wait on public hospital waiting lists is zero, that is $t^e(2) = 0$. As before, it is assumed that the length of wait to access private hospital care in all states is zero.

Given the assumptions described above, the expressions of the optimal intensity of public and private hospital care and the decision rule on the choice between public or private hospital care are modified by substituting the specific form for the parameters on health state s and expected waiting times $t^e(s)$ into equations (3.17) to (3.20) and (3.30). To illustrate, the optimal intensity of public hospital care by an uninsured individual in state $s = 1$ and state $s = 2$ are given by

$$m^*_{0,0}(1) = \sqrt{\frac{\delta}{\gamma T_m}\left[Y - T_l t\right] + \left[\frac{1}{2}\delta\left(1 + \frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta\left(1 + \frac{1}{\gamma}\right)$$

$$m^*_{0,0}(2) = \sqrt{\frac{2\delta}{\gamma T_m}\left[Y\right] + \left[\delta\left(1 + \frac{1}{\gamma}\right)\right]^2} - \delta\left(1 + \frac{1}{\gamma}\right)$$

and the optimal intensity of private hospital care in state $s = 1$ and $s = 2$ are respectively

$$m^*_{0,1}(1) = \sqrt{\frac{\delta}{\gamma}\left[\frac{Y}{(\eta p^m + p^q) + T_m}\right] + \left[\frac{1}{2}\left(2\beta + \delta + \frac{\delta}{\gamma}\right)\right]^2} - \left[\frac{1}{2}\left(2\beta + \delta + \frac{\delta}{\gamma}\right)\right]$$

$$m^*_{0,1}(2) = \sqrt{\frac{2\delta}{\gamma}\left[\frac{Y}{(\eta p^m + p^q) + T_m}\right] + \left[\beta + \delta + \frac{\delta}{\gamma}\right]^2} - \left[\beta + \delta + \frac{\delta}{\gamma}\right]$$

where the subscripts d and q in $m^*_{d,p}(s)$ denote the insurance status ($d = 0$: no private hospital insurance; $d = 1$: with private hospital insurance) and the choice of public ($q = 0$) or private care ($q = 1$) respectively. It is straightforward that irregardless of insurance status, the optimal intensity of both public and private hospital care in state $s = 0$ will be zero, that is $m^*_{d,q}(0) = 0$. The expressions for the indirect utility functions for each patient type strategy are modified accordingly. They are

$$\begin{aligned}
V_0(0) = & \; Y^\gamma \\
V_{0,0}(1) = & \left[Y - T_m m^*_{0,0}(1) - T_l t\right]^\gamma \left[\tfrac{m^*_{0,0}(1)}{m^*_{0,0}(1)+\delta}\right] \\
V_{0,1}(1) = & \left[Y - (\eta p^m + p^q + T_m) m^*_{0,1}(1)\right]^\gamma \left[\tfrac{m^*_{0,1}(1)+\beta}{m^*_{0,1}(1)+\beta+\delta}\right] \\
V_{0,0}(2) = & \left[Y - T_m m^*_{0,0}(2)\right]^\gamma \left[\tfrac{m^*_{0,0}(2)}{m^*_{0,0}(2)+\delta}\right] \\
V_{0,1}(2) = & \left[Y - (\eta p^m + p^q + T_m) m^*_{0,1}(2)\right]^\gamma \left[\tfrac{m^*_{0,1}(2)+\beta}{m^*_{0,1}(2)+\beta+2\delta}\right]
\end{aligned} \tag{3.46}$$

For this uninsured individual, the decision on the choice between obtaining public or private hospital care is made by comparing the utility accrued from each patient type strategy. More specifically, the individual will choose public hospital care in health state s

$$V_{0,0}(s) > V_{0,1}(s) \qquad s = 1, 2$$

Alternatively, private hospital care is chosen if $V_{0,0}(s) < V_{0,1}(s)$. Suppose $V_{0,q^*}(s)$ denotes the utility that corresponds to the optimal choice of either public or private hospital care where

$$V_{0,q^*}(s) = max\Big[V_{0,0}(s), V_{0,1}(s)\Big], \qquad s = 1, 2$$

The expected utility function that corresponds to the non-insurance strategy is expressed as

$$EV_0 = \pi(0)Y^\gamma + \pi(1)\Big[V_{0,q^*}(1)\Big] + \pi(2)\Big[V_{0,q^*}(2)\Big] \tag{3.47}$$

Replicating the above for the case of an individual with private hospital insurance, the optimal intensities of public care are

$$m^*_{1,0}(1) = \sqrt{\frac{\delta}{\gamma T_m}\Big[Y - P - T_l t\Big] + \Big[\frac{1}{2}\delta\Big(1 + \frac{1}{\gamma}\Big)\Big]^2} - \frac{1}{2}\delta\Big(1 + \frac{1}{\gamma}\Big)$$

$$m^*_{1,0}(2) = \sqrt{\frac{2\delta}{\gamma T_m}\Big[Y - P\Big] + \Big[\delta\Big(1 + \frac{1}{\gamma}\Big)\Big]^2} - \delta\Big(1 + \frac{1}{\gamma}\Big)$$

and for private hospital care

$$m^*_{1,1}(1) = \sqrt{\frac{\delta}{\gamma}\Big[\frac{Y - P}{\alpha(\eta p^m + p^q) + T_m}\Big] + \Big[\frac{1}{2}\Big(2\beta + \delta + \frac{\delta}{\gamma}\Big)\Big]^2} - \Big[\frac{1}{2}\Big(2\beta + \delta + \frac{\delta}{\gamma}\Big)\Big]$$

$$m^*_{1,1}(2) = \sqrt{\frac{2\delta}{\gamma}\Big[\frac{Y - P}{\alpha(\eta p^m + p^q) + T_m}\Big] + \Big[\beta + \delta + \frac{\delta}{\gamma}\Big]^2} - \Big[\beta + \delta + \frac{\delta}{\gamma}\Big]$$

Correspondingly, the indirect utility functions are

$$\begin{aligned}
V_1(0) &= \Big[Y - P\Big]^\gamma \\
V_{1,0}(1) &= \Big[Y - P - T_m m^*_{1,0}(1) - T_l t\Big]^\gamma \Big[\tfrac{m^*_{1,0}(1)}{m^*_{1,0}(1)+\delta}\Big] \\
V_{1,1}(1) &= \Big[Y - P - [\alpha(\eta p^m + p^q) + T_m] m^*_{1,1}(1)\Big]^\gamma \Big[\tfrac{m^*_{1,1}(1)+\beta}{m^*_{1,1}(1)+\beta+\delta}\Big] \\
V_{1,0}(2) &= \Big[Y - P - T_m m^*_{1,0}(2)\Big]^\gamma \Big[\tfrac{m^*_{1,0}(1)}{m^*_{1,0}(1)+2\delta}\Big] \\
V_{1,1}(2) &= \Big[Y - P - [\alpha(\eta p^m + p^q) + T_m] m^*_{1,1}(2)\Big]^\gamma \Big[\tfrac{m^*_{1,1}(2)+\beta}{m^*_{1,1}(2)+\beta+2\delta}\Big]
\end{aligned} \tag{3.48}$$

The expression for the expected utility function corresponding to the insurance strategy is hence

$$EV_1 = \pi(0)\Big[Y - P\Big]^\gamma + \pi(1)\Big[V_{1,q^*}(1)\Big] + \pi(2)\Big[V_{1,q^*}(2)\Big] \tag{3.49}$$

where

$$V_{1,q^*}(s) = max\Big[V_{1,0}(s), V_{1,1}(s)\Big], \qquad s = 1, 2$$

The decision rule for on whether to purchase private hospital insurance is characterised as follows: the individual will purchase insurance if $EV_1 > EV_0$ and not purchase insurance if $EV_1 < EV_0$. Alternatively, the inequalities may be rewritten as follows: the individual will choose to insure if

$$\pi(0)\Big[(Y-P)^\gamma - Y^\gamma\Big] + \pi(1)\Big[V_{1,q^*}(1) - V_{0,q^*}(1)\Big] + \pi(2)\Big[V_{1,q^*}(2) - V_{0,q^*}(2)\Big] > 0 \tag{3.50}$$

and not to insure if

$$\pi(0)\Big[(Y-P)^\gamma - Y^\gamma\Big] + \pi(1)\Big[V_{1,q^*}(1) - V_{0,q^*}(1)\Big] + \pi(2)\Big[V_{1,q^*}(2) - V_{0,q^*}(2)\Big] < 0 \tag{3.51}$$

Equations (3.50) and (3.51) offer insights on the factors that affect the decision to purchase private hospital insurance. Fundamentally, the decision to insure depends on the expected use of private hospital care, which is influenced by the probability of illness and the propensity to seek private care when ill. Firstly, the individual will not purchase insurance if the probability of illness is zero. This result is observed when one substitute $\pi(1) = \pi(2) = 0$ and $\pi(0) = 1$. In this scenario, $EV_1 - EV_0 < 0$ given that $(Y-P)^\gamma < Y^\gamma$ for all values of $P > 0$. Secondly, the propensity to purchase insurance is positively associated with the probability of seeking private hospital care, if and when hospital care is required. This limited result is supported by two observations from the analytical model. Firstly, individuals who always seek public hospital care when ill will choose not to purchase private hospital insurance. Secondly, individuals who are likely to always seek to obtain private hospital care can be expected to purchase insurance.

Before proceeding to validate the arguments made in the preceding section, it is important to first elaborate on the distinction between the probability of illness and the severity of illness. The former refers to the probability of the incidence of health states other than that of perfect health, which is denoted by $s = 0$. In terms of notations, the probability of illness refers to $\pi(s \neq 0)$ or $1 - \pi(0)$. The severity of illness on the other hand, within the context of describing individuals with medical conditions of different severities, refers to the distribution of poor health states, conditional on the absence of perfect health. An increase in the illness severity refers to the change from health state with illness severity s_1 to s_2 where $s_1 < s_2$, $\forall s > 0$.

To illustrate these results, consider the scenario that there are only two types of individuals: 'high users of public care' and 'high users of private care'. For convenience, the two types of individuals are referred to as Type I and Type II respectively. Suppose Type I individuals will always choose to obtain public hospital care when ill, regardless of insurance status. This may occur because Type I individuals have a weak preference for private hospital care (β parameter is small) or because waiting on hospital waiting lists confers a negligible cost (T_l is small). Conversely, suppose Type II individuals will always seek private hospital which is motivated by a strong preference for private hospital care (β parameter is large) and that waiting on public hospital waiting lists confers a large cost (T_l is large). Following these assumptions, it is the case for Type I individuals that $V_{d,0}(s) > V_{d,1}(s)$ and correspondingly for Type II individuals, $V_{d,1}(s) > V_{d,0}(s)$ for $s = 1, 2$ and where subscript d denotes the availability of insurance. For Type I individuals, the decision rule to purchase private hospital insurance is characterised as

$$EV_1 - EV_0 = \pi(0)\Big[(Y-P)^\gamma - Y^\gamma\Big] + \pi(1)\Big[V_{1,0}(1) - V_{0,0}(1)\Big] + \pi(2)\Big[V_{1,0}(2) - V_{0,0}(2)\Big] \tag{3.52}$$

Using the expressions in (3.46) and (3.48), one can observe that

$$V_{0,0}(s) > \quad V_{1,0}(s) \qquad\qquad s = 1, 2 \tag{3.53}$$

for $P > 0$ and $m^*_{0,0} > m^*_{1,0}$. Given that $(Y - P)^\gamma < Y$, $EV_1 - EV_0 < 0$. Hence, Type I individuals who always choose public hospital care will choose not to purchase private hospital insurance. Moving on to Type II individuals, the decision rule on whether to purchase insurance is characterised as

$$EV_1 - EV_0 = \pi(0)\Big[(Y-P)^\gamma - Y^\gamma\Big] + \pi(1)\Big[V_{1,1}(1) - V_{0,1}(1)\Big] + \pi(2)\Big[V_{1,1}(2) - V_{0,1}(2)\Big] \tag{3.54}$$

From (3.54), $EV_1 - EV_0 > 0$ if

$$V_{1,1}(s) > V_{0,1}(s) \qquad\qquad s = 1, 2$$

and

$$\pi(0)\Big[(Y-P)^{\gamma}-Y^{\gamma}\Big] < \pi(1)\Big[V_{1,1}(1)-V_{0,1}(1)\Big]+\pi(2)\Big[V_{1,1}(2)-V_{0,1}(2)\Big]$$

On the former, it can be easily be shown using (3.46) and (3.48) that $V_{1,1}(s) > V_{0,1}(s)$ for $s = 1, 2$ if further two conditions hold. Under the first condition,

$$\frac{Y-P}{\alpha(\eta p^m + p^q) + T_m} > \frac{Y}{\eta p^m + p^q + T_m} \tag{3.55}$$

which implies that

$$P < Y\left[1 - \frac{\alpha(\eta p^m + p^q) + T_m}{\eta p^m + p^q + T_m}\right] \tag{3.56}$$

The terms on the RHS of the equality in (3.56) can be approximated by $Y[1-\alpha]$ if the unit price of private hospital care $\eta p^m + p^q$ is significantly larger than the unit opportunity cost of time T_m. The second condition is

$$P + \Big[\alpha(\eta p^m + p^q) + T_m\Big]m^*_{1,1} > \Big[\eta p^m + p^q\Big]m^*_{0,1} \tag{3.57}$$

which require that the sum of the insurance premium P and the out-of-pocket expenditure on private hospital care given insurance cost sharing (LHS) be greater than the total expenditure on private hospital care in the absence of insurance (RHS). If the above conditions are valid, Type II individuals who always choose to obtain private hospital care when ill, will always choose to purchase private hospital insurance.

The subjective distribution of illness states influences individuals' propensity to insure. Conditional on the availability of insurance, it can be expected that individuals are more likely to seek private hospital care in the event of a non-urgent illness episode (health state $s = 1$) as opposed to a severe illness episode (health state $s = 2$). This is because waiting on public hospital waiting lists confer a positive waiting cost (denoted as $T_l t$) on individuals accessing public hospitals for elective medical care. As demonstrated in Section 3.4.1, the propensity to seek private hospital care is expected to decrease with the severity of illness. Given this, both expectations on the probability of illness and the nature of the illness episode influence the propensity to insure. Conditional on the occurrence of illness, an increase in the probability $\pi(1)$ of the occurrence of a non-urgent medical condition and a corresponding decline in the probability $\pi(2)$ of a severe medical illness is expected to increase the likelihood of purchasing private hospital insurance. Corollary, individuals who expect to require elective treatment for which access to treatment in public hospitals are rationed through the use of waiting lists have a higher incentive to purchase private hospital insurance.

In Section 3.4.1, it was shown that individuals with private hospital insurance are more likely to seek private relative to public hospital care given that the availability of insurance reduces the effective monetary price of private care. An interesting question in this context would be why individuals with private hospital insurance choose instead to obtain public hospital care. The motivation underlying this decision can be examined by comparing $V_{1,0}(s)$ and $V_{1,1}(s)$ in equation (3.48). In deciding to obtain public or private hospital care in health state $s = 1$, the insured individual trades off between the incremental benefits on health from a higher quality of care, combined with a lower level of consumption arising from having to afford the patient's share of private hospital expenses $\alpha(\eta p^m + p^q)m^*_{1,1}(1)$, with the incremental waiting cost $T_l t$ involved in seeking public hospital care. Here, individuals facing a larger coinsurance rate or those with a smaller cost of waiting have a larger propensity to seek public hospital care even when private hospital insurance is available. The propensity for insured individuals to seek public hospital care is expected to be larger for severe relative to mild illness conditions. This is because waiting times in public hospitals is zero in the case of health state $s = 2$.

The analysis above illuminates the interdependent relationship between the demand for private hospital care and hospital insurance. The decision to purchase private hospital insurance is influenced by expected utilisation of private hospital care. The choice to seek private hospital care is in turn affected, amongst others, by availability of private hospital insurance.

3.6 Summary

This chapter presents the results from a theoretical model of demand for hospital care, the choice to seek public or private hospital care and the decision to purchase private health insurance. Results from a comparative statics analysis revealed that the optimal intensity of hospital care use is increasing in the severity of individuals' medical conditions and decreasing with the opportunity cost of time. The presence of private health insurance decreases the effective price of private hospital care but does not affect the intensity of public hospital care. Conditional on the health status and the availability of insurance, individuals decide between public and private hospital care by choosing the strategy that maximises indirect utility. Individuals with more severe medical conditions are expected to have a higher probability of seeking treatment from the public sector because duration of wait for public care is comparative shorter. The availability of private hospital insurance decreases the effective price of private care and increases the probability that individuals seek private treatment. Individuals' valuation of the cost of waiting on public hospital waiting lists and their preference for quality also influence the choice between public and private treatment. The decision to purchase private health insurance will depend on individuals' perceptions on the likelihood that illness occurs, and conditional on the former, on the severity of illness.

The theoretical framework of the economic model described in this chapter is used to develop a novel simultaneous equation model that accommodates the count data feature of hospital care utilisation measures and the binary public-private patient type and insurance outcome variables. The econometric model accounts for the simultaneity between the intensity of hospital use and the decisions to seek public or private care and purchase private health insurance. This is described in Chapter 5. The empirical results are presented in Chapters 6 and 7. The hospital care utilisation measure of interest in Chapter 6 is the number of hospital admissions and in Chapter 7 is the length of hospital stay as a publicly or privately admitted patient.

Chapter 4

Data

4.1 Introduction

This study uses microdata (also referred to as Confidentalised Unit Records Files or CURFs) from the National Health Survey 2004-05 conducted by the Australian Bureau of Statistics (ABS) between August 2004 to July 2005. The microdata of the 2004-05 NHS is available in two formats: A *Basic* CURF is available on both CD-ROM and through the Remote Access Data Laboratory (RADL) accessible via the internet. A more detailed version of the microdata is the *Expanded* CURF which is accessible only through RADL. This study uses the Basic CURFs. I am grateful to the Australian Bureau of Statistics for making the microdata available through the CURF arrangements with the Australian National University. The analysis, results and the views expressed herein are those of the author and do not represent those of the ABS.

4.2 The 2004-05 National Health Survey

The Australian National Health Survey (NHS) collects data on a nationally representative sample of Australian households. The survey collects detailed individual-level information such as demographic and socioeconomic characteristics (age, gender, educational attainment, employment, personal income); health status (self assessed health, chronic and long term conditions, mental wellbeing); health risk factors (immunisation, alcohol consumption, smoking behaviour, exercise); health related actions and services use (visits to medical institutions, consultations with doctors, private health insurance), and on information at the household level (geography, dwelling structure, family structure and composition, household income).[1] The survey is conducted using face-to-face interviews and carried out every three years.[2] Trained interviewers conducted personal interviews with adult respondents and for children age 15 to 17 years where parental consent was given. For the remaining children, parents or guardians act as child proxies in answering the survey questions.

The 2004-05 NHS was conducted using a multistage area sample of private dwellings (See Section 2 of (ABS 2006b) for more details). Households in smaller states and territories such as South Australia, Tasmania and the Australian Capital Territory (ACT) are oversampled to provide reliable and detailed estimates for each state.[3] Each state and territory in Australia was initially divided into geographically contiguous areas referred to as strata. Within each stratum contains a number of Population Census Collection Districts (CD), which contains on average 250 private dwellings. Within each CD, a sample of private dwellings was selected. From each selected dwelling, a subsample of residents, consisting of one adult (age 18 years and over) and one child (age 0 to 17) was randomly selected.

The total sample consist of 25,234 households, from which the active sample is 21,808 households as a result of sample loss due to reasons such as vacant dwellings or people moving out of scope. Of the active sample, a total of 19,501 fully responding households remained with a response rate of 89.4%. Completed questionnaires were obtained for 25,906 persons.

The analysis in this study uses unit record data of these 25,906 persons contained in the NHS 2004-05 CURFs. Person level sampling weights are provided in the dataset. [4]

[1]More detailed information on the NHS 2004-05 is provided in ABS (2006a)

[2]Before the 2001 NHS, these surveys were conducted once every 5 years. Prior to 2001, the NHS was previous carried out in 1977-78, 1983 (under the title of the Australian Health Survey), 1989-90 and 1995.

[3]The sampling fraction for each state and territory is as follows: NSW (1/520), VIC (1/450), QLD (1/400), SA (1/150), WA (1/280), TAS (1/90), NT (1/335), ACT (1/75).

[4]The sampling weights will not used in the regression analysis conducted in this study. As discussed in Cameron and Trivedi (2005), sample weights are not required if the analysis has a structural or analytical approach in which the research objective is the estimation of the conditional mean (pg. 820). In contrast, sample weights should be used if the research objective is to describe or summarise the data.

4.3 Formulation of the Study Sample

The primary focus of this study is to examine the determinants of and interactions between decisions on hospital use, the choice between public or private care and the purchase of private health insurance. To this end, respondents who are under the age of 20 years, as well as those under 25 years and engaging in full-time or part-time studies when the survey was conducted were excluded in forming the study sample. This exclusion was motivated by the reason that the study should include only individuals that are of age 21 years and older who are perceived as bearing the financial (and legal)[5] responsibilities on decisions pertaining to his or her medical treatment needs. This approach is consistent with the classifications adopted by the private health insurance industry, where under private health insurance contracts, a dependent child may remain in his or her parent(s) policy if the child is unmarried and under the age of 21 years; or 25 years if the dependent child is undertaking full-time study.[6] Based on this exclusion criterion, a total of 7,345 observations were dropped from the full survey sample of 25,906.

The sample was further restricted to respondents from one family households consisting of either single persons or couple households with or without dependent children. These four categories comprised 92% of all households structure types in the full survey sample. 1,370 observations corresponding to the fifth category 'All other households' were dropped from the sample.[7] Two key reasons motivated the exclusion of the fifth household structure type. Firstly, of the three approaches - family, household and income units - that individuals residing in each selected dwelling are grouped, the income unit[8] is the most appropriate decision making unit on private health insurance.[9] At the time of the survey, private

[5]From a legal standpoint, individuals aged 18 years and over have full legal capacity, which includes decisions relating to health care although the legal age varies for some States in Australia. For example, according to the Consent to Medical Treatment and Palliative Care Act 1995 (South Australia), "A person of or over 16 years of age may make decisions about his or her own medical treatment as validly and effectively as an adult".

[6]Medibank Private http://www.medibank.com.au/homepage/family_fwac.asp. Accessed on 14 March 2007.

[7]This response category consists of multiple family households with or without dependent children under a single dwelling or group household consisting of non-family individuals co-existing in a dwelling.

[8]The income unit is defined by the ABS as a person or a group of related persons within a household whose command over income is shared. The relationships of individuals are restricted to those of registered or de facto marriage and parent/dependent child usually residing in the same household (para 7.6 on page 30, (ABS 1995))

[9]Even with income units, there are situations which calls for the income unit to be split or combined for the purpose of analysing decisions on private health insurance. See Appendix C

health insurance in Australia was purchased by single individuals, couples within a marriage or a defacto relationship, sole-parent with children and two-parent families. Household and family units may contain related or unrelated individuals where combining these individuals for the purpose to purchase private health insurance is not permitted.[10] Secondly, as demonstrated in Chapter 3, decisions surrounding the use of hospital services and or whether or not to purchase private health insurance are expected to be influenced by individuals' incomes. As a representation of the economic resources available to individuals, measures of income should ideally consider how income and expenditure are shared among related individuals or families within a household.[11] The appropriate statistical unit at which the measure of income should be examined is the income unit. Unfortunately, income measures corresponding to income units are not available in the basic version of the NHS data. Instead, this study relies on the equivalised household income.[12] Hence, dropping multiple family household structures will avoid potential complications arising from multiple income units residing within a given dwelling.

The data was further examined for incomplete or ambiguous responses on key outcome measures and explanatory variables. A further 17 observations were excluded where respondents indicated not knowing if they have private health insurance and 40 observations where the type of private health insurance policy (hospital, ancillary or both) held by individuals was not reported. A further 200 observations for which respondents purchased insurance for less than 1 year at the time of the survey were excluded from the sample. Doing so would eliminate the possibility that these individuals may not have had private health insurance at the time when hospital care was obtained, given that the outcome measures of interest is the utilisation of hospital care in the 12 months preceding the survey. 250 observations where individuals had indicated having post-school qualification but where the highest post-school educational attainment was reflected as unknown were dropped. Missing survey responses from the question on the availability of government health concession cards were imputed with an auxiliary regression using information on concession card status available in the dataset. This is

in Butler (1999).

[10]Examples include a family unit comprising of two adult siblings or a household unit comprising of two unrelated individuals. In both these examples, the individuals are required to be on separate policies if they wish to purchase private health insurance.

[11]See para 2.6 on page 5 of ABS (1995).

[12]The definition of equivalised income will be discussed in Section 4.5 below.

elaborated in Section 4.5.

From the medical care utilisation measures captured in the survey, patients who had indicated that they have been admitted into hospital at least once in the past 12 months were asked whether they were admitted as a public (Medicare) or private patient. In 106 responses to this question, the choice of patient type was neither public nor private or was reflected as unknown and were dropped. After taking into account the responses dropped from the sample as described above, the size of the working sample is 14,594. From this working sample, 2,483 respondents had indicated that they have been hospitalised at least once in the last twelve months.

4.4 Dependent Variables: Private Health Insurance and Hospital Use

The key dependent variables examined in this study are whether individuals have private hospital insurance; the frequency of admissions to hospital in the 12 months preceding the survey; the choice of hospital admission as a public or private patient and the number of nights individuals spent in hospital. Data on patient type choices and the intensity of hospital stay is only available for individuals who have been admitted into hospital at least once in the last 12 months. Furthermore, the data only captures this information from individuals' last hospitalisation episode.

4.4.1 Private Hospital Insurance Status and Duration

Information on whether or not individuals have private hospital insurance was derived from two separate questions in the survey. Individuals were first asked if they had private health insurance cover. Insured individuals were further queried on the type of coverage. The response fields for coverage types include hospital, ancillary or both hospital and ancillary coverage. As this study focuses on how private health insurance influences the decisions on the choice of public or private hospital care and the intensity of care, the relevant question pertaining to private health insurance status is whether or not individuals have private hospital insurance. Individuals are regarded as having private hospital insurance if they possessed either hospital only or hospital and ancillary coverage. The

Table 4.1: Private health insurance status and coverage type: Full Sample

	Hosp & Anci[a]	Hosp only	Anci only	Total	
No private health insurance					7,469 (51.18%)
With private health insurance					7,125 (48.82%)
	Coverage Type				
Purchased PHI before Aug 1999	4,497 (78.3%)[b]	850 (14.8%)	399 (6.9%)	5,746 (100.0%)	
Purchased PHI after Aug 1999	939 (68.1%)	299 (21.7%)	141 (10.22%)	1,379 (100.0%)	
Total	5,436 (76.3%)	1,149 (16.1%)	540 (7.6%)	7,125 (100.0%)	
Total Sample					14,594 (100.0%)

[a] *Hosp* and *Anci* refers to Hospital and Ancillary coverage respectively
[b] Percentages in parenthesis sums horizontally to 100%

variable representing the availability of private hospital insurance is coded as a dichotomous (0/1) variable which takes the value of 1 if the individual has private hospital insurance.

The survey also queried individuals on the duration of insurance cover. Using this information[13], individuals were assigned into two groups: whether they have been covered for either less than 5 years or 5 years and more. Given that the survey was conducted between August 2004 to July 2005, individuals who have had private health insurance coverage for less than 5 years at the time of the survey would have purchased the insurance coverage after August 1999. Individuals who have had insurance coverage for 5 years or more would have purchased cover before August 1999.[14]

Table 4.1 describes the full sample by private health insurance status and coverage type. In the sample of 14,594 individuals, 7,469 (51.2%) individuals did not have private health insurance. Of the remaining 7,125 (48.8%) individuals with private insurance coverage, 6,585 (92.4%) individuals had hospital cover while only 540 (7.6%) individuals had ancillary only coverage. On the duration of insurance purchase, 5,746 individuals (80.6%) purchased coverage prior to August

[13] There are 5 response categories on the question on the duration of PHI cover: (i) Not applicable (No private health insurance); (ii) less than 1 year (after August 2003); (iii) 1 year to less than 2 years; (iv) 2 years to less than 5 years and (v) 5 years or more.

[14] The date of insurance purchase may be constructed more accurately using information on the date of the NHS interview. However, the latter was not made available in the Basic CURF dataset.

Table 4.2: Private Health Insurance by Age & Coverage (June 2004)

	Percentage of Population	
Age Group	Hospital Cover	Ancillary Cover
0 – 24 years	44.0%	40.0%
25 – 85 years	42.6%	42.4%
All Ages	42.9%	41.3%

Source: Author's calculation using data in ABS (2004) and PHIAC (2005).

1999 while 1,379 individuals (19.4%) purchased it after August 1999. The composition of coverage types varies slightly by insurance duration. A slightly higher proportion of individuals insured prior to August 1999 had both hospital and ancillary coverage as compared to those who were insured for a shorter duration of time (93.1% vs. 89.8%).

Based on Table 4.1, a total of 6,585 individuals in the full sample had private hospital coverage (that is hospital or hospital with ancillary) while 5,976 individuals have ancillary coverage (ancillary only or hospital with ancillary). Therefore, the proportions of the full sample with hospital coverage and ancillary coverage are 45.1% and 40.9% respectively. These figures are broadly consistent with the national membership statistics for June 2004. Table 4.2 presents the percentages of the Australian population with hospital and ancillary coverage across three age bands: 0 – 24 years, 25 – 85 years and All Ages. These percentages were derived using insurance membership data published in PHIAC (2005) for June 2004 divided by the estimated resident population in the respective age bands published in ABS (2004) for the same year. As one would observe, the proportion of the study sample with hospital coverage (45.1%) is slightly higher than that in Table 4.2. For ancillary coverage, the proportions are comparatively similar.

The distribution of private health insurance coverage and coverage type within the sub-sample consisting of individuals reported having been hospitalised at least once in the past 12 months is described in Table 4.3. In the sample of 2,483 individuals, 1,207 (51.4%) individuals did not have private health insurance. Of the 1,276 (48.6%) individuals with private health insurance, 1,137 (94.2%) individuals had hospital coverage while the remaining 70 (5.8%) individuals had ancillary only policies. The distribution of insured individuals according to the duration of coverage and coverage type is generally comparable to that in the full sample.

Table 4.3: Private health insurance status and coverage type: Sub-Sample

No private health insurance					1,207 (51.39%)
With private health insurance					1,276 (48.61%)
	Coverage Type				
	Hosp & Anci[a]	Hosp only	Anci only	Total	
Purchased PHI before Aug 1999	789 (79.8%)[b]	142 (14.4%)	58 (5.9%)	989 (100.0%)	
Purchased PHI after Aug 1999	161 (73.9%)	45 (20.6%)	12 (5.5%)	207 (100.0%)	
Total	950 (78.7%)	187 (15.5%)	70 (5.8%)	1,207 (100.0%)	
Total Sample					2,483 (100.0%)

[a] *Hosp* and *Anci* refers to Hospital and Ancillary coverage respectively
[b] Percentages in parenthesis sums horizontally to 100%

4.4.2 Hospitalisations, Patient-Type and Length of Stay

On hospital care use, three measures of utilisation are of primary interest in this study. The first measure is the frequency of hospital admissions over the last 12 months prior to the survey. In this version of the CURF microdata, the frequency of hospitalisation is recorded as 0, 1, 2 and 3 or more. The frequency distribution of hospital admissions is presented in Table 4.4. In the full sample of 14,594 individuals, 12,005 (82.3%) individuals reported not having been admitted into hospital over the past 12 months. 1,894 (13.0%) respondents reported having been hospitalised once while 475 (3.3%) individuals were hospitalised twice and 220 (1.5%) individuals were hospitalised 3 times or more. For the purpose of computing the summary statistics for the frequency of hospital admissions, the last category '3 times or more' is replaced by the lower bound. The mean number of hospital admissions is 0.240 and the variance is 0.338. The observation that the variance in the number of hospitalisation episode exceeds the mean has implications on the econometric modeling approach. This will be further elaborated in Chapter 5.

The second and third measures of hospital use are whether individuals chose to be hospitalised as a public or private patient and the number of nights in hospital at the most recent hospitalisation episode. Information on the length of hospital stay is recorded as 0 (no nights), 1 to 2 nights, 3 to 4 nights, 5 to 7 nights and 8 nights or more. As I will elaborate in Chapter 5, the econometric

Table 4.4: Number of Hospital Admissions: Summary Statistics

Frequency of hospital admissions over 12 months	Frequency	Percent
0	12,005	82.26
1	1,894	12.98
2	475	3.25
3 or more	220	1.52
Total	14,594	100
Mean	0.240	
Variance	0.338	

model adopted in this study requires that the length of hospital stay be an integer value. Hence, the interval values on hospital nights are replaced by their lower bound wherever they occur. Column (5) of Table 4.5 presents the distribution of hospital length of stay for all the 2,483 individuals in the entire sub-sample. It is observed that a majority of these individuals stay no more than 2 nights in hospital, with 919 (37.0%) admitted on a day admission basis and 684 (27.6%) staying between 1 to 2 nights. 339 (13.7%) respondents spent between 3 to 4 nights in hospital while 313 (12.6%) stayed for 5 to 7 nights. A total of 228 (9.2%) individuals were hospitalised for 8 nights or more. The mean number of hospital nights for the entire sub-sample is 2.05 and the variance is 6.33.

The decision tree illustrated in Figure 4.1 at the end of this chapter describes the distribution of individuals in the sample by private hospital insurance status and patient type, and presents the average length of hospital stay across each of the four groups. From Figure 4.1, one can first observe that the proportion of individuals who opted to be hospitalised as private patients is overwhelmingly higher for individuals who have private hospital insurance. Of the 1,137 privately insured individuals, 933 (82.1%) sought private hospital care. In contrast, only 97 (7.2%) of the 1,346 individuals without private hospital insurance opted for private hospital care. The proportion of uninsured individuals who sought hospital care as public patients is considerably higher than that for insured individuals. 92.8% of uninsured individuals obtained hospital care as a public patient while only 17.9% of insured individuals sought public care. In terms of the frequency of admissions hospital to the past 12 months, individuals who sought public hospital care recorded a higher number of admissions (1.38, 1.39) compared with those

Table 4.5: Descriptive Statistics of Length of Stay by Insurance and Patient Type

	No Private Health Insurance		With Private Health Insurance		
Nights	Public Patient (1)	Private Patient (2)	Public Patient (3)	Private Patient (4)	Total (5)
0 nights	418 (33.5%)	38 (39.2%)	90 (44.1%)	368 (40.0%)	919 (37.0%)
1-2 nights	364 (29.1%)	38 (39.2%)	46 (22.6%)	233 (25.3%)	684 (27.6%)
3-4 nights	181 (14.5%)	7 (7.2%)	27 (13.2%)	124 (13.3%)	339 (13.7%)
5-7 nights	152 (12.2%)	9 (9.3%)	22 (10.8%)	125 (13.9%)	313 (12.6%)
8 or more nights	134 (10.7%)	5 (5.2%)	19 (9.3%)	69 (7.5%)	228 (9.2%)
Total	1,249	97	204	933	2,483
Mean	2.19	1.48	1.91	1.95	2.05
Variance	6.70	4.50	6.65	5.94	6.33

Note: Percentages in parenthesis sums vertically but may not sum up to 100% due to rounding. Cells are number of respondents.

who obtained private care (1.34, 1.31). Moving on to the intensity of hospital stay, uninsured individuals who obtained public hospital care recorded the highest mean number of hospital nights (2.19 nights). In contrast, the average length of stay (1.48 nights) is lowest for uninsured individuals who sought private hospital care. One would observe that amongst individuals who sought private care, insured individuals stay on average 0.47 nights longer than uninsured individuals (1.48 vs. 1.95 nights).

Columns (1) to (4) of Table 4.5 presents the distribution of hospital length of stay by insurance and patient type. Two broad trends can be observed. Firstly, hospitalisation that involves day-admissions, that is zero nights in hospital, is lower for publicly admitted patients who do not have private hospital insurance relative to the remaining three subgroups. For example, 33.5% of uninsured public patients were admitted on a day basis compared to 39.2% for insured public patients and 39.2% for uninsured private patients. Secondly, long hospital stays are associated with hospital admissions as a public patient relative to private patient - 10.7% of uninsured public patients and 9.3% of insured public patients reported having stayed in hospital for a duration of 8 nights or more as compared to 5.2% and 7.5% for uninsured and insured private patients respectively. The differences in the distribution of hospital stay across the four subgroups are expected to be influenced, amongst others, by heterogeneity in patients' medical conditions and the direct and indirect prices of medical care that individuals face.

4.5 Explanatory Variables

The following sections describe the two study samples using relevant individual and household-specific information collected in the survey. This information can be classified into six broad categories: demographic composition, socioeconomic characteristics, health status, risk factors and geography. The descriptive statistics of the variables within each of the six categories are presented in Table 4.6 for the full study sample consisting of 14,594 individuals and Table 4.7 for the sub-sample corresponding to the 2,483 individuals who reported having been hospitalised at least once in the 12 months preceding the survey. An additional sub-sample of interest is the 12,005 individuals who have reported not being hospitalised in the 12 months leading up to survey.[15] The descriptive statistics for this sub-sample is presented in Table 4.8. Apart from describing the characteristics of the two study samples, the following discussion also compares the hospitalised and non-hospitalised sub-samples wherever it is appropriate. Readers are referred to Table 4.9 for the definitions of the variables.

As elaborated at the beginning of this chapter, missing or ambiguous responses on key explanatory variables were dropped from the sample in formulating the study sample. Missing responses on the availability of government concession cards were imputed for 683 respondents. The types of government concession cards include those issued by the Department of Veteran Affairs (DVA), Health Care Cards, the Pensioner Concession Card and the Commonwealth Senior Health Cards. Eligibility criteria vary according to the concession card in question but generally, individuals from low income households, seniors and pensioners and individuals in disadvantaged circumstances are eligible to apply.[16] A simple probit regression on concession card status using data that is available was performed with household income decile and age as explanatory variables. The estimates from the regression were used to calculate an expected probability of having a concession card. Observations with missing responses were replaced by

[15] The sum of the sample size of the hospitalised (2,463) and non-hospitalised (12,005) sub-samples does not add up to the full sample (14,594). This is because some observations from the full sample were dropped in the formulation of the hospitalised sub-sample as these have missing or ambiguous responses on important dependent and explanatory variables such as whether the respondent was admitted into a public or private hospital. This was described earlier in Section 4.3.

[16] More information on the types of cards and the eligibility rules can be found at http://www.centrelink.gov.au/internet/internet.nsf/payments/conc_cards.htm [Assessed on 15 June 2009]

the expected probability values.

4.5.1 Demographic Variables

The key demographic variables that are of relevance to this study are gender, age, marital status and income unit type. From Tables 4.6 to 4.8, we first observe a higher proportion of females as compared to males in the full sample and both the hospitalised and non-hospitalised sub-samples. The proportion of females is lower in the non-hospitalised sub-sample (53%) relative to the hospitalised sample (60%). The ages of respondents vary from a minimum of 22 years to a maximum of 85 years. The average age of individuals in the hospitalised sample (52.4 years) is approximately 3.3 years older as compared to the non-hospitalised sample (49.1 years). The information on respondents' age is available only in five-year age intervals in the version of the data that is utilised in the study. Hence, respondents' ages are represented by the middle value of each age interval. In both study samples, approximately 15% to 20% of females respondents are of childbearing age, which is defined as being in the age range of 20 to 39 years. The proportion of females in this age category is smaller in the non-hospitalised group (15.0%) as compared to the hospitalised group (19.7%). On marital status, approximately 55% of individuals reported that they are married in a registered or defacto marriage. The distributions of households by income unit types is fairly similar across respondents in the full and sub-samples. The two major income unit categories are households from couple units (33.2% in full sample, 33.3% in the hospitalised sample) and one-person units (33.5%, 35.0%), followed by units comprising of couples with dependents (26.3%, 25.3%) and one-parent units (6.9%, 6.6%).

4.5.2 Socioeconomic Variables

The main socioeconomic variables that are relevant to this study are income, educational attainment, employment status and occupational type. On measures of income, two types of individual and household income are available in the data. The first measure is the gross weekly personal cash income of the respondent.[17]

[17] Only regular and recurring cash income are included. The components of cash income are employee cash income (wages and salary), unincorporated business cash income (profit/loss from unincorporated business or share in partnership), government cash pensions and allowances (students and the unemployed, pensions for aged and those with disability) and other cash

The second measure is the gross equivalised cash income of the household. The equivalised cash income of the household is calculated by first summing the gross (pre-tax) weekly personal cash income for all household members to derive the total gross household income and thereafter dividing this total by an equivalence factor. The equivalence factor depends on the number of adults and children living in a given household[18]. Equivalising household incomes allows for comparative analysis across households with different household size and composition. Both personal and equivalised household income are available only in the form of income deciles instead of actual values. Indicative values are constructed using information published in ABS (2006a) on the income ranges corresponding to each income decile. For the first to the ninth deciles, the indicative value is calculated as a simple average of the lower and the upper decile cut-off values. This is described in Table 4.10. As described at the bottom of Tables 4.6 and 4.7, the average gross weekly equivalised cash income of households in the full and sub-sample is \$612.38 and \$542.47 respectively. Comparing between the non-hospitalised and hospitalised sub-samples, one would observe that the household income in the former, at \$627.31, is significantly higher than that of the latter.

It was reported above that total of 2,090 observations where the measure of household income was either reported as unknown or not stated were dropped. The parameter estimates from the regression analysis obtained where listwise deletion is used to handle item non-response will be biased if the missing data is not missing completedly at random (MCAR). The assumption of MCAR is violated if individuals or households with high income are those who did not provide information on their income. Listwise deletion have been shown to be acceptable if the missing observations constitute less than 5% or less of the total sample (Schafer 1997) but however for this study this proportion is considerably higher. A variety of approaches have been developed to handle missing data and are discussed in Cameron and Trivedi (2005). These are however not explored in this study and will be deferred for future work.

A source of information on the amount of education received by respondents

---

income (property, superannuation, dividends and interest). See pages 136-138 in ABS (2006b) for more information.

[18]The ABS calculates the household equivalence factor using the 'modified OECD' equivalence scale of allocating weights to each individual in the household. The first adult (over the age of 15 years) is assigned a weight of 1 point. Thereafter, each additional adult receives a weight of 0.5 points while each child under the age of 15 is allotted 0.3 points. The household equivalence factor is derived by summing up the weights for all individuals in the household. See Explanatory Notes in Appendix 3 of ABS (2005)

in the sample is the highest level of post-school educational attainment. The response categories are school qualifications; basic/skilled vocational qualification; undergraduate and associate diploma; and bachelor degree, postgraduate diploma and higher. The distribution of survey respondents by educational attainment is roughly similar across the full and sub-samples. Approximately half of respondents in both samples have no post-school qualification, while roughly 23% of individuals have basic or vocational qualifications. 10% to 11% of respondents have diplomas while 16% to 18% have bachelors degrees or higher. Information on employment status, sector and occupation types are also collected in the survey. As reported in Tables 4.6 and 4.7, the proportion of respondents engaged in either full-time or part-time employment is higher in the full as compared to the sub-sample. In the full sample, 42.2% of respondents are in full-time employment as compared to 28.3% in the sub-sample. Correspondingly, 55.1% of individuals in the sub-sample are out of the labour force, relative to 40.7% in the full sample. Among employed individuals, the three largest occupational types categories are "Professionals" (12.7%, 9.4%), "Intermediate Clerical, Sales and Service Workers" (9.8% in full sample, 7.7% in sub-sample), and "Associate Professionals" (8.0%, 6.4%).

On the issuance of Government health concession cards, the proportion of respondents with these cards in the full-sample (42.1%) and that of the non-hospitalised sample (39.5%) is considerably lower than that of the sub-sample (54.3%). The types of Government health concession cards in question include those issued by the Department of Veterans' Affairs (DVA), Health Care Cards, the Pensioner Concession Card and the Commonwealth Senior Health Cards.

4.5.3 Measures of Health Status

The data contains a series of self-reported health measures that describes the health status of the individuals surveyed. The relevant measures are a five-point self-assessed measure of general health and the types and number of long-term chronic medical conditions. We can observe from Tables 4.6 and 4.7 that the distribution of individuals by self-assessed health in the full and sub-samples differ significantly. A higher proportion of individuals in sub-sample, which contains respondents who reported having been hospitalised at least once in the last 12 months, rated their health as being "poor" (12.8% in sub sample, 5.6% in full sample) and "fair" (19.4% vs. 13.5%). Correspondingly, a lower proportion of individuals in the sub-sample rated their health as "very good" (26.7% vs 34.1%) or "excellent" (12.1% vs. 18.1%).

The prevalence of long-term and chronic medical conditions of respondents in the two samples is presented in the summary tables. By definition, long-term conditions are medical conditions which are current at the time of the survey, had lasted at least six months prior to the survey and is expected to last for six months or more. The summary statistics describe the proportion of respondents in both samples that have indicated that they suffer from medical conditions in each of the International Statistical Classification of Diseases, 10th Revision, Australian Modification (ICD10-AM) disease categories. Medical conditions that are especially prevalent in respondents from both the full and sub-samples are diseases of the eye (e.g Cataract, Glaucoma), diseases of the musculoskeletal system and connective tissue (e.g. Gout, Arthritis) and diseases of the respiratory system (e.g. Bronchitis, Asthma, Chronic Sinusitis). The prevalence of medical conditions in disease categories such as musculoskeletal, circulatory, endocrine and ear are relatively higher in the sub-sample as compared to the full sample. As given in foot of Tables 4.6 and 4.7, the average number of long-term chronic conditions suffered by individuals in the sub-sample is 3.48, compared with 2.97 in full sample and 2.86 in the non-hospitalised sample.

4.5.4 Health Risk Indicators

The survey collects information on respondents' behaviour in relation to four health related risk factors that influence the health of individuals. The health risk factors are the consumption of alcohol and tobacco, overweight and physical inactivity. Tables 4.6 and 4.7 presents the summary statistics of the key health risk indicators that are of interest in this study. The first indicator is whether or not individuals are considered as being of high alcohol risk measured using the frequency and intensity of alcohol consumption over a period of 3 days. The proportion of respondents that are of high alcohol risk is higher in the full sample (14.9%) as compared with the hospitalised sub-sample (12.9%). The second indicator of health risk is the consumption of tobacco. Approximately 20% to 22% of respondents in both samples are regular smokers, defined as individuals who are current smokers who smoke on a daily basis. The third health risk indicator is whether or not the respondent is Grade 2 overweight or higher, defined as having a Body Mass Index of 30 or more. In both samples, 20% to 22% of respondents are overweight by this measure. The final health risk indicator is the measure of physical activity, defined by whether or not individuals walked for sports, recreation and fitness at least once over the last two weeks. Close to half of all respondents reported having done so.

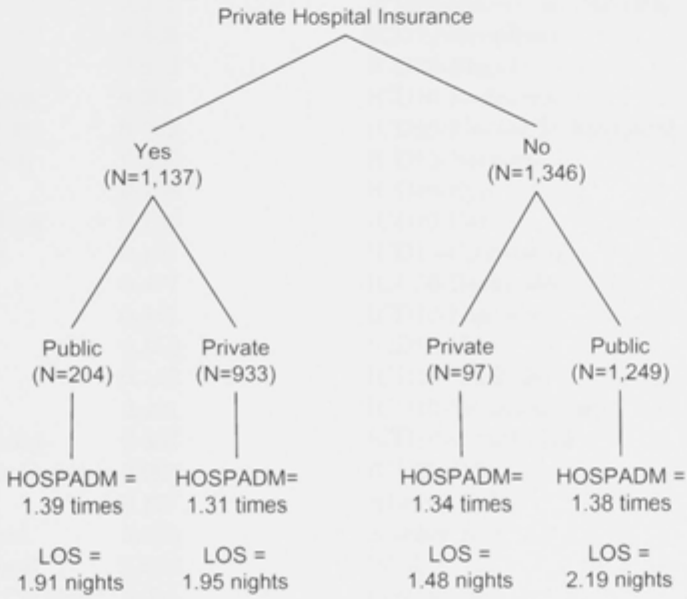
4.5.5 Geography

The distribution of respondents across the States and Territories in Australia and by remoteness category is presented in Tables 4.6 and 4.7. The remoteness indicator is based on the Australian Standard Geographical Classification (ASGC) developed by the ABS. Approximately 60% of respondents in both samples are located in major cities in Australia while 24% are located in inner regional areas. Roughly 16% of respondents are in the "ASGC - Others" category, which include outer regional areas, remote, very remote and migratory Australia.

4.5.6 Concluding Comments

This study uses data from the 2004-05 National Health Survey to empirically examine the determinants of the demand for hospital care and private health insurance in Australia. The data is appropriate for this purpose as it contains detailed information on individuals' use of health care services and private health insurance status. In addition, the data contains a wealth of information on individuals' characteristics such as age, household income, employment and health status. An important limitation of the data however is that the information on key outcome variables of interest, namely the number of hospital admissions and hospital nights, is made available as interval values as opposed to continuous values which limits the richness of the data. There is also the possibility of inaccurate reporting given that the NHS data is self reported.

Figure 4.1: Decision Tree: Insurance, Patient Type, Number of Hospital Admissions and Length of Stay



Legend: Number of hospital admissions in the last 12 months (HOSPADM). Average length of stay at the most recent hospitalisation (LOS)

Table 4.6: Means of explanatory variables: Full-Sample

Sample Size N=14,594

Binary explanatory variables

Variable	Mean	Variable	Mean
Female	0.543	SAH-Very Good	0.341
Childbear	0.157	SAH-Excellent	0.181
Maristat	0.552	ICD10-Infectious/Parasitic	0.012
Depchild	0.333	ICD10-Neoplasm	0.031
IU-Couple	0.332	ICD10-Blood	0.020
IU-Couple_Dep	0.263	ICD10-Endocrine	0.184
IU-One_Parent	0.069	ICD10-Mental/Behavioural	0.134
IU-One_Person	0.335	ICD10-Nervous	0.104
COB-Aust	0.738	ICD10-Eye	0.698
COB-Main_Eng	0.125	ICD10-Ear	0.185
COB-Others	0.137	ICD10-Circulatory	0.287
Edu-School	0.477	ICD10-Respiratory	0.335
Edu-Voc	0.232	ICD10-Digestive	0.100
Edu-Dip	0.110	ICD10-Skin	0.045
Edu-Degree	0.182	ICD10-Muscular	0.457
Hconcard	0.421	ICD10-Genitourinary	0.047
Occup-N_Emloy	0.407	ICD10-Congenital	0.047
Occup-Mgmr/Adm	0.064	ICD10-Others	0.010
Occup-Prof.	0.127	Alcohol 3-day	0.149
Occup-A/Prof.	0.080	Smoker Reg	0.215
Occup-TradesP	0.066	Walk	0.514
Occup-Adv Clr/Svc	0.021	Overweigh	0.195
Occup-Int Clr/Svc	0.098	NSW	0.205
Occup-Prod/Trans	0.048	VIC	0.164
Occup-Ele Clr/Svc	0.040	QLD	0.161
Occup-Labour	0.048	SA	0.177
Employ-FT	0.422	WA	0.108
Employ-PT	0.171	TAS	0.109
Employ-Not	0.022	NT	0.006
Employ-NILF	0.385	ACT	0.072
SAH-Poor	0.056	ASGC-Major Cities	0.611
SAH-Fair	0.135	ASGC-Inner Region	0.231
SAH-Good	0.288	ASGC-Others	0.158

Continuous and Count explanatory variables

	Mean	Std. Dev.	Min	Max
AGE	49.74	16.73	22	85
HHINC	612.38	381.47	119.00	1279.00
LTCOND	2.97	1.74	0	5

Table 4.7: Means of explanatory variables: Hospitalised Sample

Sample Size N=2,483

Binary explanatory variables

Variable	Mean	Variable	Mean
Female	0.603	SAH-Good	0.290
Childbear	0.197	SAH-Very Good	0.267
Maristat	0.550	SAH-Excellent	0.121
Depchild	0.318	ICD10-Infectious/Parasitic	0.016
IU-Couple	0.333	ICD10-Neoplasm	0.068
IU-Couple_Dep	0.253	ICD10-Blood	0.034
IU-One_Parent	0.066	ICD10-Endocrine	0.249
IU-One_Person	0.350	ICD10-Mental/Behavioural	0.159
COB-Aust	0.754	ICD10-Nervous	0.122
COB-Main_Eng	0.123	ICD10-Eye	0.745
COB-Others	0.123	ICD10-Ear	0.231
Edu-School	0.500	ICD10-Circulatory	0.396
Edu-Voc	0.237	ICD10-Respiratory	0.347
Edu-Dip	0.103	ICD10-Digestive	0.173
Edu-Degree	0.160	ICD10-Skin	0.050
Hconcard	0.543	ICD10-Muscular	0.538
Occup-N_Emloy	0.551	ICD10-Genitourinary	0.085
Occup-Mgmr/Adm	0.050	ICD10-Congenital	0.013
Occup-Prof.	0.094	ICD10-Others	0.177
Occup-A/Prof.	0.064	Alcohol 3-day	0.129
Occup-TradesP	0.043	Smoker Reg	0.198
Occup-Adv Clr/Svc	0.014	Walk	0.497
Occup-Int Clr/Svc	0.077	Overweigh	0.224
Occup-Prod/Trans	0.032	NSW	0.210
Occup-Ele Clr/Svc	0.037	VIC	0.162
Occup-Labour	0.038	QLD	0.158
Employ-FT	0.283	SA	0.170
Employ-PT	0.166	WA	0.125
Employ-Not	0.019	TAS	0.109
Employ-NILF	0.532	NT	0.003
Public Sector	0.104	ACT	0.063
Private Sector	0.345	ASGC-Major Cities	0.596
SAH-Poor	0.128	ASGC-Inner Region	0.247
SAH-Fair	0.194	ASGC-Others	0.158

Continuous and Count explanatory variables

	Mean	Std. Dev.	Min	Max
AGE	52.44	18.06	22	85
HHINC	542.47	372.34	119.00	1279.00
LTCOND	3.48	1.66	0	5

Table 4.8: Means of explanatory variables: Non Hospitalised Sub-Sample

Sample Size N=12,005

Binary explanatory variables

Variable	Mean	Variable	Mean
Female	0.531	SAH-Very Good	0.357
Childbear	0.150	SAH-Excellent	0.194
Maristat	0.554	ICD10-Infectious/Parasitic	0.011
Depchild	0.337	ICD10-Neoplasm	0.023
IU-Couple	0.333	ICD10-Blood	0.017
IU-Couple_Dep	0.267	ICD10-Endocrine	0.169
IU-One_Parent	0.070	ICD10-Mental/Behavioural	0.129
IU-One_Person	0.330	ICD10-Nervous	0.101
COB-Aust	0.733	ICD10-Eye	0.688
COB-Main_Eng	0.126	ICD10-Ear	0.174
COB-Others	0.140	ICD10-Circulatory	0.263
Edu-School	0.472	ICD10-Respiratory	0.333
Edu-Voc	0.230	ICD10-Digestive	0.084
Edu-Dip	0.111	ICD10-Skin	0.044
Edu-Degree	0.187	ICD10-Muscular	0.439
Hconcard	0.395	ICD10-Genitourinary	0.039
Occup-N_Emloy	0.376	ICD10-Congenital	0.008
Occup-Mgmr/Adm	0.067	ICD10-Others	0.117
Occup-Prof.	0.134	Alcohol 3-day	0.154
Occup-A/Prof.	0.083	Smoker Reg	0.218
Occup-TradesP	0.071	Walk	0.518
Occup-Adv Clr/Svc	0.023	Overweigh	0.190
Occup-Int Clr/Svc	0.103	NSW	0.203
Occup-Prod/Trans	0.052	VIC	0.164
Occup-Ele Clr/Svc	0.041	QLD	0.162
Occup-Labour	0.051	SA	0.178
Employ-FT	0.451	WA	0.106
Employ-PT	0.173	TAS	0.109
Employ-Not	0.023	NT	0.006
Employ-NILF	0.353	ACT	0.074
SAH-Poor	0.040	ASGC-Major Cities	0.615
SAH-Fair	0.122	ASGC-Inner Region	0.227
SAH-Good	0.288	ASGC-Others	0.158

Continuous and Count explanatory variables

	Mean	Std. Dev.	Min	Max
AGE	49.08	16.33	22	85
HHINC	627.31	381.87	119.00	1279.00
LTCOND	2.86	1.73	0	5

Table 4.9: Variable names and description

Variable	Description
Maristat	= 1 if the respondent is married in a registered or defacto marriage
Depchild	= 1 if the respondent has at least one dependent child
Female	= 1 if the respondent is female
Age	= The middle value in each age interval decile
Age-Sq	= Squared age
Childbearing	= 1 if the respondent is female and age between 30 to 39 years
Country of Birth (COB)	
Australia	= 1 if the respondent is born in Australia.
Main English	= 1 if the respondent is born in main English speaking countries
Others	= 1 if the respondent is born in other countries
Education	
School	= 1 if the respondent has no post-school education
Vocation	= 1 if the respondent has a basic or skilled vocational qualification
Diploma	= 1 if the respondent has a undergraduate or associate diploma
Degree	= 1 if the respondent has a Bachelor degree or higher
Hconcard	= 1 if the respondent has a Government health concession card
Household Inc	= Gross weekly equivalised cash income of household. Middle values of decile
Household Inc-Sq	= Square of Household Inc
Occupation	
Not Employed	= 1 if the individual is not employed
Manager/Admin	= 1 occupation is in category "Managers and Administrators"
Professional	= 1 occupation is in category "Professionals"
Asc Professional	= 1 occupation is in category "Associate Professionals"
Tradesperson	= 1 occupation is in category "Tradesperson/Related Workers"
Adv Clerical/Service	= 1 occupation is in category "Advanced Clerical/Service Workers"
Int Clerical/Service	= 1 occupation is in category "Intermediate Clerical/Service Workers"
Production/Transport	= 1 occupation is in category "Intermediate Production/Transport Workers"
Ele Clerical/Service	= 1 occupation is in category "Elementary Clerical/Sales/Service Workers"
Labourer	= 1 occupation is in category "Labourers and Related Workers"
Employment	
Full-time	= 1 if the respondent is engaging in full-time employment
Part-time	= 1 if the respondent is engaging in part-time employment
Unemployed	= 1 if the respondent is unemployed
NILF	= 1 if the respondent is not in the labour force
Public Sector	= 1 if the respondent works in the public sector
Private Sector	= 1 if the respondent works in the private sector
LT Chronic Cond	= The number of long term chronic conditions
SAH	
Poor	= 1 if the respondent self-assessed health is poor
Fair	= 1 if the respondent self-assessed health is fair
Good	= 1 if the respondent self-assessed health is good
Very Good	= 1 if the respondent self-assessed health is very good
Excellent	= 1 if the respondent self-assessed health is excellent
ICD10	
Infectious/Parasitic	=1 Infectious & parasitic diseases
Neoplasm	=1 Neoplasm
Blood	=1 Diseases of the blood/blood forming organs
Endocrine	=1 Endocrine, nutritional & metabolic diseases
Mental/Behavioural	=1 Mental & behavioural problems
Nervous	=1 Diseases of the nervous system
Eye	=1 Diseases of the eye and adnexa

Table 4.9: Variable names and description: Cont.

Variable	Description
Ear	=1 Diseases of the ear and mastoid
Circulatory	=1 Diseases of the circulatory system
Respiratory	=1 Diseases of the respiratory system
Digestive	=1 Diseases of the digestive system
Skin	=1 Diseases of the skin & subcutaneous tissue
Muscular	=1 Diseases of the musculoskeletal system & connective tissue
Genitourinary	=1 Diseases of the genito-urinary system
Congenital	=1 Congenital malformations, deformations & chromosomal abnormalities
Others	=1 Symptoms, signs & conditions not elsewhere classified
Alcohol 3-day	= 1 if the respondent's alcohol 3-day risk level is high
Smoker Regular	= 1 if the respondent currently smokes daily
Walk	= 1 if the respondent walked for sport, recreation or fitness (last 2 weeks)
Overweigh	= 1 if the respondent is Grade 2 or 3 overweigh
NSW	= 1 if the respondent lives in New South Wales
VIC	= 1 if the respondent lives in Victoria
QLD	= 1 if the respondent lives in Queensland
SA	= 1 if the respondent lives in South Australia
WA	= 1 if the respondent lives in Western Australia
TAS	= 1 if the respondent lives in Tasmania
NT	= 1 if the respondent lives in Northern Territory
ACT	= 1 if the respondent lives in Australian Capital Territory
ASGC_Major	= 1 if the ASGC remoteness area category is "Major Cities"
ASGC_Inner	= 1 if the ASGC remoteness area category is "Inner Regional Australia"
ASGC_Others	= 1 if the ASGC remoteness area category is "Others"

Table 4.10: Intra Decile Income Range and Indicative Value

Decile	Income Range ($)	Indicative Value ($)
1	< 238	119
2	238 to 294	266
3	295 to 379	337
4	380 to 478	429
5	479 to 583	531
6	584 to 636	636
7	689 to 822	755.5
8	823 to 996	909.5
9	997 to 1278	1137.5
10	≥ 1279	1279

Chapter 5

Econometric Modeling and Estimation

5.1 Introduction

This chapter contributes to the literature on the econometric analysis of count data models with endogenous regressors. Within this literature, a variety of methods have been developed which include the GMM approach by Mullahy (1997) and Windmeijer and Santos Silva (1997), the FIML approach by Terza (1998) and Greene (2007) and the two-step residual inclusion and predictor substitution methods. These were surveyed in Chapter 2.4.3. In this chapter, a novel simultaneous equation econometric model is developed that accommodates count and binary outcomes variables as well endogenous binary regressors. The structure of the econometric model is based on the theoretical framework of the economic model of demand for hospital care and private hospital insurance described in Chapter 3. The model is estimated to empirically examine the determinants of the demand for hospital care and hospital insurance.

The chapter is organised as follows: Section 5.2 discusses the issues of discreteness and the non-negative integer value (or count) nature of the dependent variables. The section further explores the problem of self-selection in the utilisation of hospital care and the choice of patient type and examines its implications for the design of an appropriate econometric model. Section 5.3 presents a two-equation econometric model of demand for hospital care and private hospital insurance where the hospital care utilisation measure of interest is the frequency of hospital admissions. Section 5.4 expands on the framework outlined in Section 5.3 and develops a three-equation econometric model of demand for hospital care, the choice of hospital admission as a public or private patient and the choice to purchase private hospital insurance. The hospital care utilisation measure of interest here is the length of hospital stay. Section 5.5 concludes the chapter with a discussion of the estimation approach.

5.2 Bridging Theory and Practice: Designing the Econometric Model

From the theoretical model of demand for hospital care and private hospital insurance described in Chapter 3, the results of interest are (1) the expressions on the optimal intensity of hospital care $m^*_{d,q}(s)$; (2) the optimal choice between public or private hospital care which is the outcome of the decision rule $V_{d,q^*}(s) = max\big[V_{d,0}(s), V_{d,1}(s)\big]$; and (3) the decision that underpins the insurance choice $EV_{d^*} = max\big[EV_1, EV_0\big]$ where the subscripts d and q denote the insurance status ($d = 0$: no private hospital insurance; $d = 1$: with private hospital insurance) and the choice of public ($q = 0$) or private care ($q = 1$) respectively. These expressions form a system of ten equations where $m^*_{d,q}(s)$ and $V_{d,q}(s)$ each have four equations with EV_d consisting of two equations.

From the perspective of econometric analysis, estimating the above system of equations is not possible as not all ten equations are observed given the data. The first issue to consider in the design of the econometric model is the discreteness in the outcome variables for insurance and patient type choices. On the former, one observes from the data whether or not individuals have private hospital insurance. For individuals with private hospital insurance, one can imply that $EV_1 > EV_0$, where the equality is reversed for individuals without private hospital insurance. Similarly, in the choice to seek hospital care as a public or private patient, what one observes from the data is whether individuals obtained public or private hospital care. The former implies that $V_{d,0}(s) > V_{d,1}(s)$, and the reverse $V_{d,0}(s) < V_{d,1}(s)$ is true for individuals who obtained private hospital care. One can observe that the utility function $V_{d,q}(s)$ from each patient type strategy q depends on the availability of insurance, denoted by d. This is because of the sequential decision making process surrounding the insurance and patient type choice. Prior to the incidence of illness, the individual decides whether to purchase insurance. On the onset of illness in state s, the individual decides whether to seek hospital care as a public or private patient, depending on the availability of insurance. This scenario is an example of selectivity or self-selection given that the patient type choice depends on a prior decision to purchase insurance. The issue of self-selection will be discussed further later in this section.

An approach to model the discreteness in the insurance and patient type choice variables is the discrete choice model. Using the insurance decision as an illustration, consider the decision on whether to purchase private hospital insurance. Suppose subscript i denotes the i-th observation of N individuals and define $d_i^* = (EV_1 - EV_0)_i$ where

$$d_i^* = W_i\gamma + \eta_i \tag{5.1}$$

where W_i is a vector of exogenous regressors that are invariant across the insurance strategy, γ is a vector of coefficients and η_i is an error term. The functions in (5.1) may be generalised to include regressors that are both varying and invariant across the insurance alternatives. This is however not applicable given that the data employed in this study does not contain information on insurance premiums or waiting times in public hospitals which can, if available, serve as alternative-varying regressors on the insurance and patient type decisions. Suppose the binary insurance variable assumes the value of 1 if $d^* > 0$, that is

$$d_i = 1[d^* > 0] \tag{5.2}$$

From (5.1), the probability that individual i decides to purchase insurance (that is $d = 1$) is given by

$$\begin{aligned} P[d_i = 1] = &\ P[d_i^* > 0] \\ = &\ P[W_i\gamma + \eta_i > 0] \\ = &\ P[\eta_i > -W_i\gamma] \end{aligned} \tag{5.3}$$

Assuming that η is normally distributed with mean zero and variance σ_η^2, η is symmetrically distributed around zero and

$$\begin{aligned} P[d_i = 1] = &\ P[\eta_i < W_i\gamma] \\ = &\ \Phi(\tfrac{W_i\gamma}{\sigma_\eta}) \\ P[d_i = 0] = &\ 1 - \Phi(\tfrac{W_i\gamma}{\sigma_\eta}) \end{aligned} \tag{5.4}$$

where Φ is the cumulative standard normal distribution. Given that γ and σ_η are not separately identifiable, it is frequently assumed that $\sigma_\eta = 1$. The resultant model is commonly referred to as the probit model[1] and is readily estimated via maximum-likelihood.

A second consideration on the design of an appropriate econometric model concerns the count data nature of the hospital care utilisation measures available in the data. These measures, which include examples like the number of hospital admissions or the length of hospital stay, take on non-negative integer values. The simplest model for count data is the Poisson regression model (PRM). To elaborate on the PRM, suppose m_i is the hospital utilisation measure of interest for individual i, X_i a vector of exogenous covariates and θ a set of parameters. Under the PRM, m_i given X_i follows a Poisson distribution with probability density function

$$f(m_i|X_i) = \frac{\exp^{-\mu_i}\mu_i^{m_i}}{m_i!} \tag{5.5}$$

The conditional mean μ_i or $E(m_i|X_i)$ may be specified as

$$\mu_i = \exp(X_i\theta) \tag{5.6}$$

A major limitation of the PRM is the property of equidispersion that follows the assumption of Poisson distribution. As discussed in Chapter 4, the hospital utilisation measures in the data sample exhibit overdispersion in that the unconditional variance is greater than unconditional mean. To accommodate the presence of overdispersion, one can consider introducing a normally distributed variable as a heterogeneity term in the conditional mean equation.[2] Using (5.6), the conditional mean can be respecified as

$$\begin{aligned} \mu_i = &\ \exp(X_i\theta + \xi_i) \\ = &\ \exp(X_i\theta)\exp(\xi_i) \end{aligned} \tag{5.7}$$

where $\exp(\xi)$ is distributed log-normal. In addition to allowing one to account for overdispersion in the data, the Poisson-lognormal mixture provides a convenient framework to accommodate the presence of endogeneous regressors in the

[1]See Maddala (1983), pp. 13 - 26, for a discussion of regression models where the dependent variable is dichotomous.

[2] Greene (2007) proposed the lognormal Poisson model as an alternative to the standard log gamma count data models for introducing heterogeneity in the conditional mean equation in traditional count data models which also serves as a convenient platform for further extensions into two-part models such as zero inflation, hurdle and sample selection models.

conditional mean μ resulting from selectivity in the utilisation of hospital care. This model, referred to as the lognormal random effects Poisson model, is one of the several models that will be estimated in the empirical analysis.

A third consideration on the design of an appropriate econometric model is that of selectivity or self-selection. As we have seen in Section 3.4.1 the decision to seek hospital care as a public or private patient, conditional on the insurance choice, depends on the net utility that accrue across the alternatives. The same applies to the decision to purchase private hospital insurance which is likely to depend, amongst others, on the expected use of private hospital care. One approach to characterise the choice to receive public or private hospital care is the binary choice model. Let q_i^* denote the net utility accruing to individuals when obtaining public versus private hospital care. Suppose we assume that

$$q_i = 1[Z_i\alpha + \beta d_i + v_i > 0] \tag{5.8}$$

where Z_i and α are vectors containing the exogenous covariates and the coefficients; d_i the binary insurance variable and the error term v_i. In equation (5.8), d_i is endogenous given that the decision to purchase private hospital insurance is based on individual self-selection. To accommodate the presence of the endogenous insurance binary variable in the patient type choice equation, the patient type choice equation in (5.8) and the insurance choice equation in (5.1) are combined to form

$$\begin{aligned} q_i = &\ 1[Z_i\alpha + \beta d_i + v_i > 0] \\ d_i = &\ 1[W_i\gamma + \eta_i > 0] \end{aligned} \tag{5.9}$$

where it is assumed that v and η are independent of W and Z and are distributed as bivariate normal with mean zero, with each having unit variance and correlation parameter ρ. In notational term, the equivalent expression is $[v, \eta] \sim N_2[(0,0),(1,1),\rho]$. If $\rho = 0$, then d_i and v_i are uncorrelated and equation (5.8) can be estimated using a simple probit model. If $\rho \neq 0$, d_i and v_i are correlated, estimation of (5.8) using a simple probit model produces inconsistent estimates of α and β. From equation (5.8), the effect of the availability of private hospital insurance d on the probability of obtaining private hospital care q is of primary interest. The average treatment effect of insurance d, conditional on the exogenous covariates Z is given as $\Phi(Z\alpha + \beta d) - \Phi(Z\alpha)$.

The problem of selectivity also applies to the hospital care utilisation equation.

This is because rather than observing a measure of hospital care intensity m^* under each insurance and patient type strategy, one observes in the data the length of hospital stay, given the choice to obtain public or private care and the availability of private hospital insurance. Suppose the conditional mean equation in (5.7) is modified to include binary variables

$$\mu_i = \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i + \xi_i) \tag{5.10}$$

where X_i denotes a vector of exogenous covariates and the heterogeneity term ξ_i. The binary variables d_i and q_i represent whether or not the individual has private hospital insurance and chose to receive public or private hospital care respectively. In equation (5.10), both d_i and q_i are endogenous given that the decision to purchase insurance and the choice to receive public or private care are based on individual self-selection. If individuals who because of unobserved individual specific reasons are more likely to stay longer in hospitals (that is those with higher ξ_i are more likely to purchase private health insurance), then d_i and ξ_i will be correlated. To accommodate the endogeneity of d_i and q_i, one can allow the error term ξ in (5.10) to correlate with the error terms η and v in the patient type and insurance equations described in (5.9). For example, one can assume that ξ_i, v_i and η_i are distributed multivariate normal (MVN) with mean vector zero with covariance matrix

$$\begin{pmatrix} \xi_i \\ v_i \\ \eta_i \end{pmatrix} \sim N_3 \left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{pmatrix} \right]$$

Detailed discussions on the application of this approach are deferred to Sections 5.3 and 5.4 below. If $\rho_{12}, \rho_{13} \neq 0$, estimation using single count data models such as the Poisson regression model or the Negative Binomial Model will produce inconsistent coefficient estimates of θ and λs. Correspondingly, if $\rho_{12} = \rho_{13} = 0$, one can estimate the utilisation equation using single equation methods.

Two questions of interest can be examined using the model specification in (5.10). The first question concerns whether or not the average intensity of hospital care use differs between publicly and privately admitted patients, conditional on insurance d and exogenous covariates X. This is the average treatment effect of q on hospital utilisation measure m and is given as $\exp(X\theta + \lambda_1 d + \lambda_2)$ - $\exp(X\theta + \lambda_1 d)$. The second question of interest is whether or not the moral hazard effect is present for private hospital care. This can be examined by augmenting the conditional mean equation (5.10) with an interaction term $d_i \cdot q_i$

$$\mu_i = \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i + \lambda_3 d_i \cdot q_i + \xi_i) \tag{5.11}$$

Here, the moral hazard effect is given as $\mathrm{E}(m_i|q_i = 1, d_i = 1, X)$ - $\mathrm{E}(m_i|q_i = 1, d_i = 0, X)$.

5.3 An Econometric Model of the Demand for Hospital Admissions and Private Hospital Insurance

This section describes a two-equation econometric model employed to empirically examine the demand for hospital admission and private hospital insurance. The hospital utilisation measure of interest here is the frequency of hospital admissions. Let the dependent variable m_i be the observed frequency of hospital admission by individual i $(i = 1, \ldots, N)$. Furthermore, let us assume that conditional on the exogenous covariates X_i and the endogenous variable d_i, m_i follows a Poisson distribution with probability density function

$$f(m_i \mid X_i, d_i) = \frac{\exp^{-\mu_i} \mu_i^{m_i}}{m_i!} \tag{5.12}$$

where the conditional mean parameter μ_i is

$$\mu_i = \exp(X_i\theta + \lambda_1 d_i) \tag{5.13}$$

To accommodate the presence of overdispersion observed in the data, a heterogeneity term is introduced into the conditional mean equation μ_i as a normally distributed random variable with mean 0 and variance σ^2. This heterogeneity term is standardised by the standard deviation σ and ξ_i, where ξ_i is distributed standard normal, that is $\xi_i \sim \mathrm{N}[0, 1]$. The conditional mean equation is rewritten as

$$\begin{aligned} \mu_i &= \exp(X_i\theta + \lambda_1 d_i + \sigma\xi_i) \\ &= \exp(X_i\theta + \lambda_1 d_i)\exp(\sigma\xi_i) \end{aligned} \tag{5.14}$$

The decision rule surrounding the decision to purchase private hospital insurance is given by a continuous latent variable d_i^* where

$$d_i^* = W_i\gamma + \eta_i \tag{5.15}$$

where $\eta_i \sim \mathrm{N}[0,1]$. d_i^* is not observed in the data. Instead, we observe the indicator variable d_i where

$$d_i = 1[d_i^* \geq 0] \tag{5.16}$$

The insurance binary variable d_i in the conditional mean equation in (5.14) is allowed to be endogenous by assuming that ξ_i and η_i are correlated. More specifically, it is assumed that ξ_i and η_i are distributed bivariate normal, that is

$$[\xi_i, \eta_i] \sim N_2[(0,0),(1,1),\rho] \tag{5.17}$$

In the above notation $N_2[(\mu_1,\mu_2),(\sigma_1^2,\sigma_2^2),\rho]$, μ denotes the mean, σ^2 the variance and ρ the correlation parameter. By the assumption of joint normality[3], η_i conditional on ξ_i may be expressed as

$$\eta_i = \rho\xi_i + \epsilon_i(1-\rho^2)^{1/2}, \quad \epsilon_i \sim N[0,1] \tag{5.18}$$

Substituting (5.18) into (5.15) and using the decision rule (5.16) for observing d_i, we can derive the probability of observing $d_i = 1$ which is expressed as

$$\begin{aligned} P(d_i = 1) = \; & P\left(\epsilon_i > -\frac{W_i\gamma + \rho\xi_i}{(1-\rho^2)^{1/2}}\right) \\ = \; & P\left(\epsilon_i < \frac{W_i\gamma + \rho\xi_i}{(1-\rho^2)^{1/2}}\right) \end{aligned} \tag{5.19}$$

where the second line follows given the symmetry of the normal distribution. The probability of observing $d_i = 0$ is

$$P(d_i = 0) = P\left(\epsilon_i > \frac{W_i\gamma + \rho\xi_i}{(1-\rho^2)^{1/2}}\right) \tag{5.20}$$

Using the above assumptions, let us now proceed to specify the joint conditional density of the data. Let the joint conditional density function of the

[3]See Section 3.10.1 in page 87 of Greene (2000).

observed data $f(m_i, d_i \,|\, \Omega_i)$ be expressed as

$$f(m_i, d_i \,|\, \Omega_i) = \int_{-\infty}^{+\infty} f(m_i, d_i \,|\, \Omega_i, \xi_i)\phi(\xi_i)d\xi_i \tag{5.21}$$

where $\phi(\xi_i)$ is the standard normal density and $\Omega_i = (X_i \cup W_i)$. Given the previous assumption that m_i and d_i are related only through the correlations between ξ_i and η_i, m_i conditioned ξ_i is independent of d_i. Hence, $f(m_i, d_i \,|\, \Omega_i)$ in (5.21) may be expressed as

$$f(m_i, d_i \,|\, \Omega_i, \xi_i) = f(m_i \,|\, X_i, d_i, \xi_i) \cdot g(d_i \,|\, W_i, \xi_i) \tag{5.22}$$

where $f(m_i \,|\, X_i, d_i, \xi_i)$ is the conditional Poisson density function in (5.13) and $g(d_i \,|\, W_i, \xi_i)$ is the conditional density function of d_i given W_i and ξ_i. Using (5.19) and (5.20), $g(d_i \,|\, W_i, \xi_i)$ may be expressed as

$$g(d_i \,|\, W_i, \xi_i) = \Phi\left[y_i \cdot \frac{W_i\gamma + \rho\xi_i}{(1-\rho^2)^{1/2}}\right] \tag{5.23}$$

where $y_i = 2d_i - 1$ and Φ denotes the cumulative normal density function. The joint conditional density function of the data is derived by substituting (5.22) and (5.23) into (5.21) to obtain

$$f(m_i, d_i \,|\, \Omega_i) = \int_{-\infty}^{+\infty} f(m_i \,|\, X_i, d_i, \xi_i) \cdot \Phi\left[y_i \cdot \frac{W_i\gamma + \rho\xi_i}{(1-\rho^2)^{1/2}}\right]\phi(\xi_i)d\xi_i \tag{5.24}$$

Equation (5.24) is used to construct the log-likelihood function which will be used to estimate the two-equation model. The estimation strategy will be discussed in Section 5.5. In the next section, I will expand on the two-equation model outlined in this section and develop a three equation econometric model of demand for hospital care, the choice of hospital admission as a public or private patient and the choice to purchase private hospital insurance.

5.4 An Econometric Model of the Demand for Hospital Stay, the Choice of Public or Private Patient and Private Hospital Insurance

This section describes a three-equation econometric model employed to empirically examine the demand for hospital stay, the choice of hospital admission as a public or private patient and private hospital insurance. The hospital utilisation measure of interest here is the length of hospital stay. Let the dependent variable m_i be the observed hospital length of stay by individual i ($i = 1, \ldots, N$). Furthermore, assume that conditional on the exogenous covariates X_i and the endogenous variables q_i and d_i, m_i follows a Poisson distribution with probability density function

$$f(m_i \mid X_i, q_i, d_i, \xi_i) = \frac{\exp^{-\mu_i} \mu_i^{m_i}}{m_i!} \tag{5.25}$$

where the conditional mean parameter μ_i is

$$\begin{aligned} \mu_i = & \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i + \sigma\xi_i) \\ = & \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i)\exp(\sigma\xi_i) \end{aligned} \tag{5.26}$$

Similar to Section 5.3, the heterogeneity term ξ_i is introduced to accommodate the presence of overdispersion. The decision rule surrounding the binary variable representing the choice of hospital admission as a public or private patient is given by a continuous latent variable q_i^* where

$$q_i^* = Z_i\alpha + \beta_1 d_i + v_i \tag{5.27}$$

where $v_i \sim \mathrm{N}[0, 1]$. q_i^* is not observed in the data. Instead, the indicator variable q_i is observed where

$$q_i = 1[q_i^* \geq 0] \tag{5.28}$$

The decision rule surrounding the decision to purchase private hospital insurance is given by d_i^* where

$$d_i^* = W_i\gamma + \eta_i \tag{5.29}$$

where $\eta_i \sim \mathrm{N}[0, 1]$. As above, the indicator variable d_i is observed where

$$d_i = 1[d_i^* \geq 0] \tag{5.30}$$

The patient type and insurance binary variables in equations (5.27) in (5.29) are allowed to be endogenous by assuming that ξ_i, v_i and η_i are correlated. One possible specification is the assumption that ξ_i, v_i and η_i are distributed multivariate normal (MVN) with mean vector zero and covariance Σ where

$$\Sigma = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix} \tag{5.31}$$

Let $g(\xi_i, v_i, \eta_i \mid \Omega_i)$ denote the conditional MVN density where

$$g(\xi_i, v_i, \eta_i \mid \Omega_i) = (2\pi)^{-3/2}|\Sigma|^{-1/2}e^{[-1/2(\varepsilon_i')(\Sigma^{-1})(\varepsilon_i)]}$$

where $\Omega_i = (X_i \cup Z_i \cup W_i)$ and $\varepsilon_i = (\xi_i \; v_i \; \eta_i)$. Following Terza (1998), the joint conditional density for the observed data $f(m_i, q_i, d_i \,|\, \Omega_i)$ for individual i can be expressed as

$$\int_{-\infty}^{\infty} \Big[(1-q_i)(1-d_i)f(m_i \mid X_i, q_i = 0, d_i = 0, \xi_i)\; P(q_i = 0, d_i = 0 \mid \Omega_i, \xi_i) +$$

$$(q_i)(1-d_i)f(m_i \mid X_i, q_i = 1, d_i = 0, \xi_i)P(q_i = 1, d_i = 0 \mid \Omega_i, \xi_i) +$$

$$(1-q_i)(d_i)f(m_i \mid X_i, q_i = 0, d_i = 1, \xi_i)P(q_i = 0, d_i = 1 \mid \Omega_i, \xi_i) +$$

$$(q_i)(d_i)f(m_i \mid X_i, q_i = 1, d_i = 1, \xi_i)\; P(q_i = 1, d_i = 1 \mid \Omega_i, \xi_i)\Big]\, d\xi_i \tag{5.32}$$

where $f(m_i \,|\, X_i, q_i, d_i, \xi_i)$ is the conditional probability density function of m_i as defined in (5.25). The model can be estimated by constructing the overall log-likelihood function which involves taking the logarithms of (5.32) and thereafter summing the result for all $i = 1, \ldots, N$. Given that (5.32) does not have a closed form solution, the overall log-likelihood function may be approximated using simulation methods and estimated via maximum simulated likelihood. This approach is computationally cumbersome as it involves drawing random numbers from the truncated multivariate normal distribution. A simpler approach involves decomposing the trivariate normal density function into a series of conditional bivariate normal probability density functions. This method is more tractable as it reduces the number of integrals that are required to compute the likelihood function. This approach is adopted in this study.[4] The assumption that ξ_i, v_i and η_i are trivariate normal with covariance matrix in (5.31) implies that every pair of them is a bivariate normal. Specifically,

$$[\xi_i, v_i] \sim N_2[(0,0),(1,1),\rho_{12}] \tag{5.33}$$

$$[\xi_i, \eta_i] \sim N_2[(0,0),(1,1),\rho_{13}] \tag{5.34}$$

$$[v_i, \eta_i] \sim N_2[(0,0),(1,1),\rho_{23}] \tag{5.35}$$

This in turn implies that $(v_i \,|\, \xi_i)$ and $(\eta_i \,|\, \xi_i)$ are distributed bivariate normal

$$\begin{pmatrix} v_i \,|\, \xi_i \\ \eta_i \,|\, \xi_i \end{pmatrix} \sim N_2 \left[\begin{pmatrix} \rho_{12}\xi_i \\ \rho_{13}\xi_i \end{pmatrix}, \begin{pmatrix} 1-\rho_{12} & \rho_{23}-\rho_{12}\rho_{13} \\ \rho_{23}-\rho_{12}\rho_{13} & 1-\rho_{13} \end{pmatrix} \right] \tag{5.36}$$

From (5.36), (5.27), (5.28), (5.29) and (5.30), we can deduce that the joint probability of the four possible outcomes of the pair (q_i, d_i) conditional on Z_i, W_i and ξ_i can be succinctly written as

$$g(q_i, d_i \,|\, Z_i, W_i, \xi_i) = \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*] \tag{5.37}$$

where

$$\Theta_1 = \frac{Z_i\alpha + \beta_1 d_i + \rho_{12}\xi_i}{(1-\rho_{12}^2)^{1/2}}$$

$$\Theta_2 = \frac{W_i\gamma + \rho_{13}\xi_i}{(1-\rho_{13}^2)^{1/2}}$$

$$\rho^* = y_{1i} \cdot y_{2i} \cdot \frac{(\rho_{23}-\rho_{12}\rho_{13})}{\sqrt{1-\rho_{12}^2}\sqrt{1-\rho_{13}^2}}$$

[4] See Section 3.1, pages 14-18 of Greene (2007) for an application of this approach to count data models with sample selection.

In the above, $y_{1i} = 2q_i - 1$ and $y_{2i} = 2d_i - 1$. Φ_2 denote the bivariate normal cumulative density function.

Using the expression in (5.37), the joint conditional density for the observed data which was originally specified in (5.32) can be re-written as follows. Let the joint conditional density for the observed data $f(m_i, q_i, d_i \,|\, \Omega_i)$ be expressed as

$$f(m_i, q_i, d_i \,|\, \Omega_i) = \int_{-\infty}^{+\infty} f(m_i, q_i, d_i \,|\, \Omega_i, \xi_i)\phi(\xi_i)d\xi_i \tag{5.38}$$

where $\phi(\xi_i)$ is the standard normal density. Given the previous assumption that m_i, q_i and d_i are related only through the correlations between ξ_i, v_i and η_i, conditioned on ξ_i, m_i is independent of q_i and d_i. Hence, $f(m_i, q_i, d_i \,|\, \Omega_i, \xi_i)$ in (5.38) may be expressed as

$$f(m_i, q_i, d_i \,|\, \Omega_i, \xi_i) = f(m_i \,|\, X_i, q_i, d_i, \xi_i) \cdot g(q_i, d_i \,|\, Z_i, W_i, \xi_i) \tag{5.39}$$

Substituting (5.37) into (5.39), we obtain

$$f(m_i, q_i, d_i \,|\, \Omega_i) = \int_{-\infty}^{+\infty} f(m_i \,|\, \Omega_i, q_i, d_i, \xi_i) \cdot \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*]\, \phi(\xi_i)d\xi_i \tag{5.40}$$

Equation (5.40) will be used to construct the log-likelihood function which we will use to estimate the three-equation model. The estimation strategy for the three equation econometric model outlined above will be discussed in the next section.

5.5 Estimation Strategy

The solutions to the joint conditional density functions in (5.24) and (5.40) require the evaluation of one integral. If these expressions have a closed-form solution, the models can be estimated using maximum likelihood. Consider the estimation of the joint conditional density function in (5.40).[5] Suppose a vector of parameters, denoted by Θ, is introduced into the joint conditional density function $f(m_i, q_i, d_i \,|\, \Omega_i, \Theta)$, together with the i subscript which denotes the observations

[5] These principles are similarly applied in the estimation of the two equation model based on the joint conditional density function in (5.24)

for i-th individual. For a sample of N independent observations of m_i, q_i and d_i, the likelihood and log-likelihood[6] functions are formulated using (5.40) and are expressed as follows

$$\mathrm{L}(\Theta) = \prod_{i=1}^{N} f(m_i, q_i, d_i \mid \Omega_i, \Theta) \tag{5.41}$$

$$\ln \mathrm{L}(\Theta) = \sum_{i=1}^{N} \ln f(m_i, q_i, d_i \mid \Omega_i, \Theta) \tag{5.42}$$

The maximum likelihood (ML) estimate is the parameter vector $\hat{\Theta}_{\mathrm{ML}}$ that maximises the likelihood or log-likelihood of observing the data in our sample. It is likely that (5.40) does not have a closed-form expression. For this case, one may approximate the integral using deterministic numerical integration techniques or quadrature.[7] Alternatively, (5.40) may be approximated using Monte Carlo simulations. This study adopts the simulation approach. As in (5.40), the joint conditional density function for the i-th observation in the sample is

$$f(m_i, q_i, d_i \,|\, \Omega_i) = \int_{-\infty}^{+\infty} f(m_i \,|\, \Omega_i, q_i, d_i, \xi_i) \cdot \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*]\, \phi(\xi_i) d\xi_i$$

Let ξ_i^s denote the s-th draw of ξ from the standard normal density $\phi(\xi_i)$. The simulated joint conditional density function for the i-th observation is

$$\widehat{f}(m_i, q_i, d_i \,|\, \Omega_i) = \frac{1}{S} \sum_{1}^{S} f(m_i \,|\, \Omega_i, q_i, d_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*]$$

Correspondingly, the simulated likelihood and log-simulated likelihood functions are

[6]Because $f(m, q, d \,|\, \Omega, \Theta)$ is the joint conditional density function rather than the full joint density function $f(m, q, d, \Omega \,|\, \Theta)$, the likelihood function constructed using the former is the conditional (log)likelihood function which is in most applications required for consistent estimation of the model (Cameron and Trivedi 2005)

[7]See Cameron and Trivedi (2005), Section 12.3.1, pages 388 - 390 for a discussion of quadratures techniques.

$$\widehat{\mathrm{L}}(\Theta) = \prod_{i=1}^{N} \frac{1}{S} \sum_{1}^{S} f(m_i \mid \Omega_i, q_i, d_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*] \tag{5.43}$$

$$\ln \widehat{\mathrm{L}}(\Theta) = \sum_{i=1}^{N} \ln\left\{ \frac{1}{S} \sum_{1}^{S} f(m_i \mid \Omega_i, q_i, d_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*] \right\} \tag{5.44}$$

The principle of ML is applied to obtain an estimate of Θ. The maximum simulated likelihood (MSL) estimator $\widehat{\Theta}_{\mathrm{MSL}}$ maximises the simulated log-likelihood function in (5.44).

The number of simulations S has a considerable effect on the properties of the MSL estimator. Gouriéroux and Monfort (1996) showed that the MSL estimator is asymptotically equivalent to the ML estimator if the ratio of square root N and S approaches zero ($\sqrt{N}/S \rightarrow 0$) when the sample size N and the number of simulations S approaches infinity. While this consistency condition provides some indication on how S should increase given an increase in the sample size N, it does not provide any guidance of the appropriate number of simulations S for a given sample size N. A more formal test-based approach for choosing the number of simulations S is proposed in Hajivassiliou (2000) which is based on the principle of selecting a value of S to reduce the simulation noise to a desirable level. Clearly, the benefits of increasing S to minimise simulation noise has to be balanced with the computational burden that comes with increasing of the number of simulations.

This study addressed the task of choosing an appropriate number of simulations S as follows: First and foremost, the Halton sequence was used to generate quasi-random draws that is required for the simulation of the log-likelihood function. Unlike the generation of pseudo-random numbers which selects S pseudo-random points within the domain of integration, the Halton sequence is a quasi-Monte Carlo method that creates draws based on non-random, but more uniformly distributed selection of points over the integration domain.[8] Simulations using the Halton sequence have been demonstrated to be considerably more accurate, that is to lower simulation errors, with a significantly smaller number of

[8]A comprehensive and descriptive guide to the Halton sequence is provided in Section 9.3.3 of Train (2003)

draws and computational time as compared to the pseudo-random method.[9] The Halton sequence is generated in `Stata` using the `-mdraw` program and saved as part of the data in the dataset. To simulate the log-likelihood function in 5.40, the uniformly distributed quasi-random draws from the Halton sequence are converted to random draws from the standard normal distribution using the inverse cumulative normal transformation. Secondly, in an attempt to select a practical number of simulations, S is increased stepwise by a factor of 2 starting from a minimum of 50 to a maximum of 2000 for a given model specification. Thereafter, the regression estimates were examined to see if the results vary significantly for increasing values of S. The choice on the number of simulations is determined as the lowest number of simulations for which the estimates obtained are observed not to vary significantly with higher values of S.

The Berndt, Hall, Hall and Hausman (BHHH) quasi-Newton algorithm was used to maximise the simulated likelihood using the statistical software `Stata`. Numerical derivatives were used via the `-lf-` method in `Stata` which requires one to specify only the log-likelihood function. The variance of the MSL estimates was computed using the robust 'sandwich' formula (White 1982). The robust approach, as opposed to the information matrix and outer product formulae, is more appropriate as it takes into account the influence of simulation noise that is present when the number simulations S is finite (Mcfadden and Train 2000). In addition, the robust 'sandwich' formula produces accurate standard errors of the MSL estimates in the event that the joint density function is misspecified, that is the true joint density function of the data is not as that in (5.40).

In the data, the observed length of hospital stay is recorded for the most recent hospitalisation episode y, where ($y = 1, 2, 3$ or more). For each set of observations y, the conditional mean for length of stay is expressed as $E(m \mid X, Y = y, \sigma)$. The conditional mean of length of stay for the sample is expressed as $E(m \mid X, \sigma) = \sum_y E(m \mid X, y, \sigma)$ which is calculated as a weighted average of the mean length of stay for each realisation of Y. The empirical distribution of y is used as weights for the computation.

Marginal effects were calculated using the appropriate formulae depending on the functional form assumptions for continuous and discrete variables. Given the probit structure of the patient type and insurance equations, the marginal

[9]Bhat (2001) and Train (2003) found that 100 Halton-based draws provide at least the same accuracy than with 1000 pseudo-random draws. Also, the use of the Halton sequence has shown to dramatically decrease the computation time to complete the simulations.

effect of a change in the continuous variable X_k is given as $\phi(X\hat{\beta}) \cdot \partial(X\hat{\beta})/\partial X_k$ where $\hat{\beta}$ are the estimates of the coefficients. For discrete explanatory variables, the marginal effect when X_k changes from 0 to 1 is given as $\Phi(X\hat{\beta} \,|\, X_k = 1) - \Phi(X\hat{\beta} \,|\, X_k = 0)$. Given the exponential mean equation in the hospital use equation, the marginal effect of a change in a continuous variable is X_k is $\exp(X\hat{\beta} + 0.5\hat{\sigma}) \cdot \partial(X\hat{\beta} + 0.5\hat{\sigma})/\partial X_k$. For discrete explanatory variables, the marginal effect is given by $\exp(X\hat{\beta}+0.5\hat{\sigma} \,|\, X_k = 1) - \exp(X\hat{\beta}+0.5\hat{\sigma} \,|\, X_k = 0)$. In all instance, the marginal effects are computed with the remaining covariates at their sample means. Standard errors of the marginal effects are calculated using the delta method via the `-predictnl-` in `Stata`.[10]

[10] An alternative approach is to calculate the standard errors of the marginal effects via Monte Carlo techniques. See Deb and Trivedi (2006).

Chapter 6

Demand for Hospital Admissions and Private Hospital Insurance

6.1 Introduction

This chapter contributes to the literature on the demand for health care and health insurance in a mixed public and private health care system. As reviewed in Chapter 2, empirical studies where the health utilisation measures of interest are characterised as non-negative integer values or counts have largely employed instrumental variable techniques such as the two-step residual inclusion and predictor substitution methods to account for the simultaneity between insurance and health care utilisation. In this chapter, the simultaneous equation model described in Chapter 5.3 is applied to analyse the determinants of the intensity of hospital admissions and the choice to purchase private health insurance. The results suggest that the insurance binary variable is not endogenous which implies that one can examine the utilisation and insurance equations with separate regressions. The chapter is organised as follows. The choice of explanatory variables for the hospital admission and insurance equations is first discussed in Section 6.2. Issues pertaining to the identification of the econometric model and the number of simulation draws are presented here. Issues on model selection between the simultaneous equation model and the single equation version are discussed in Section 6.3. The empirical results of the determinants of private health insurance are detailed in Section 6.4. The determinants of the intensity of hospital admissions are discussed in Section 6.5. Section 6.6 concludes with a discussion of the results.

6.2 Explanatory Variables, Exclusion Restrictions and Simulation Draws

Table 6.1 presents the explanatory variables included in the hospital admission and insurance equations. First and foremost, the insurance binary variable was included as an endogenous regressor on the right hand side of the hospital admission equation. The remaining explanatory variables in each of the two equations can be classified into the following categories: demographics; socioeconomic characteristics; health risk; health status and geographic indicators. The results from previous studies that used data from Australia suggest that health status (e.g. the presence of chronic health conditions) plays an important role in determining the use of health care services while income is an important factor in the decision to purchase insurance (Cameron et al. 1988, Cameron and Trivedi 1991). To facilitate the comparison of the results in this study with these Australia based studies, a similar set of explanatory variables was chosen. Demographic variables such as gender, income unit type and age were included in both equations. A childbearing variable, which is a binary variable that represents females between the ages of 25 to 40 years was included to capture the effects of childbearing on hospital admissions. Country of birth was included in the insurance choice equation. Of the socioeconomic variables, the equivalised household income was included in both equations. The level of educational attainment was included as regressors in insurance equation. Two different variables capturing information on the individuals' employment characteristics were included separately in each of the two equations. The first variable was the individuals' employment status, that is whether the individual was employed full-time, part-time, unemployed or not in the labour force (NILF). This was included in the hospital admission equation. Information on individuals' occupation type was included in the insurance equation. Also in the insurance equation was information on whether or not individuals have health concession cards. Health risk factors such as tobacco and alcohol consumption were included in the insurance equation. Two measures of individuals' health status were included. The first consists of a set of binary variables of the ICD10 disease categories. The second is a count variable of the number of long term chronic medical conditions that individuals suffered from. These health status indicators were included in both equations. Lastly, information on the locality of individuals' were captured using state/territory and remoteness dummies.

Table 6.1: Explanatory variables in hospital admission & insurance equations

Endogenous Regressors	Equations: Hospital Admission	Equations: Insurance
Insurance	x	
Exogenous Regressors		
A. Demographics		
Female	x	x
Income Unit: Dependents	x	x
Income Unit: Couple	x	x
Age, Age-squared	x	x
Childbearing	x	
Country of Birth		x
B. Socioeconomic		
Income, Income-squared	x	x
Education		x
Employment Status	x	
Occupational Category		x
Health Concession Card		x
C. Health Risk		
Regular smoker		x
Alcohol		x
D. Health Status		
ICD-10 Chronic Conditions	x	x
Number of Chronic conditions	x	x
E. Geography		
State/Territories	x	x
Remoteness	x	x

There is an issue of whether the econometric model is identified given the presence of an endogenous regressor in the hospital admission equation. Formally speaking, the model is identified by the nonlinearity of the functional form assumed.[1] To add robustness of the identification of the model, exclusions restrictions are applied in that there is at least one variable that is in the insurance equation but not in the hospital admission equation. To this effect, variables measuring health risk such as smoking and alcohol consumption are included only in the insurance equation. These health risk measures are proxies for individuals' attitudes toward risk that is likely to affect the decision to purchase health insurance. While there has been some evidence that risk attitudes influence the use of preventive medical care, it is not likely that they play a role in the utilisation of curative hospital care (Anderson and Mellor 2008). In addition, variables such as the childbearing indicator, education attainment, and the availability of health concession card is included only in the insurance equation as guided by the related studies cited above.

Estimation of the lognormal random effects Poisson and the simultaneous equation model described in Chapter 5.5 requires one to determine an optimal number of simulations used to simulate the likelihood function. Here, the choice of the number of simulations S was determined in a stepwise manner in which S was increased from 50 to 3000. The choice on the number of simulations is determined as the lowest number of simulations for which the estimates obtained are observed not to vary significantly with higher values of S. The analysis below used S=3000 based on Halton quasi-random draws.[2] Convergence for the estimation of the simultaneous equation model was achieved after 47 iterations requiring approximately 22 hours to complete on an Intel 2.67 Ghz processor with 6 GB RAM.

---

[1]See point 6 on page 668 of Greene (2000).

[2]Deb and Trivedi (2006) remarked that simulations in nonlinear simultaneous equation models as that adopted in this study, where the dependent variables from some equations enters as regressors in other equations, require considerably larger number of simulation draws as compared to seemingly unrelated system of equations model that are often used in multinomial choice models. In their analysis, the authors used 2000 simulations based on the Halton sequence on a sample consisting of 8129 observations. If one were to take the choice on the number of simulations S=2000 given the sample size N=8129 in Deb and Trivedi (2006) as a point of reference to decide on the number of simulations required for the sample size of N=2406 in this study, the minimum number of simulations required to fulfil the consistency requirement (that S increases more than $\sqrt{N}$) is $2000 + \sqrt{14049 - 8129} \approx 2076$.

Table 6.2: Estimates of correlation parameter & model selection

Model	Correlation	Selection Criterion		
	ρ	Loglikelihood[c]	AIC	BIC
(1) SEM (2 equation)	-0.45	-16222.45	32648.89	33422.91
(2) Single Eq ($\rho = 0$)		-16223.62	32649.23	33415.66

Model	Null H_0	LR Stat[b]	Best Model LR Test	AIC	BIC
(1) vs. (2)	$\rho = 0$	-2.33	(2)	(1)	(2)

***,**, * denote significance at 1%, 5% and 10% respectively.

a. The correlation parameter estimates reported here are the arc-tangent functions of the correlation parameter ρ

b. Critical value for LR test: $\chi^2_{1,\alpha=0.05} = 3.84$

c. The log likelihood value for Model (2) is the sum of log likelihood values from the two single equation models.

6.3 Model Selection

In the empirical analysis, both the simultaneous equation model (SEM) and separate single equation models were estimated. The former is the two equation simultaneous model described in Chapter 5.3 which treats the insurance binary variable on the right hand side of the hospital admission equation as endogenous. Under the SEM, the correlation parameter ρ measures the degree of correlation between the unobservables in the hospital admission and insurance equations. For the single equation models, the hospital admission and insurance equations were estimated using the lognormal random effects Poisson and the probit regression model respectively. Table 6.2 reports the estimates of the arc-tangent function of the correlation parameter, the log-likelihood values and the informational criteria values from the SEM and the single equation models. The information criterion statistics presented are the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC).

As reported in Table 6.2, the estimate on the correlation parameter ρ is not statistically significant. This result suggest that the insurance binary regressor in the hospital admission equation is exogenous and that the hospital admission and insurance equations may be estimated separately. The results from the model selection criteria are supportive of this view. Based on the LR statistics, one cannot reject the null hypothesis that $\rho = 0$. The AIC prefers the SEM while the more stringent BIC indicated that Model 2 is preferred. Hence, there is strong justification for estimating separate single equation models over the SEM. Given this result, the discussion in the following sections will be based on the estimation results from the use of the probit regression to model the demand for hospital insurance and the lognormal random effects Poisson to model the demand for hospital admission.

6.4 Demand for Hospital Insurance

Columns 2 and 3 of Table 6.3 presents the marginal effects and their respective standard errors[3] in the regression analysis for the demand for private hospital insurance. Given the nonlinear nature of the probit model, the regression coefficients cannot be interpreted directly as it is with linear regression models. Hence, the discussion focuses on the marginal effects, which are interpreted as the increase in the probability of being insured given a change in the explanatory variable.[4]

6.4.1 Demographic Variables

Holding all else constant, the propensity to purchase private hospital insurance by females is higher than that for males. The marginal effect of change in the female binary regressor on the probability of insurance is 0.035. On average, the proportion of females with private health insurance is 3.5 percentage points greater than males. The propensity to insure is positively associated with age. An additional year corresponds to a 1 percentage point increase in the probability of insurance.

On the propensity to insure by income unit types, individuals from couple income units are 0.91 percentage points more likely to purchase private health insurance compared to individuals from singles. Similarly, income units with dependent children are 5.4 percentage points more likely than units without dependents to be privately insured. There is evidence that the propensity to insure depends on whether or not individuals were born in Australia, with the results suggesting that respondents born outside of Australia are less likely to have private health insurance. The proportion of individuals from main English speaking countries (e.g. Zealand, Ireland and United Kingdom) with private health insurance is 11.6

[3]The standard errors of the marginal effect coefficients are computed via the delta method using the -predictnl- command in Stata.

[4]For binary explanatory variables, dF/dX denote the change in $P(Insured\,|\,X)$ when the explanatory variable X changes from 0 to 1. For continuous variables, dF/dX_k is computed as $\phi(X\hat{\beta}) \cdot \delta(X\hat{\beta})/\delta X_k$.

Table 6.3: Regression Results - Demand for Hospital Insurance & Admissions

	N=14,594			
	Hospital Insurance		Hospital Admissions	
	dF/dX	S.E	dF/dX	S.E
Heterogeneity σ [a]			-0.935***	0.026
Insurance			0.014***	0.004
Female	0.035***	0.011	-0.0056	0.007
Age	0.0099***	0.00050	-0.00041**	0.0002
Childbearing			0.038***	0.015
Couple	0.091***	0.010	0.0011	0.004
Depchild	0.054***	0.012	0.0041	0.004
Country of Birth:				
Main English	-0.116***	0.013		
Others	-0.117***	0.013		
Health Card	-0.202***	0.015		
Education:				
Vocational	0.019	0.012		
Diploma	0.052***	0.016		
Degree	0.109***	0.016		
Household Inc[b]	0.045***	0.002	0.0039	0.0072
Household Inc-Sq				
Employment Status:				
Full-Time			-0.040***	0.0062
Part-Time			-0.018***	0.0046
Occupation:				
Manager/Admin	0.142***	0.024		
Professional	0.019	0.020		
Asc Professional	0.039*	0.021		
Tradesperson	-0.043*	0.022		
Adv Clerical/Service	0.116***	0.035		
Int Clerical/Service	0.0035	0.019		
Production/Transport	-0.074***	0.024		
Ele Clerical/Service	-0.0070**	0.0032		
Labourer	-0.117***	0.023		
ICD10:				
Infectious/Parasitic	-0.052	0.040	0.021	0.016
Neoplasm	0.038	0.026	0.092***	0.015
Blood	-0.020	0.033	0.016	0.011
Endocrine	0.029**	0.013	0.011	0.0044
Mental/Behavioural	-0.029**	0.014	0.0050	0.0047
Nervous	0.015	0.016	0.0075	0.0053
Eye	0.050***	0.012	0.0082	0.0042
Ear	-0.019	0.012	0.0076*	0.0043
Circulatory	-0.0088	0.012	0.025***	0.0046
Respiratory	0.0038	0.010	-0.055*	0.0033
Digestive	0.015	0.015	0.052***	0.0074

Continue on the next page

Table 6.3: Continued from the previous page

	N=14,049			
	Hospital Insurance		Hospital Admissions	
	dF/dX	S.E	dF/dX^a	S.E
Skin	0.030	0.022	-0.00034	0.0071
Muscular	0.0033	0.010	0.010***	0.0036
Genitourinary	0.043**	0.022	0.050***	0.0097
Congenital	0.069	0.047	0.018	0.017
Others	0.013	0.014	0.021***	0.0053
Alcohol 3-day Risk	-0.037***	0.013		
Smoker Regular	-0.168***	0.011		
Region				
VIC	0.027*	0.015	-0.0029	0.0050
QLD	0.016	0.016	-0.0094*	0.0049
SA	0.062***	0.015	-0.066	0.0048
WA	0.071***	0.017	0.0097	0.062
TAS	0.085***	0.019	-0.011*	0.056
NT	0.241***	0.056	0.0066	0.023
ACT	-0.045**	0.020	-0.0090	0.065
Remoteness				
Inner Aus	-0.048***	0.013	0.046	0.0044
Others	-0.098***	0.014	0.040	0.0050

***, **, * denote significance at 1%, 5% and 10 % respectively.

a. This refers to the estimate of standard deviation of the heterogeneity term σ.

b. Marginal effect given a \$100 increase in weekly household income.

percentage points lower compared to their Australian born counterparts. Those born in countries in the 'Others' category (e.g. Germany, Vietnam and Italy) are 11.7 percentage points less likely to have insurance.

It can be argued that the age and income unit type variables discussed above performs in part the role of proxies for the 'economic price' of hospital insurance. This 'price' of insurance is commonly defined as the difference between the insurance premium and the expected benefit or payout (Phelps 1997).[5] In Australia, regulations require that insurance premiums be community rated. Insurance funds are not allowed to discriminate on the basis of age, sex, health

[5]One approach to express the price of insurance is the ratio of the insurance premium and the expected benefits (Butler 1999). In this specification, the ratio of premium to expected benefit is interpreted as the price paid per dollar of expected benefits received. If the premium is actuarially fair, that is the premium equals the expected benefit, the price of insurance is 1. With the presence of a loading fee L applied by insurers unto insurance premiums, the price of insurance is given as $(1 + L)$.

status and claims history in setting the premiums.[6] With community rated premiums, given that the benefits from insurance is expected to be increasing with age[7], the economic price of insurance is hence expected to be negatively correlated with age. Therefore, the observed positive effect of age on the propensity to insure may in part represent this economic price effect. In addition, to the extent that individuals' health deteriorates with age, the age variable may capture the health effects if heterogeneity in individuals' health status are not completely or adequately accounted for using the health status measures available in the data. In terms of the propensity to insure across income unit types, we should expect that the probability of having insurance is higher in income units with dependent children as compared to those without given that the economic price of insurance is comparatively lower for the former.[8] This is consistent with what we observe from the results.

Differences in the propensity to insure across income unit types may be the outcome of the interaction between residual household income effects and the incentivisation through the Medicare Levy Surcharge. 'Couple' income units on average have higher equivalised household income as compared to 'single' income units.[9] Hence, the positive marginal effect of the couple binary variable may capture additional income effects that remain after having accounted for households' equivalised income. The difference in the propensity to insure between couple

[6]An exception to community rated premium is the Lifetime Community Rating policy that came into effect in July 2000 which allows private health insurance funds to vary insurance premiums according to individuals' age at the time of first purchase of private health insurance and the number of years individuals remained insured.

[7]Butler (1999) constructed estimates of hospital benefits of individuals by age, sex and state in 1995 using data published by the Private Health Insurance Adminstration Council (PHIAC). In the author's calculations (see Figure 1, p.14), the age gradient in hospital benefits for males is approximately flat between the ages of 5 to 39, moderately increasing for ages 40 to 59 years and rapidly raising for ages 60 years and above. The hospital benefits estimates for females are similar in trend to the males, except for the ages 20 to 44 years where the benefits received by females within these age groupings are high as a result of using private hospital services for maternity and childbearing.

[8]Butler (1999) argues that cross-subsidisation in favour of families with children may occur as a result of community rated premiums which allow the premium for couples to be double that of singles but do not allow for any further premium increases according to the number of dependent children. The author showed that the estimated price of hospital insurance is lower for family as compared to singles policies for all ages up to 50-54 years.

[9]Based on approximation from the interval-value measure of equivalised household income available in the data, the mean equivalised household income for couple and single income units in the sample are \$633.89 and \$413.68 respectively. The average unequivalised household income for couple units can be calculated as \$633.89 x 1.5 = \$950.84, where the latter is the equivalence weight for a two-adult household. For single units, the equivalised and unequivalised household income are the same.

and single income units is obfuscated by the Medicare Levy Surcharge income threshold which for couples is double that for single individuals. Untangling the income effects from those induced by the Medicare Levy Surcharge will require more detailed information on households' income which is not available in this data set.

6.4.2 Socioeconomic Variables

Moving on to the socioeconomic factors that influence the purchase of insurance, the propensity to purchase private hospital insurance is positively associated with income of households. An increase of $100 in the weekly equivalised cash household income is associated with an increase in the probability insurance by 4.5 percentage points. This result is likely to be driven by pure income effects and well as the incentives created through the Medicare Levy Surcharge as discussed above. Post-school educational attainment is positively associated with the purchase of insurance. Individuals with diplomas, and with bachelor degrees or higher, are 5.2 and 10.9 percentage points more likely respectively to be privately insured than those with their counterparts with no post-school education qualifications. A significant factor that influences whether individuals purchase private hospital insurance is the availability of government health concession cards.[10] The regression estimates indicate that individuals with concession cards are 20.2 percentage points less likely to be privately insured. Those with concession cards are more likely to be less economically well off, older and of poorer health status. These individuals may perceive themselves as being high users of public hospital care and hence do not need to have private hospital insurance. The propensity to insure differs across occupational groups where individuals in professional and related occupations such as managers and administrators are more likely to purchase private health insurance whereas those in production/transport or are labourers are less likely to have insurance. The reference category here comprises of unemployed individuals and those who are not in the labour force.[11]

[10] Types of government health concession cards include the Pensioner Concession Card, Health Care Card, Commonwealth Senior Health Card and the Department of Veterans' Affairs Card. Cardholders are generally eligible for a range of health care related concessions from cheaper prescription medicines, bulk-billed General Practitioner appointments and higher benefits under the Medicare Safety Net.

[11] An alternative variable that may be used to examine the effect of occupation or employment on insurance purchase is the individuals' employment status. There is no difference in the propensity to purchase insurance among individuals who are in either full-time or part-time

6.4.3 Health Status and Health Risk Factors

Three sets of explanatory variables that describe respondents' health were separately included in the regression analysis. First, a set of dummy variables representing the sixteen ICD10-AM disease categories[12] of long-term chronic conditions reported by survey respondents were included to capture heterogeneity in the health status of individuals. Mental and behavioral problems and medical conditions associated with the circulatory & muscular system and of the ear are negatively associated with insurance purchase. Having a chronic medical condition of the endocrine system (e.g. diabetes, high cholesterol) and conditions relating to the eye (e.g. cataract, glaucoma) are positively associated with the purchase of insurance. It is particularly surprising that having a chronic condition of the circulatory system is negatively associated with the propensity to purchase insurance given that the conditions that fall within this category such as ischaemic heart diseases, haemorrhoids and varicose veins are associated with high volumes and long waiting lists in public hospitals (Australian Institute of Health and Welfare 2008). The second measure of health status is the number of long-term chronic medical conditions from which individuals suffered. This measure reflects the extent of good health of individuals, where a higher number of chronic conditions implies a lower health status. The results indicate that the propensity to purchase insurance is increasing in the number of long-term medical conditions. The third measure of health status did not produce any statistically significant results. This is a binary variable that indicates if the individual has at least one chronic condition requiring medical procedures that are associated with high volume and hence long waiting lists in public hospitals.[13] One would expect that the presence of medical conditions for which treatment is associated with

---

employment as compared with the individuals who are unemployed or not in the labour force.

[12]The sixteen categories are infectious and parasitic diseases; diseases of the neoplasm; disease of blood and blood forming organs; endocrine, nutritional and metabolic diseases; mental and behavioural problems, diseases of the nervous system; diseases of the eye and adnexa; diseases of the ear and mastoid; diseases of the circulatory system; diseases of the respiratory system; diseases of the digestive system; diseases of the skin and subcutaneous system; diseases of the musculoskeletal system and connective tissue; diseases of the genito-urinary system; congenital malformations, deformations and chromosomal abnormalities; symptoms, signs and conditions not elsewhere classified.

[13]These conditions are referred to as *indicator procedures* (Australian Institute of Health and Welfare 2003): cataract extraction, cholecystectomy, coronary artery bypass graft, cystoscopy, haemorrhoidectomy, hysterectomy, inguinal herniorrhaphy, myringoplasty, myringotomy, prostatectomy, septoplasty, tonsillectomy, total hip replacement, total knee replacement and varicose veins stripping and ligation.

long waiting times in public hospitals to be positively associated with private hospital insurance purchase.

The probability of purchasing insurance is positively associated with good health habits. Health risk factors such as alcohol risk and regular smoking generally decrease the propensity to purchase private hospital insurance.[14] These variables behave as proxies for individuals' health status, risk aversion and attitudes towards good health.

6.4.4 Geography

Dummy variables representing the states and territories in Australia and the remoteness classification of respondents' residences are included to capture the geographical effects on the propensity to purchase insurance. Individuals living in Victoria, South Australia, Western Australia and the Northern Territories have a higher probability of purchasing private hospital insurance relative to those living in New South Wales. On the propensity to insure by remoteness classification, individuals residing in inner and outer regional areas of Australia are less likely than their counterparts living in major cities to purchase private hospital insurance. This may be because private hospital facilities are limited in supply in regional areas (Lokuge et al. 2005), hence reducing the incentives for individuals residing in more remote parts of Australia to purchase insurance.

6.5 Demand for Hospital Admissions

Columns 4 & 5 of Table 6.3 presents the regression results for the demand for hospital admissions. First and foremost, the coefficient on the estimate of σ on the heterogeneity term is -0.94 and statistically significant. This result suggests the presence of overdispersion in the data while implies that the use of the simple Poisson regression model is inappropriate.[15]

[14]Cutler et al. 2008 showed that risk tolerance affects the propensity to insure in addition to risk type. The authors examined the purchase of five types of insurance: life insurance; acute private health insurance; annuities; long-term care insurance and supplementary Medigap plans in the United States. The results showed that individuals who undertake risky activities (smoking, have a drinking problem, possess a risky job) or do not engage in risk reducing behaviour (usage of preventive health care and seat belts) are less likely to purchase these insurance. The effects of risk preference heterogeneity varies across the five insurance markets.

[15]For a Poisson lognormal model, the conditional variance $V[m_i \mid X_i]$ is given by $E[m_i \mid X_i, \xi_i]\{1 + \tau E[m_i \mid X_i, \xi_i]\}$ where $\tau = [\exp(\sigma^2) - 1]$ (See equations 2.2-23 and 2.2-26

The marginal effect of the insurance variable as presented in Table 6.3 is 0.014 and is statistically significant. The interpretation of this result is that the difference in the expected number of hospital admissions per year between individuals with insurance and those without insurance is 0.014. An alternative interpretation of the insurance effect is the proportional change in the expected number of hospital admissions when the insurance binary variable changes from 0 to 1. This is calculated as the exponential on the coefficient estimate on the insurance binary variable.[16] For a coefficient estimate of 0.173, the annual number of hospitalisations by those with private health insurance is 1.19 times the number of those without such insurance. Everything else constant, this estimate suggest that having private hospital insurance increases the expected number of hospital admission by 19 percentage points each year. Given that the definition of hospital admission in question includes both admissions into public and private hospitals, the positive insurance effect on hospital admissions is likely to be driven by the higher frequency of private hospital admissions by individuals with private hospital insurance as compared to those without. This result is expected and consistent with the results from the theoretical model discussed in Chapter 3.3.1 which showed that the availability of insurance reduces the effective monetary price for private hospital care and increases utilisation.

Moving on to the demographic variables, the demand for hospital admissions is higher for females in their childbearing years of 25 to 40. The frequency of hospital admissions by females in this age category is 0.038 more than for women in the other age categories. The intensity of hospital admissions does not vary across couple or single income unit types or whether households have dependent children. From the estimate of the marginal effect, age has an overall positive effect on the frequency of hospital admissions. The coefficient estimates which were not reported above revealed a quadratic relationship between age and the intensity of hospital care use: the expected number of hospital admissions initially decreases with age and before increasing at higher age values.

Of the socioeconomic variables, the expected number of hospital admissions are 0.040 and 0.018 less for individuals engaged in full-time and part-time employment respectively relative to those who are unemployed. As suggested by the

in Greene (2007)). Overdispersion is present in the data if $V[m_i \mid X_i] > E[m_i \mid X_i, \xi_i]$ which occurs if $|\sigma| > 0$.

[16]The proportional change in the expected number of hospital admissions arising from a change of the binary variable from 0 to 1 is calculated as $E(m \mid d = 1, X)/E(m \mid d = 0, X) = e^{\beta_d}$ where β_d is the coefficient on the insurance binary variable.

results of the theoretical model, a possible explanation for this empirical result is that working individuals face a higher opportunity cost of time involved in seeking hospital care and hence utilise hospital care at a lower intensity. The intensity of hospital admissions is not influenced by individuals' household income.

In terms of the effects of health status on the intensity of hospitalisation, the expected frequency of hospital admissions is increasing in the number of chronic conditions that individuals have. An additional chronic condition increases the expected frequency of hospitalisation by 0.018 (Not reported in Table 6.3). Of the ICD-10 chronic conditions binary variables, having diseases of the Neoplasm, Ear, the Circulatory, Digestive, Muscular and Genitourinary systems are positively associated with a higher number of hospital admissions. In contrast, having a respiratory condition is negatively associated with the utilisation of hospital care.

Lastly, on the geographic variables, respondents from Queensland and Tasmania are hospitalised at a lower frequency as compared to their counterparts from New South Wales. The frequency of hospital admissions does not appear to vary by the remoteness of localities.

6.6 Discussion and Concluding Remarks

The initial results from the simultaneous equation model suggest that the insurance binary variable in the hospital admission equation is not endogenous. An implication is that the hospital admission equation and the insurance equation may be estimated using two separate regressions. One conclusion that can be drawn from the exogeneity of the insurance variable is that there is no evidence of self selection into insurance. As discussed in Chapter 2.4, insurance status may be correlated with individuals' health status which can be either unobserved or inadequately accounted for with the health status proxies that are available. Although there is no evidence of self selection, the estimates of the insurance effect on hospital admissions suggest the presence of moral hazard. The expected number of hospital admissions is 19% higher for individuals with private health insurance as compared to those who are not privately insured. The results obtained in this study are consistent with the literature in on some aspects but differ on others. Cameron et al. (1988) and Harmon and Nolan (2001) found evidence of both self selection and moral hazard in hospital use for the case of Australia and the UK respectively.[17] Riphahn, Wambach, and Million (2003) found evidence of adverse selection into add-on insurance using German data but concluded that there are no moral hazard effects once self selection has been accounted for.

There is one important caveat in using the term "moral hazard effects" for the estimated insurance effects in this study. Within the context of a health system where both public and private health care coexist, the moral hazard effects refers to the incremental use of *private* health care resulting from a decrease in the effective price of private health care due to the presence of private insurance. In this study as well as those that were cited above, information on whether the hospital use was public or private was not available and hence the estimated insurance effect here is the incremental utilisation of *both public and private* hospital care as a result of private health insurance. The issue of the moral hazard effect of private health insurance is re-examined in Chapter 7 using data on hospital length of stay where information is available on whether the hospitalisation episode in question was public or private.

The results obtained in this study on the determinants of private health insurance status are broadly consistent with Australian studies by Cameron and Trivedi (1991) and Savage and Wright (2003) as well as those from international studies. Demographic and socioeconomic factors such as age and gender, marital status, education attainment, household income and the availability of government concession cards have significant influences on the propensity to insure. Health status appears to have a more limited effect in the decision to purchase insurance but this result is not unexpected given that the purpose of private health insurance is to insure against medical expenditures in private hospitals. Individuals who are of significant health risk and expect to incur large expenditures on medical care have access to hospital care in the public system at zero monetary cost.

[17] The presence of self selection effects were not explicited mentioned in Harmon and Nolan (2001) but the authors found that the insurance effects roughly doubles from 3.1% if insurance status is taken as exogenous to 5.8% when insurance is treated as endogenous. This result is indicative of the presence of advantageous selection as opposed to adverse selection into insurance that is more frequently observed in insurance studies.

Chapter 7

Demand for Public & Private Hospital Care and Hospital Insurance

7.1 Introduction

As reviewed in Chapter 2, previous Australian studies have examined the relationship between private health insurance and the intensity of health care use (Savage and Wright 2003, Cameron et al. 1988) while several Australian and UK studies have investigated the determinants that influence the choice between public or private health care (Srivastava and Zhao 2008, Propper 2000, Martin and Smith 1999). The results presented here is the first attempt to empirically examine the demand for health insurance, public or private choice and the intensity of health care in a simultaneous framework. The results are based on the three-equation econometric model described in Chapter 5.4 which accommodates the count data feature of hospital length of stay and the binary public-private type and insurance outcomes variables. The simultaneity between the intensity of hospital use, and the decisions to seek public or private hospital care and purchase private health insurance are considered in the econometric modeling.

The chapter is organised as follows: The choice of explanatory variables for the insurance, patient-type and length of hospital stay equations are first discussed in Section 7.2. Issues pertaining to the identification of the econometric model and the number of simulation draws are presented here. Issues on model selection between the simultaneous equation model, the nested variants and the single equation version are discussed in Section 7.3. The empirical results of how private hospital insurance influences the choice of public or private hospital care, and how the intensity of hospital care, vis-à-vis the length of hospital stay, varies by patient type and insurance status are detailed in Section 7.4. Section 7.5 further explores the determinants that influence the choice of patient type and the intensity of care. Section 7.6 discusses the sensitivity of the results to the imputations on the length of stay dependent variable. Section 7.7 concludes with a discussion of the results. The determinants of the demand for private hospital insurance have been discussed in Chapter 6. Given that the results for the sub-sample are comparatively similar to that of the full sample, the discussion would not be repeated here. As a reference, the regression results on the determinants of the demand for private hospital insurance are presented in Appendix C located at the end of this chapter.

7.2 Explanatory Variables, Exclusion Restrictions and Simulation Draws

Table 7.1 presents the explanatory variables included in the length of stay, public/private patient type and insurance equations. The first set of explanatory variables described in the table are the endogenous patient type and insurance variables that were included on the righthand side of the length of stay and patient type equations. In the former, an interaction term consisting of the two endogenous variables was included. The inclusion of these variables was guided by the results from the economic model described in Chapter 3 in which the expressions of the optimal intensity of hospital care varies by the insurance and patient type choices. From the perspective of the empirical analysis, the interaction term allows one to examine the effect of private health insurance on the length of hospital stay for public and privately admitted patients separately. In the public/private patient type equation, a private health insurance dummy variable was included as a regressor given that the decision on the choice to receive hospital care as a public or private patient is expected to depend on the availability of private hospital insurance.

The remaining explanatory variables in each of the three equations are classified into the following categories: demographics; socioeconomic characteristics; health risk; health status and geographic indicators. To facilitate the comparison

Table 7.1: Explanatory variables in each of the three equations

	Equations		
Endogenous Regressors	**Length of Stay**	**Public/Private**	**Insurance**
Public/Private Patient	x		
Insurance	x	x	
Insurance*Public/Private	x		
Exogenous Regressors			
A. Demographics			
Female	x	x	x
Income Unit: Dependents	x	x	x
Income Unit: Couple	x	x	x
Age, Age-squared	x	x	x
Childbearing	x		
Country of Birth		x	x
B. Socioeconomic			
Income, Income-squared	x	x	x
Education			x
Employment Status	x		
Employment Sector		x	
Occupational Category			x
Health Concession Card			x
C. Health Risk			
Regular smoker		x	x
Alcohol		x	x
D. Health Status			
ICD-10 Chronic Conditions	x	x	x
E. Geography			
State/Territories	x	x	x
Remoteness	x	x	x

of the results in this study with related studies such as Cameron et al. (1988), Cameron and Trivedi (1991), Savage and Wright (2003) and Propper (2000), a similar set of explanatory variables was chosen. Demographic variables such as gender, income unit type and age are included in all three equations. A child-bearing variable, which is a binary variable that represents females between the ages of 25 to 40 years was included to capture the effects of childbearing on the length of hospital stay. Country of birth was included in the patient type and insurance choice equations. Of the socioeconomic variables, the equivalised household income was included in all three equations. The level of educational attainment was included as a regressor in the insurance equation. Three different variables capturing information on the individual's employment characteristics were included in each of the three equations. The first variable is the employment status of individuals, that is whether respondents were employed full-time, part-time, unemployed or not in the labour force (NILF). The employment sector variable reflects whether employed individuals work in the public or private sector. These two employment variables were included in the length of stay and public/private choice equations respectively. Lastly, information on individuals' occupation type was included in the insurance equation. Also in the insurance equation is information on whether or not the individual has a health concession card. Health risk factors such as tobacco and alcohol consumption are included in the public/private patient type and insurance equations. Health status indicators, which consist of binary variables of the ICD10 disease categories, are included in all three equations. Lastly, information on the locality of individuals' is captured by state/territory and remoteness dummies.

There is an issue of whether or not the econometric model is identified given the presence of endogenous regressors in the length of stay and public/private patient equations. Formally speaking, the model is identified by the nonlinearity of the functional form assumed.[1] To add robustness to to the identification of the model , exclusions restrictions are applied in that there is at least one variable in the insurance equation but not in the patient type and length of stay equations. In addition, there should be at least one variable in the patient type equation that is not in the length of stay equation. To this effect, as in the case for Chapter 6, variables measuring health risk such as smoking and alcohol consumption are included only in the insurance equation. The employment sector variable is

[1]See point 6 on page 668 of Greene (2000).

Table 7.2: Estimates of correlation parameters & model selection

Model	Correlation[a]			Selection Criteria		
	ρ_{12}	ρ_{13}	ρ_{23}	Loglikelihood[c]	AIC	BIC
(1) SEM	0.205	0.160	-0.382***	-6792.56	13851.11	14624.80
(2) Single Eq ($\rho_{ij} = 0$)				-6796.13	13852.26	14838.75

Model	Null H_0	LR Stat	Best Model		
			LR Test	AIC	BIC
(1) vs. (2)	$\rho_{ij} = 0$	-7.14	(1)	(1)	(1)

***,**, * denote significance at 1%, 5% and 10% respectively.

a. The correlation parameter estimates reported here are the arc-tangent functions of the correlation parameter ρ

c. The log likelihood value for Model (4) is the sum of log likelihood values from the three single equation models.

included only in the patient type choice equation as there is some evidence in Propper (2000) that public sector workers are more likely to seek public hospital care.

Moving on to the issue on the number of simulations, the choice of the number of simulations S was determined in a stepwise manner in which S is increased from 50 to 2000 as described in Chapter 5.5. The choice on the number of simulations is determined as the lowest number of simulations for which the estimates obtained are observed not to vary significantly with higher values of S. The analysis below used S=2000 based on Halton quasi-random draws.[2] Convergence was achieved after 150 iterations requiring approximately 7 hours to complete on an Intel 2.67 Ghz processor with 6 GB RAM.

7.3 Model Selection

In the empirical analysis, the full simultaneous equation model (SEM) described in Chapter 5 was estimated. This model treats the insurance and public/private patient choice binary variables on the right hand sides of the length of stay and patient type choice equation as endogenous. Under the SEM, in addition to the coefficients parameters on the regressors, three correlation parameters that measure the degree of correlation between the endogenous regressors and the unobservables in each of three regression equations were estimated. In addition,

[2]If one were to take the choice on the number of simulations S=2000 given the sample size N=8129 in Deb and Trivedi (2006) as a point of reference to decide on the number of simulations required for the sample size of N=2406 in this study, the minimum number of simulations required to fulfil the consistency requirement (that S increases more than $\sqrt{N}$) is $2000 - \sqrt{8129 - 2406} \approx 1924$.

each of the three equations was estimated separately as single equation models. Table 7.2 reports the estimates of the arc-tangent function of the correlation parameters, the log-likelihood value, and information criterion values from the full SEM and the single equation models. The information criterion statistics presented are the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC). Model 1 refers to the full SEM. In Model 2, the single equation model for the length of stay equation is the lognormal random effects Poisson and the single equation model for the public/private patient choice and the insurance choice was the probit model. Examining the estimates of the correlation parameters from Model 1 using Table 7.2, one observes that only the correlation parameter ρ_{23} is statistically significant from zero. Both parameters ρ_{12} (p-value = 0.41) and ρ_{13} (p-value = 0.28) were found be statistically insignificant.

Formal statistical methods were employed to assist in choosing between models 1 and 2. The three methods are the log likelihood ratio test (LR) and the information criterion AIC and BIC. The results from the model selection tests are presented at the bottom of Table 7.2. For the LR test, the null hypothesis H_0 and the LR statistics (LR Stat) are presented. The results indicate a strong preference for the SEM over the single equation models.

In the light of this result, the discussion of the empirical results in the following section will based on Model 1. In the discussion of the insurance and patient effects on hospital length of stay in Section 7.4, the results from Model 1 will be compared with that obtained under separate single equation models (Model 2) to examine how the regression estimates differ under the endogeneity and exogeneity assumptions of the public/private patient type and insurance binary variables.

7.4 Insurance and Patient Type Effects

Table 7.3 presents the coefficients, marginal effects and the respective standard errors of the insurance and patient-type binary variables in the public/private choice and hospital length of stay equations. Two sets of coefficients are presented, with each obtained under the endogeneity and exogeneity assumptions. Under the former, the results are that obtained from the simultaneous equation model (henceforth joint model). Under the exogeneity assumption, the public/private patient type and the insurance binary variables are treated as exogenous regressors in the length of stay and public/private choice equation. The single equation

Table 7.3: Key coefficients and marginal effects under endogenous and exogenous assumptions

	Endogenous				Exogenous[a]			
	Coeff	S.E	dF/dX	S.E	Coeff	S.E	dF/dX	S.E
				Public/Private Patient				
Insurance	2.766***	0.179	0.815***[b]	0.030	2.253***	0.077	0.714***	0.017
				Hospital Length of Stay				
Patient-Type	-0.995***	0.514	-1.105*	0.570	-0.512***	0.159	-0.575***	0.174
Moral Hazard Effect[d]			0.429	0.279			0.479***	0.122
Insurance on Pub_Pat[c]			0.026	0.713			-0.036	0.127
Correlation Parameters								
ρ_{13}	0.205	0.249						
ρ_{13}	0.160	0.148						
ρ_{23}	-0.382***	0.147						
Log likelihood[e]	-6792.56				-6796.13			

***, **, * denote significance at 1%, 5% and 10% respectively.

a. Regression models under the exogenous assumptions are the lognormal random effects Poisson and Probit models.

b. P(Private Patient | Insured, $\bar{X}$) - P(Private Patient | Non-Insured, $\bar{X}$)

c. E(LOS | Insured, Public, $\bar{X}$) - E(LOS | Non-Insured, Public, $\bar{X}$)

d. E(LOS | Insured, Private, $\bar{X}$) - E(LOS | Non-Insured, Private, $\bar{X}$)

e. Under the exogeneity assumption, this refers to the sum of loglikelihood values from three single equation models.

Probit and the lognormal random effects Poisson regression models are applied to estimate the public/private choice equation and the hospital length of stay equation respectively. Estimates of the three correlation parameters from the joint model are presented at the bottom of Table 7.3. These estimates reflect the degree of correlation between the insurance binary variable and the unobservables in the public/private patient choice and hospital length of stay equation which provides evidence on whether the insurance binary variable is endogenous. The following discussion of the results focuses on the estimates from the joint model and where appropriate contrasts these results with that obtained under the exogeneity assumption.

In the *public/private patient choice equation*, the estimates of the coefficient and marginal effect of the insurance binary variable are positive and statistically significant. All else being equal, individuals with private hospital insurance are 81.5 percent points more likely to admit into hospital as a private patient rather than a public patient. This result is expected and is consistent with the results from the theoretical model discussed in Chapter 3.4.1 which showed that the availability of private hospital insurance reduces the effective monetary price for private hospital care and increase the probability that insured individuals seek private relative to public hospital care.

Moving on to the *hospital length of stay equation*, the marginal effect of the patient-type binary variable is -1.11 and is highly significant. The marginal effect of the patient-type binary variable is interpreted as follows: controlling for other explanatory variables that influence the intensity of hospital care, the average length of hospital stay by individuals who chose to be admitted as a private patient is 1.11 nights shorter than compared with publicly admitted (Medicare) patients. It is highly plausible that this result is driven by the presence of systematic differences in the types of medical treatments provided to individuals who seek private as opposed to public hospital care. Generally, patients who opt for private hospital care seek medical and surgical treatment for conditions that are elective in nature. Admissions for elective surgery typically involve shorter hospital stays where many are performed on a day-admission basis.[3] One can infer from the result that the patient type binary variable acts as a proxy for the case-mix that broadly differentiates the categories of medical conditions for which individuals seek public or private hospital care. This result is consistent with the insights from theoretical model. First and foremost, as demonstrated in Chapter 3.3.1, the optimal intensity of hospital care increases with illness severity. Secondly, individuals with more severe illness conditions are likely to seek public relative to private hospital care. Hence, to the extent that the severity of individuals' illness conditions is reflected in the need to use hospital care at a higher intensity, one can expect that individuals seeking public care stay in hospital for a longer duration of time as compared to those seeking private hospital care.

The insurance and patient-type binary variables, combined with an interaction term between the variables allow one to examine the effect of insurance on the length of hospital stay for private and public patients separately. Here, two effects are of interest. The first is the *moral hazard effect*[4] which is defined as the difference in the expected length of hospital stay between privately admitted individuals with or without private hospital insurance. From a theoretical

[3]Sundararajan et al. (2004) found that the increase in private hospital activity between 1998-99 and 2002-03 is driven largely by hospital admissions for surgical and elective procedures. This increase followed the expansion in the proportion of the Victorian population with private health insurance from 1997 to 2001. Hopkins and Frech (2001) examined the utilisation of public and private hospitals between 2000 and 2001 and found that the number of same-day separations from private hospitals increased significantly more than that of public hospitals

[4]The conditional mean equation is $\mathrm{E}(LOS \,|\, \beta_0 + \beta_1 patype + \beta_2 insurance + \beta_3 p\_type * insurance + \beta X)$. The moral hazard effect is calculated as $\mathrm{E}(LOS \,|\, insurance = 1, patype = 1, \bar{X})$ - $\mathrm{E}(LOS \,|\, insurance = 0, patype = 1, \bar{X})$.

perspective, as demonstrated in Chapter 3.3.1, individuals with private hospital insurance face a lower effective monetary price for private hospital care as compared to those without insurance. As a result, the former is expected to use private hospital care at a greater intensity. Hence, one would expect that the moral hazard effect is positive. Empirically, based on the data in this sample, there is no evidence to suggest the presence of the moral hazard effect among individuals who chose to receive private hospital care. The estimate of this effect is 0.43 but is not statistically significant. This is in contrast with the estimates obtained from under the exogeneity assumption which indicate that the expected length of private hospital stay by privately insured individuals is 0.48 nights longer than that for the uninsured.

The second result of interest is the effect of insurance on length of hospital stay for publicly admitted patients. This is termed as the *insurance on public patient effect*.[5] The insurance on public patient effect is defined as the expected difference in the length of stay between publicly admitted individuals with or without private hospital insurance. The theoretical results suggest that the availability of private hospital insurance does not affect the intensity of public hospital care amongst patients who chose to obtain public care. The empirical evidence supports this view. The estimate of the insurance effect amongst publicly admitted patients is not statistically significant.

The estimates of the correlation parameters ρ_{23} is statistically significant. This result suggest that the insurance binary variables in the length of hospital stay. This result supports the simultaneous equation approach in taking into account the endogeneity of the insurance binary variable in the specification of the econometric model.

7.5 Determinants of Patient Type Choice and Intensity of Care

The following two sections present the regression results on the determinants that influence the choice between hospital admission as a public or private patient and the length of hospital stay. The results are based on the joint model specification that was discussed in the preceding sections.

[5]The insurance on public patient effect is calculated as E($LOS \mid insurance = 1, patype = 0, \bar{X}$) - E($LOS \mid insurance = 0, patype = 0, \bar{X}$).

Table 7.4: Regression Results - Public/Private Choice and Hospital Length of Stay

	N=2,483			
	Public Private Patient		Length of Hospital Stay	
	dF/dX	S.E	dF/dX	S.E
Heterogeneity σ [a]			1.052***	0.031
Female	0.043	0.028	0.0067	0.082
Age	0.005***	0.001	0.022***	0.004
Childbearing			0.864***	0.216
Couple	0.026	0.030	0.104	0.078
Depchild	0.084*	0.038	0.197	0.111
Country of Birth:				
Main English	-0.030	0.038		
Others	-0.077**	0.036		
Household Inc[b]	0.017**	0.001	0.004	0.022
Household Inc-Sq				
Employment Status:				
Full-Time			-0.296***	0.103
Part-Time			-0.148	0.096
Employment Sector:				
Private	0.065	0.043		
Unemployed+NILF	0.028	0.047		
ICD10:				
Infectious/Parasitic	0.107	0.108	-0.117	0.262
Neoplasm	-0.077*	0.044	-0.058	0.130
Blood	-0.026	0.079	0.105	0.201
Endocrine	-0.057*	0.030	-0.030	0.082
Mental/Behavioural	-0.019	0.038	0.224**	0.108
Nervous	-0.089**	0.036	-0.065	0.104
Eye	0.052	0.035	0.055	0.090
Ear	-0.034	0.032	-0.070	0.083
Circulatory	-0.037	0.029	0.021	0.079
Respiratory	0.020	0.027	-0.048	0.069
Digestive	-0.037	0.033	0.013	0.091
Skin	-0.068	0.055	-0.040	0.146
Muscular	0.056**	0.027	-0.178**	0.077
Genitourinary	-0.021	0.043	-0.0024	0.118
Congenital	0.046	0.116	0.713*	0.420
Others	-0.012	0.034	0.103	0.093
Alcohol 3-day Risk	0.031	0.047		
Smoker Regular	-0.187	0.037		

Continued on next page

Table 7.4: Continued from previous page.

	Public Private Patient		Length of Hospital Stay	
	dF/dX	S.E	dF/dX	S.E
Region				
VIC	-0.005	0.042	0.139	0.120
QLD	0.117***	0.045	0.194	0.132
SA	-0.014	0.040	0.170	0.121
WA	-0.027	0.044	0.447***	0.155
TAS	0.137**	0.055	0.541***	0.185
NT	0.061	0.103	0.159	0.622
ACT	0.066	0.064	-0.122	0.159
Remoteness				
Inner Aus	-0.032	0.035	0.050	0.091
Others	-0.042	0.038	0.071	0.103

***, **, * denote significance at 1%, 5% and 10 % respectively.

a. The estimate refers to the coefficient on the heterogeneity term σ.

b. Marginal effect given a $100 increase in weekly household income.

7.5.1 Choice of Public or Private Patient

The marginal effect estimates of the regressors on the choice of hospital admission as a public or private patient are presented in columns 2 and 3 of Table 7.4. Of the demographic variables, holding all else equal, the presence of dependent children in the household and the respondents' age are positively related with the propensity to seek hospital care as a private patient. Compared with income units without dependent children, units with dependent children are 8.4 percentage points more likely to seek private hospital care. An increase in an individual's age by one year increases the probability of seeking private care by 0.5 percentage points. Individuals whose origin of birth is neither Australia nor the main English speaking countries are 7.7 percentage points less likely to seek private care compared to Australian born individuals. This result may be due to differences in the preference for private hospital care across individuals from different ethic and cultural backgrounds. The propensity for private hospital care does not differ by gender as well as between single and couple income unit types. Moving on to the socioeconomic variables, the propensity to seek private hospital care is positively associated with household income. A $100 increase [6] in the equivalised household income increases the propensity for private hospital care by 1.7 percentage points.

[6] The mean equivalised household income in the sample is $543.19 per week.

One key factor that influences individuals' choice of hospital admission as a public or private patient is the health condition for which hospital care was obtained. For example, one would expect that individuals are more likely to seek private care for elective treatments that are associated with long waiting times in the public hospitals. Unfortunately, information on types of medical conditions is not available in the data set that is used in this study. Instead, the ICD10 categories of long-term and chronic medical conditions that respondents are suffering from are used as proxies for individuals' health status. As reported in Table 7.4, having a neoplasm, or diseases of the endocrine or nervous system decrease the propensity that the individual seeks private hospital care. On the other hand, individuals suffering from diseases of the musculoskeletal system are more likely to have obtained private care.

Finally, there is evidence of a geographical effect on the patient type choice on hospital admission. Compared to respondents from New South Wales, individuals from Queensland and Tasmania are more likely to seek hospital care as a private patient. Individuals living in regional and rural areas does not appear to differ in their propensity to obtain public or private care when compared to their metropolitan counterparts.

7.5.2 Length of Inpatient Stay

Columns 4 to 5 of Table 7.4 presents the regression results for the expected length of stay in hospital. First and foremost, the positive and statistically significant estimate on the standard deviation (σ) of the heterogeneity term in the conditional mean strongly suggests the presence of overdispersion[7] in the data, which suggest that the simple Poisson regression model is inappropriate. For the demographic variables, holding all else constant, age has a small and positive effect on the length of time individuals stay in hospital. There is strong evidence linking a higher intensity of inpatient stay for childbirth given that females in the childbearing years stay in hospital for an average 0.86 nights more. Conditional on having accounted for childbearing effects, the intensity in the utilisation of hospital care does not differ by gender. In addition, the intensity of care does not appear to vary across income unit types.

[7] For the Poisson lognormal model, the conditional variance $V[m_i \mid X_i]$ is given by $E[m_i \mid X_i, \xi_i]\{1 + \tau E[m_i \mid X_i, \xi_i]\}$ where $\tau = [\exp(\sigma^2) - 1]$ (See equations 2.2-23 and 2.2-26 in Greene (2007)). Overdispersion is present in the data if $V[m_i \mid X_i] > E[m_i \mid X_i, \xi_i]$ which occurs if $\sigma > 0$.

Of the socioeconomic variables, the expected length of hospital stay is 0.30 nights shorter for individuals engaged in full-time employment relative to those who are unemployed. A possible explanation for this result may - as suggested by the theoretical model - that individuals in full-time employment face a higher opportunity cost of time involved in seeking hospital care which can otherwise be devoted to work or leisure. The length of hospital stay is not influenced by individuals' household income. In the length of stay equation, two sets of health indicators were included as proxies for individuals' health status. The first set of health indicators are the binary variables representing the ICD10 disease categories for chronic and long-term conditions. The second is a count measure of the number of chronic and long-term conditions from which individuals suffer. A priori, one would expect that individuals with poorer health should on average require a greater intensity of care when hospitalised. As presented in Table 7.4, mental & behavioural health conditions are associated with relatively longer length of stay. On the other hand, muscular conditions are associated with a lower intensity of hospital nights. Incidentally, as mentioned in the discussion of the results on admission choice as a public or private patient, individuals with muscular conditions are more likely to seek private as opposed to public hospital care. The marginal effect estimate on the count measure of medical conditions is not significant. This is contrary to expectations, though it is plausible that this definition of health status may not be sufficiently precise and sensitive to capture heterogeneity in health status severity, particularly in relation to defining the intensity of hospital care that individuals need.

Finally, in terms of the geographical effects, individuals from Western Australia and Tasmania have on average a longer length of stay as compared to those from New South Wales. Length of hospital stay does not appear to be influenced by remoteness of locality. To the extent that individuals' health status is adequately controlled for, the geographical variations in the length of stay observed for Western Australia and Tasmania may be indicative of differences in medical norms and practices surrounding the treatment of hospital patients.

7.6 Sensitivity Analysis

As discussed in Chapter 4, the length of hospital stay variable which was originally made available as intervals values have been imputed by their lower bound

Table 7.5: Sensitivity Analysis: Lower and Upper Bound Assumptions

Variable	Lower Bound		Upper Bound	
	Joint	RE Poisson	Joint	RE Poisson
Patient_Type	-1.105*	-0.575***	-1.235**	-0.635***
Moral Hazard	0.429	0.479***	0.517	0.545***
Ins Pub_Pat	0.026	-0.036	-0.072	-0.113

wherever they occur. To assess the sensitivity of the results to this imputation, the joint model and the single equation lognormal Poisson were re-estimated with the length of stay variable taking the upper bound values.[8] The estimates of the marginal effects on the patient type binary variable, the moral hazard effect and the insurance on public patient effect where the length of stay variable takes either the lower bound or upper bound value are presented in Table 7.5. In all three estimates, the magnitude of the marginal effects for the upper bound is slightly larger than that when the lower bound was used. For example, in the case of the joint model, the difference in the lower and upper bound estimate on the length of hospital stay by public and private patients is 0.13. Apart from small changes in the magnitude of the estimates, the results appear to be quite robust with respect to how the interval values are imputed.

A limitation of the strategy to replace the interval values by their lower and upper bound is that the upper bound for the largest category (8 nights or more) is unknown. As a result, the lower bound value of 8 nights was used in the sensitivity analysis involving upper bound values. This is likely to lead to an underestimation of the differences in the average length of stay between private and publicly admitted patients if the mean number of hospital nights by public patients in the largest category is greater than that for private patients. If the latter were to be correct, this further reinforces the study's findings that hospital admissions by private patients involve shorter length of hospital stay than public patients.

[8] Observations with interval values of "1 to 2 nights" were replaced by 2 nights, "3 to 4" nights by 4 and "5 to 7" nights by 7. Observations with "8 or more nights" take the value of 8 as before.

7.7 Discussion and Concluding Remarks

Individuals' decision-making on the utilisation of hospital services in the mixed public-private hospital system in Australia involve the decision on whether to purchase health insurance, to obtain public or private hospital care and the intensity of care. Previous Australia-based studies have examined only the demand for private health insurance and health care, while several Australian and UK studies have investigated the determinants that influence the choice of public or private health care. To my knowledge, this work is the first attempt to empirically examine the demand for health insurance, public or private choice and the intensity of health care in a simultaneous framework. This approach enables one to isolate and identify the intertwining factors that motivate the three decisions surrounding the use of hospital care. To achieve this, a simultaneous equation count data regression model was developed which allows for simultaneity in the insurance and patient type decisions. The empirical results revealed that insurance choice is an endogenous variable in both the public/private patient choice and the hospital care utilisation equation which supports the simultaneous equation modeling approach.

The results in the current study suggest that the availability of private hospital insurance is a key factor that influences the decision to seek hospital care as a private patient. This result is similar to that in Srivastava and Zhao (2008) where the authors found that individuals with private cover are 76 percentage points more likely to seek private hospital care relative to public care.[9] This result is also consistent with Gertler and Roland (1997) who found that private health insurance is associated with significant increases in the frequency of visits to private medical care providers and a reduction in visits to public providers for both curative and preventive care in the case of Jamaica. The findings in the current study also indicate that individuals' household income has a positive effect on the propensity to seek private hospital care. In addition to the traditional income effects, one possible channel by which income can affect the propensity for private hospital care is through the relationship between income and the monetary valuation of the time spent on hospital waiting lists (Propper 1990, 1995). If the

[9] Although both studies use the same dataset, the minor difference in this result compared with that obtained in the current study is likely to be due to the differences in the empirical strategy. For example, Srivastava and Zhao (2008) considers adults age 18 and over while this study focuses on respondents age 25 and over. There are also some differences in the explanatory variables that was used in both studies.

disutility of waiting on hospital waiting lists is positively associated with income, one would expect that high income individuals, all else being equal, would prefer private as compared to public hospital care in which the latter is frequently associated with significant waiting lists. Apart from insurance and income, the results from this study indicate that employment in the private sector, age and the presence of dependent children are factors that increases the probability of obtaining private hospital care.

The results in this study indicate that the average length of hospital stay by privately admitted patients is 1.11 nights shorter than that of public (Medicare) patients after controlling for the effects of other factors that influence the intensity of hospital stay.[10] This is suggestive that systematic differences exist in the types of medical conditions that individuals choose to seek public or private hospital care. This finding is consistent with the evidence presented in Sundararajan et al. (2004) and Hopkins and Frech (2001) and supportive of the view that the public hospital system is utilised by patients with more complex and severe medical conditions requiring a greater intensity of treatment than that in private hospitals.

From a policy perspective, the results of this study suggest that the impact of private health insurance on alleviating the burden on the public hospital system is not expected to be large. With the increase in the uptake of private hospital insurance, individuals that are most likely to substitute private for public hospital care are those already waiting on public hospital waiting lists or have been discouraged by the long queues and have forgone seeking treatment altogether. Given that the expected duration of wait on public hospital waiting lists is inversely related to the severity of medical conditions, and the urgency of treatments, what follows is that individuals who seek private hospital care do so for non-urgent medical conditions where the required treatment is simpler and elective in nature. Hence, the effects of government initiatives to encourage the purchase of private hospital insurance are likely to be limited to reducing public hospital waiting lists and lowering waiting times for public treatment. However, the available evidence suggests that this impact is likely to be small.[11]

[10] This is likely to be a lower-bound estimate given that the interval values of hospital length of stay available in the data are represented by their lower bound values.

[11] For example, Duckett (2005) concluded that contrary to popular rhetoric on the benefits and effectiveness of private health insurance in relieving demand on the public hospital system, funding the provision of elective surgery directly through the public system is likely to be more effective in reducing public hospital waiting times.

The empirical results in this study did not find any significant moral hazard effect amongst patients who sought hospital care as a private patient. This result is in contrast with the findings of Australian based studies by Savage and Wright (2003) and Cameron et al. (1988) who found significant moral hazard effects among specific sub-population groups. For example in Savage and Wright (2003), the authors estimated that the duration of private hospital stay is approximately 1.5 to 3.2 times longer amongst individuals with insurance for elderly couples, couples with dependents and young singles.[12] Similarly, Cameron et al. (1988) found a higher number of hospital days for insured relative to non-insured individuals in lower income groups but not for those in higher income brackets. Comparability of the results in this study from the preceding ones however is limited given that the studies differ in the data employed as well as the empirical methods. One significant methodological difference is that the current study adopted the approach of jointly modeling public/private hospitalisation choice and length of hospital stay and taking into consideration the endogeneity of the insurance variable in influencing these two outcomes. In comparison, the study by Savage and Wright (2003) examined the effects of insurance on the duration of hospital stay by considering only privately admitted patients while Cameron et al. (1988) on the other hand does not make the public/private distinction. A second difference lies in the treatment of the study sample in the analysis. Savage and Wright (2003) estimated separate regressions models for individuals from different ages groups and income unit types while Cameron et al. (1988) distinguished between individuals from different income groups. On this regard, given the constraints in the size of the sample in the current study, the approach here was to estimate a model using a pooled sample and to control for the effects of these covariates on the outcomes through the use of binary variables as regressors. An alternative is the use of interaction terms to allow the moral hazard effect to vary across sub-populations of interest but this approach is potentially cumbersome and is likely to lead to difficulties in the interpretation of the results given that it involves the interaction of at least three or four explanatory variables. One can consider estimating the simultaneous equation model developed in

[12] The authors found that the estimated moral hazard effect differs for individuals from different income unit composition. The length of hospital stay by elderly individuals from couple-type income units with private hospital insurance are 3.23 times higher than equivalent individuals who are uninsured. Duration of stay by privately insured couples with dependents are 2.78 times higher as compared to the equivalent without insurance. No evidence of moral hazard were observed for the remaining income unit groups.

this study using the same dataset that was utilised in Savage and Wright (2003) and adopting similar methodological approaches to validate their results. This however will not be addressed in this study and left as a potential area for future work.

In the analysis carried out in this chapter as well as Chapter 6, the use of goodness of fit to evaluate the performance of the single equation model against the simultaneous equation models would not be an appropriate strategy for model comparison. This is because the objective in the empirical analysis is not to maximise how well these models fit the data, but instead to obtain consistent estimates of the parameters. Of primary interest are the marginal effects of the insurance and patient type binary variables which in some applications are found to be endogenous due to the significance of some of the correlation parameters. This strongly suggest that the system of equation approach is necessary and justified. It would be to examine how the results would vary if different distributional assumptions were adopted. A potential candidate is the Negative Binomial regression model with latent factors which handles endogenous regressors. Variants of models that are similar to this were applied in Deb and Trivedi (2006) and Atella and Deb (2008). This however is beyond the scope of this study and may be another area for future research.

Chapter 8

Conclusions

8.1 Contributions and key findings of the study

This study contributes to the understanding of the determinants of individuals' decisions to seek hospital care and purchase private health insurance in a mixed public and private hospital system as that of Australia. In Chapter 3, a mathematical model with explicit function forms was developed to theoretically examine the determinants of the intensity of care hospital care use, the choice to seek public or private care and the decision to purchase private hospital insurance. One feature that differentiates this inquiry from those undertaken in previous studies is the use of explicit forms in the theoretical model. This strategy facilitates the use of comparative statics to identify how the utilisation and insurance decisions are influenced by the parameters of the model. A second feature of the study lies in the examination of the relationship between the severity of individuals' medical conditions and the decision to seek public or private health care. The theoretical model demonstrates that the intensity of health care use, the choice between public or private care and the decision to purchase insurance are interdependent. One key result from the analysis is that individuals with more severe medical conditions are expected to have a higher probability of seeking treatment from the public sector because the duration of wait for public care is shorter due to priority setting in the public sector which is based on the clinical urgency of patients' medical conditions. Also, the availability of private hospital insurance reduces the effective price of private hospital care and increases both the probability that individuals seek private treatment and the intensity at which private hospital care is utilised.

The structure of the theoretical model described in Chapter 3 was utilised as a guide to develop a novel simultaneous equation econometric model the accommodates count and binary outcomes variables as well as endogenous binary regressors. Although a variety of methods have been developed to analyse count data models with endogenous regressors, there has so far been little attempts to extend these models to a system of simultaneous equations. This is described in Chapter 5. The econometric model is employed in Chapter 6 to analyse the determinants of the intensity of hospital admissions and the decision to purchase private health insurance using household data from the 2004-05 National Health Survey in Australia. The endogeneity of the private health insurance binary regressor in the hospital admission equation is accounted for although the results indicate that there are no self selection effects into insurance. A key result from the analysis is that having private hospital insurance increases the expected number of hospital admissions by 19 percentage points each year. The findings also showed that the expected intensity of hospital admissions is higher for females in the childbearing years and for those who are not in employment.

Chapter 7 empirically examines the determinants of the intensity of hospital care use and the decisions to seek public or private hospital care and purchase private health insurance using a system of simultaneous equations. Previous studies have examined each of these separately or in combination with one other theme. The simultaneous equation model described in Chapter 5 allows for the simultaneity of the insurance and patient type decisions. The results suggest that the insurance binary variable is endogenous in both the public/private patient choice and hospital care utilisation equations. Individuals with private hospital insurance are 82 percentage points more likely to seek hospital care as a private patient. The results also show that the expected length of hospital stay by private patients is on average 1.11 nights shorter than that of public patients which suggests that systematic differences exist in the types of medical conditions for which individuals seek public or private treatment.

The empirical finding that hospital admissions by privately admitted patients involve shorter length of stay is consistent with the results from the theoretical model in Chapter 3 where it was shown that individuals with less severe medical conditions are expected to have a higher probability of seeking treatment from the private sector. Given that the expected duration of wait on public hospital waiting lists is inversely related to the severity of medical conditions, and the corresponding urgency of treatments, individuals who seek private hospital care is expected to do so for non-urgent medical conditions where the required treatment is simpler and elective in nature. The empirical result is also consistent with existing evidence in the literature which suggest that the public hospital system is utilised by patients with more complex and severe medical conditions requiring a greater intensity of treatment than that in private hospitals. On a policy dimension, the effects of government initiatives to encourage the purchase of private hospital insurance are likely to be limited to reducing public hospital waiting lists and lowering waiting times for public treatment.

8.2 Overall strengths and weaknesses

A key strength of this study lies in the structural approach to the empirical analysis. The econometric model that is employed is premised on a microeconomic model that describes how individuals make decisions to use hospital care and purchase private health insurance in a mixed public and private system such as that in Australia. From the theoretical model, we observe that the intensity of hospital care and decisions on patient type and insurance choices are outcomes of individuals' utility maximising behaviour. In the econometric modeling in Chapter 7, careful attention is given to account for the simultaneity of insurance binary variable in the patient type and hospital intensity equations as well as the patient type variable in the hospital intensity equation.

Overall, the lack of more detailed data on key outcome variables is an important limitation of the study. One limitation of the data is that information on the number of hospital nights is made available as interval values which constraints the richness of the data. Appropriate measures have been undertaken to overcome this limitations and sensitivity analysis have shown that the results obtained do not vary significantly. A second constraint with the data is that it captures information on individuals' patient type choice and length of stay only from the last hospital episode for which one cannot analyse the dynamics of hospital care use. Overall, the study utilises self-reported data for the analysis and, as with most self-reported data, there is the possibility of inaccurate reporting. However, in the absence of additional data that allows one to validate the accuracy of the data used in this study, it is impossible to determine the extent of misreporting.

8.3 Future research

One area for future research is to conduct policy simulations to examine how policy instruments (e.g. through the tax system) can influence changes to private health insurance and consequently the effects on the utilisation of public and private hospital care and health care expenditures. This area of inquiry has not been examined in this study as this exercise requires detailed information on household income and family structure, both of which are not available in the data. Two potentially feasible datasets that can be employed for this purpose are the Household Expenditure Survey collected by the Australian Bureau of Statistics and the Household, Income and Labour Dynamics in Australia (HILDA) data. These datasets contained detailed information on household income, expenditure and family composition which can be used to examine the impact of taxes on the decision to purchase private health insurance. These may be combined with the results from this study to predict the effects on the utilisation of hospital care. A second area of future research would involve the use of hospital administrative data such as the National Hospital Morbidity Database maintained by the Australian Institute of Health and Welfare (AIHW) or the Victoria Admitted Episodes Database. These datasets contains individual-level information such as length of hospital stay, patient admission and hospital types, diagnosis of medical conditions, and the medical treatments performed which can potentially be tracked across time. The nature of the data allows one to examine the dynamics of hospital care use which can potentially reveal interesting and policy relevant insights.

Bibliography

ABS (1995). A provisional framework for household income, consumption, saving and wealth. 6549.0 Australian Bureau of Statistics, Canberra.

ABS (2004). Australian demographic statistics. 3101.0, Australian Bureau of Statistics, 2004.

ABS (2005). Household income and income distribution, Australia.

ABS (2006a). National health survey - Confidentialised Unit Record Files. Information Paper 4324.0, Australian Bureau of Statistics, Canberra.

ABS (2006b). National health survey: User's guide - electronic publication 2004-05. 4363.0.55.001, Australian Bureau of Statistics, Canberra.

Anderson, L. R. and J. M. Mellor (2008). Predicting health behaviours with an experimental measure of risk preference. *Journal of Health Economics 27*, 1260–1274.

Arrow, K. J. (1963, December). Uncertainty and the welfare economics of medical care. *American Economic Review 53*(5), 941–973.

Arthur, D. V. (1976). Uncertainty, waiting time and capacity utilisation: A stochastic theory of product quality. *Journal of Political Economy 84*, 523–542.

Atella, V. and P. Deb (2008). Are primary care physicans, public and private sector specialists substitutes or complements? Evidence from a simultaneous equations model for count data. *Journal of Health Economics 27*, 770–785.

Australian Institute of Health and Welfare (2003). *Elective surgery waiting times National Minimum Dataset.* National Health Data Dictionary. Version 12. AIHW Cat. No. HWI 54. Canberra.

Australian Institute of Health and Welfare (2008). Australian hospital statistics 2006-07. Health Services Series No 31. Cat. no. HSE 55. Canberra: AIHW.

Barrett, G. F. and R. Conlon (2003). Adverse selection and the decline in private health insurance coverage in Australia: 1989-95. *Economic Record 79*, 279–296.

Barros, P. P., M. P. Machado, and A. Sanz-de Galdeano (2008). Moral hazard and the demand for health services: A matching estimator approach. *Journal of Health Economics 27*, 1006–1025.

Barzel, Y. (1974). A theory of rationing by waiting. *Journal of Law and Economics 17*, 73–95.

Becker, S. G. (1965). A theory of the allocation of time. *Economic Journal 75*, 493–517.

Besley, T. and S. Coate (1991). Public provision of private goods and the redistribtion of income. *The American Economic Review 81*, 979–984.

Besley, T., J. Hall, and I. Preston (1999). The demand for private health insurance: do waiting lists matter? *Journal of Public Economics 72*, 155–181.

Bhat, C. R. (2001). Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transport Research: Part B 35*, 677–693.

Bishai, D. M. and H. C. Lang (2000). The willingness to pay for wait reduction: the disutility of queues for cataract surgery in Canada, Denmark, and Spain. *Journal of Health Economics 19*, 219–230.

Butler, J. R. G. (1999). Esimating elasticities of demand for private health insurance in Australia. *National Centre for Epidemiology and Population Health Working Paper Number* 43.

Butler, J. R. G. (2002). Policy change and private health insurance: did the cheapest policy do the trick? *Australian Health Review 25*(6).

Cameron, C. A. and P. K. Trivedi (1986). Regression analysis of count data. *Journal of Applied Econometrics 1*, 29–53.

Cameron, C. A. and P. K. Trivedi (1991). The role of income and health risk in the choice of health insurance: evidence from Australia. *Journal of Public Economics 45*, 1–28.

Cameron, C. A. and P. K. Trivedi (1998). *Regression analysis of count data.* Cambridge University Press.

Cameron, C. A. and P. K. Trivedi (2005). *Microeconometrics: Methods and Applications.* Cambridge University Press, New York.

Cameron, C. A., P. K. Trivedi, F. Milne, and J. Piggott (1988). A microeconometric model of the demand for health care and health insurance in Australia. *Review of Economic Studies 55*(1), 85–106.

Centre for Spatial Economics (2008). The economic cost of wait times in Canada. January 2008.

Colombo, F. and N. Tapay (2004). *The OECD Health Project. Private Health Insurance in OECD Countries.* OECD.

Commonwealth Department of Health and Aged Care (1999). Private health insurance. Commonwealth Department of Health and Aged Care, Report No. 2571.

Costa, J. and J. Garcia (2003). Demand for private health insurance: how important is the quality gap. *Health Economics 12*, 587–599.

Cullis, J. G. and P. R. Jones (1986). Rationing by waiting lists: An implication. *American Economic Review 76*, 250–256.

Culyer, A. J. and J. G. Cullis (1976). Some economics of hospital waiting lists in the NHS. *Journal of Social Policy 5*, 239–264.

Cutler, D. M., A. Finkelstein, and K. McGarry (January 2008). Preference heterogeneity and insurance markets: explaining a puzzle of insurance. Working Paper 13746, National Bureau of Economic Research.

Cutler, D. M. and R. J. Zeckhauser (2000). The anatomy of health insurance. In A. Culyer and N. J.P. (Eds.), *Handbook of Health Economics*, Chapter 11. Elsevier Science B.V.

Deb, P. and P. K. Trivedi (2006). Specification and simulated likelihood estimation of a non-normal treatment-outcome model with selection: Application to health care utilisation. *Econometrics Journal 9*, 307–331.

Duckett, J. (2005). Private care and public waiting. *Australian Health Review 29*(1), 87–93.

Ehrlich, I. and G. Becker (1972). Market insurance, self-insurance and self-protection. *Journal of Political Economy 80*, 623–648.

Friedman, M. and L. J. Savage (1948). The utility analysis of choices involving risk. *Journal of Political Economy 56*, 279–304.

Gertler, P. and S. Roland (1997). Private health insurance and public expenditures in Jamaica. *Journal of Econometrics 77*, 237–257.

Goddard, J., M. Malek, and M. Tavakoli (1995). An economic model of the market for hospital treatments for non-urgent conditions. *Health Economics 4*, 41–55.

Goldman, D. and T. Philipson (2007). Integrated insurance design in the presence of multiple medical technologies. *NBER Working Paper* No. 12870.

Gouriéroux, C. and A. Monfort (1996). *Simulation-based econometric methods.* Oxford University Press.

Greene, W. (2000). *Econometric Analysis* (Fourth ed.). Prentice-Hall.

Greene, W. (2007). Functional form and heterogeneity in models for count data. *Department of Economics Working Paper* 07-10, Stern School of Business, New York University.

Hajivassiliou, V. A. (2000). Some practical issues in maximum simulated likelihood. In *Simulation-based inference in econometrics : methods and applications.* Cambridge University Press.

Hall, J., R. De Abreu Lourenco, and R. Viney (1999). Carrots and sticks – the fall and fall of private health insurance in Australia. *Health Economics 8*, 653–660.

Hanning, B. (2002). Has the increase in private health insurance uptake affect the Victoria public hospital surgical waiting lists? *Australian Health Review 25*(6), 64–71.

Harmon, C. and B. Nolan (2001). Health insurance and health services utilisation in Ireland. *Health Economics 10*, 135–145.

Hopkins, S. and H. Frech (2001). The rise of private health insurance in Australia: early effects on insurance and hospital markets. *Economic and Labour Relations Review 12*, 225–238.

Industry Comission (1997). *Private Health insurance.* Report No. 57: Australian Government Publishing Service Canberra.

Iversen, T. (1997). The effect of a private sector on the waiting time in a national health service. *Journal of Health Economics 16*, 381–396.

Johannesson, M., P.-O. Johansson, and T. Söderqvist (1998). Time spent on waiting lists for medical care: an insurance approach. *Journal of Health Economics 17*, 627–644.

Jones, A. M. (2000). Health econometrics. In A. Culyer and N. J.P. (Eds.), *Handbook of Health Economics*, Chapter 6. Elsevier Science B.V.

Lindsay, C. and B. Feigenbaum (1984). Rationing by waiting lists. *American Economic Review 74*, 404–417.

Lokuge, B., R. Denniss, and T. A. Faunce (2005). Private health insurance and regional australia. *The Medical Journal of Australia 182*(6), 290–293.

Maddala, G. (1983). *Limited-Dependent and Qualitative variables in Econometrics.* Cambridge University Press, UK.

Manning, W. G., J. P. Newhouse, N. Duan, E. B. Keeler, A. Leibowitz, and M. S. Marquis (1987). Health insurance and the demand for medical care: Evidence from a randomised experiment. *American Economic Review 77*(3), 251–277.

Martin, S. and P. C. Smith (1999). Rationing by waiting lists: an empirical investigation. *Journal of Public Economics 71*, 141–164.

McAvinchey, I. D. and A. Yannopoulos (1993). Elasticity estimates from a dynamic model of interrelated demands for private and public acute health care. *Journal of Health Economics 12*, 171–186.

Mcfadden, D. and K. Train (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics 15*, 447–470.

McGuire, T. G. (2000). Physician agency. In A. Culyer and N. J.P. (Eds.), *Handbook of Health Economics*, Chapter 9. Elsevier Science B.V.

Mullahy, J. (1997). Instrumenal-variable estimation of count data models: applications to models of cigarette smoking behaviour. *The Review of Economics and Statistics 79*(4).

Newhouse, J. P. and the Insurance Experiment Group (1993). *Free For All? Lessons from the Health Insurance Experiments*. Havard University Press, Cambridge.

Nyman, J. (1999). The value of health insurance: the access motive. *Journal of Health Economics 18*, 141–152.

Organisation for Economic Cooperation and Development (2006). Projecting OECD health and long-term care expenditures: what are the main drivers? *OECD Economics Department Working Papers*, No. 477.

Pauly, M. V. (1986, June). The economics of moral hazard: comment. *The American Economic Review 58*(3), 531–537. Part 1.

Phelps, C. E. (1997). *Health Economics*. Addison-Wesley Educational Publisher Inc.

PHIAC (2005). 2004/05 Annual Report. Private Health Insurance Administration Council, Canberra.

PHIAC (2010). Quarterly statistics, December 2009. Private Health Insurance Administration Council, Canberra.

Propper, C. (1990). Contingent valuation of time spent on NHS waiting lists. *Economic Journal 100*, 193–199.

Propper, C. (1993). Constrained choice sets in the U.K. demand for private medical insurance. *Journal of Public Economics 51*, 287–307.

Propper, C. (1995). The disutility of time spent on the United Kingdom's National Health Service waiting lists. *The Journal of Human Resource 30*(4), 677–700.

Propper, C. (2000). The demand for private health care in the U.K. *Journal of Health Economics 19*, 855–876.

Riphahn, R. T., A. Wambach, and A. Million (2003). Incetive effects in the demand for health care: a bivariate panel count data model. *Journal of Applied Econometrics* (18), 387–405.

Rothschild, M. and J. E. Stiglitz (1976). Equilibrium in competitive insurance markets: an essay on the economics of imperfect information. *Quarterly Journal of Economics 90*(4), 630–649.

Savage, E. and D. Wright (2003). Moral hazard and adverse selection in Australian private hospitals: 1989-1990. *Journal of Health Economics 22*, 331–359.

Schafer, J. L. (1997). *Analysis of incomplete multivariate data.* London: Chapman and Hall.

Srivastava, P. and X. Zhao (2008). Impact of private health insurance on the choice of public versus private hospital services. *The University of York. HEDG Working Paper* 08/17: July 2008.

Sundararajan, V., K. Brown, T. Henderson, and D. Hindle (2004). Effects of increased private health insurance on hospital utilisation in Victoria. *Australian Health Review 28*(3), 320–329.

Terza, J. V. (1998). Estimating count data models with endogenous switching: sample selection and endogenous treatment effects. *Journal of Econometrics 84*, 129–154.

Terza, J. V., A. Basu, and P. Rathouz (2008). Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. *Journal of Health Economics 27*, 531–543.

Train, K. (2003). *Discrete choice methods with simulation.* Cambridge University Press.

Vera-Hernández, A. M. (1999). Duplicate coverage and demand for health care: the case of Catalonia. *Health Economics 8*, 579–598.

Von Neumann, J. and O. Morgenstern (1944). *Theory of games and economic behaviour.* Princeton University Press, Princeton, NJ.

White, H. (1982). Maximum likelihood estimation of misspecified models. *Econometrica 50*(1), 1–25.

Windmeijer, F. A. G. and J. M. C. Santos Silva (1997). Endogeneity in count data models: an application to demand for health care. *Journal of Applied Econometrics 12*, 281–294.

Zweifel, P. and W. G. Manning (2000). Moral hazard and consumer incentives in health care. In A. Culyer and N. J.P. (Eds.), *Handbook of Health Economics*, Chapter 8. Elsevier Science B.V.

Appendix A

Derivations for Economic Model

Workings

This section presents the detailed derivations for the computations in the preceding sections.

Deriving $m^*_{0,0}(s)$

To derive $m^*_{0,0}(s)$ in each health state s, first substitute $q = 0$, (3.2) and (3.10) into (3.15) and differentiate the result with respect to $m_{0,0}(s)$ to obtain

$$\gamma \bar{C}^{\gamma-1}\left[\frac{m}{m+\delta s}\right] = \frac{\bar{C}^{\gamma}}{T_m}\left[\frac{\delta s}{(m+\delta s)^2}\right] \tag{A.1}$$

Using (A.1) and rearranging the terms, we can obtain

$$m^2 + \delta s\left(1+\frac{1}{\gamma}\right)m = \frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] \tag{A.2}$$

We can now solve for m in the quadratic equation above by completing the square by first adding $\left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2$ to both sides of the equation. After some rearranging, we obtain

$$m^2 + \delta s\left(1+\frac{1}{\gamma}\right)m + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2 = \frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2 \tag{A.3}$$

which is equivalent to

$$\left[m + \frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)\right]^2 = \frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)\right]^2 \tag{A.4}$$

Taking the square root of both sides in equation (A.4), the optimal intensity $m_{0,0}(s)$ is expressed as

$$m^*_{0,0}(s) = \pm\sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right) \tag{A.5}$$

where the solution in (A.5) is defined only if $\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)\right]^2 \geq 0$ which implies that $Y - T_l t^e(s) \geq -\gamma T_m \delta s\left[\frac{1}{2}\left(1 + \frac{1}{\gamma}\right)\right]^2$. Given that the intensity of hospital care m^* can only assume non-negative values, the solution in (A.5) is restricted to

$$+\sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right) \tag{A.6}$$

and

$$Y - T_l t^e(s) \geq 0$$

Deriving $m^*_{1,0}(s)$

Correspondingly, the solutions to the optimal intensity of public hospital care for an individual with insurance are

$$m^*_{1,0}(s) = \pm\sqrt{\frac{\delta s}{\gamma T_m}\left[Y - P - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right) \tag{A.7}$$

For the same reasons as that described above, the solution is restricted to

$$m_{1,0}^*(s) = +\sqrt{\frac{\delta s}{\gamma T_m}\left[Y - P - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right) \quad \text{(A.8)}$$

and

$$Y - P - T_l t^e(s) \geq 0$$

Deriving $m_{0,1}^*(s)$ and $m_{1,1}^*(s)$

Similarly, the solutions to the optimal intensity of private hospital care for an individual without and with insurance are respectively

$$m_{0,1}^*(s) = +\sqrt{\frac{\delta s}{\gamma}\left[\frac{Y}{(\eta p^m + p^q) + T_m}\right] + \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right]^2} - \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right] \quad \text{(A.9)}$$

$$m_{1,1}^*(s) = +\sqrt{\frac{\delta s}{\gamma}\left[\frac{Y-P}{\alpha(\eta p^m + p^q) + T_m}\right] + \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right]^2} - \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right] \quad \text{(A.10)}$$

and

$$\frac{Y}{(\eta p^m + p^q) + T_m}, \frac{Y-P}{(\eta p^m + p^q) + T_m} \geq 0$$

Change in $m_{d,q}^*(s)$ given unit change in s

To examine how $m_{0,0}^*(s)$ changes with a unit increase in illness severity s from s to $s+1$, substitute s and $s+1$ into (3.17) to obtain

$$m_{0,0}^*(s) = \sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right) \quad \text{(A.11)}$$

$$m_{0,0}^*(s+1) = \sqrt{\frac{\delta(s+1)}{\gamma T_m}\left[Y - T_l t^e(s+1)\right] + \left[\frac{1}{2}\delta(s+1)\left(1+\frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta(s+1)\left(1+\frac{1}{\gamma}\right) \quad \text{(A.12)}$$

From (A.11) and (A.12) above, we can observe that

$$\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] \leq \frac{\delta(s+1)}{\gamma T_m}\left[Y - T_l t^e(s+1)\right] \tag{A.13}$$

given that $t^e(s) > t^e(s+1)$. Also, for $Y - T_l t^e(s) \geq 0$,

$$\sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)\right]^2} \geq \frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right) \tag{A.14}$$

Correspondingly, for $Y - T_l t^e(s+1) \geq 0$,

$$m^*_{0,0}(s+1) = \sqrt{\frac{\delta(s+1)}{\gamma T_m}\left[Y - T_l t^e(s+1)\right] + \left[\frac{1}{2}\delta(s+1)\left(1 + \frac{1}{\gamma}\right)\right]^2} \geq \frac{1}{2}\delta(s+1)\left(1+\frac{1}{\gamma}\right) \tag{A.15}$$

On the basis of the conditions in (A.13), (A.14) and (A.15), one can conclude that

$$m^*_{0,0}(s+1) \geq m^*_{0,0}(s)$$

The same argument applies to the remaining three sets of optimal solutions to $m^*_{0,1}(s), m^*_{1,0}$ and $m^*_{1,1}$

Proof: $s\frac{\Delta m^*_{0,0}}{\Delta s} \leq m^*_{0,0}$

As shown in (3.17), $m^*_{0,0}(s)$ is

$$m^*_{0,0}(s) = \sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)\right]^2} - \frac{1}{2}\delta s\left(1 + \frac{1}{\gamma}\right)$$

Hence, we can derive $s\frac{\Delta m^*_{0,0}}{\Delta s}$ which is

$$s\frac{\Delta m^*_{0,0}}{\Delta s} = \frac{\frac{1}{2}\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2}{\sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2}} - \frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right) \qquad \text{(A.16)}$$

Using the above, we can proof that $s\frac{\Delta m^*_{0,0}}{\Delta s} \leq m^*_{0,0}$ by showing that

$$\frac{\frac{1}{2}\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2}{\sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2}} \leq \sqrt{\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2} \qquad \text{(A.17)}$$

Cross multiplying the denominator on the LHS with the RHS in A.17, we obtain

$$\frac{1}{2}\frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2 \leq \frac{\delta s}{\gamma T_m}\left[Y - T_l t^e(s)\right] + \left[\frac{1}{2}\delta s\left(1+\frac{1}{\gamma}\right)\right]^2 \qquad \text{(A.18)}$$

which is true. The same arguments can be applied to show that $s\frac{\Delta m^*_{0,1}}{\Delta s} \leq m^*_{0,1} + \beta$

Proof: $-1 \leq \frac{\partial m^*_{0,1}}{\partial \beta} \leq 0$

Using (3.19), $\frac{\partial m^*_{0,1}}{\partial \beta}$ is expressed as

$$\frac{\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)}{\sqrt{\frac{\delta s}{\gamma}\left(\frac{Y}{\bar{p}}\right) + \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right]^2}} - 1$$

For $Y \geq 0$,

$$0 \leq \frac{\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)}{\sqrt{\frac{\delta s}{\gamma}\left(\frac{Y}{\tilde{p}}\right) + \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right]^2}} \leq 1$$

Hence,

$$-1 \leq \frac{\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)}{\sqrt{\frac{\delta s}{\gamma}\left(\frac{Y}{\tilde{p}}\right) + \left[\frac{1}{2}\left(2\beta + \delta s + \frac{\delta s}{\gamma}\right)\right]^2}} - 1 \leq 0$$

Appendix B

Estimation Program Codes

-start of program codes-

```
cap prog drop progname
program define progname
version 9.0
args lnf theta1 theta2 theta3 theta4 theta5 theta6 theta7

local tt4 = `theta4'
local tt5 = `theta5'
local tt6 = `theta6'


if `tt4' < -8 {
    local tt4 = -8}
if `tt4' > 8 {
    local tt4 = 8}

if `tt5' < -8 {
    local tt4 = -8}
if `tt5' > 8 {
    local tt4 = 8}

if `tt6' < -8 {
    local tt4 = -8}
if `tt6' > 8 {
    local tt4 = 8}

tempvar rho12 rho13 rho23

qui gen double `rho12' = 0
```

```
qui gen double `rho13' = 0
qui gen double `rho23' = 0

qui replace `rho12' =[exp(2*`tt4')-1]/[exp(2*`tt4')+1]
qui replace `rho13' =[exp(2*`tt5')-1]/[exp(2*`tt5')+1]
qui replace `rho23' =[exp(2*`tt6')-1]/[exp(2*`tt6')+1]

if (`rho12'==. | `rho13'==. | `rho23'==.) {
        qui replace `lnf'=.
        exit}

local R12=`rho12'
local R13=`rho13'
local R23=`rho23'

tempvar den1 den2 den3 den4 touse1 touse2 touse3 touse4 tempvar simden1 simden2 simden3 simden4
local repl = -insert number of replications desired-

qui gen double `den1' = 0
qui gen double `simden1' = 0
qui gen double `touse1'=0

tempvar q1i q2i
qui gen byte `q1i' = (2*($ML_y2 =0)-1)
qui gen byte `q2i' = (2*($ML_y3 =0)-1)

forvalues i=1/`repl' {
        qui replace `touse1' = exp(-exp(`theta1')*exp(`theta7'*xi`i'))*((exp(`theta1')
        *exp(`theta7'*xi`i'))^($ML_y1)/(exp(lngamma($ML_y1 + 1)))
        *binorm(`q1i'*(`theta2' + `R12'*xi`i')/sqrt(1-(`R12'^(2))),`q2i'*(`theta3'
+ `R13'*xi`i')
        /sqrt(1-(`R13'^(2))), `q1i'*`q2i'*(`R23' - `R12'*`R13'))

        qui replace `den1' = `den1' + `touse1'}

qui replace `simden1' = ln(`den1'/`repl')
qui replace `lnf' = `simden1'
end
```

-end of program codes-

Appendix C

Regression Results: Demand for Private Hospital Insurance

Table C.1: Demand for Private Health Insurance: Hospital Table

Explanatory Variables	Coeff	*S.E*	*dF/dX*	S.E
Female	0.196***	0.068	0.077***	0.027
Age	1.258***	0.237	0.009***	0.001
Age-squared	-0.857***	0.226		
Childbearing	-0.112	0.135	-0.044	0.053
Couple	0.267***	0.067	0.105***	0.026
Depchild	-0.140	0.091	-0.055	0.036
Country of Birth:				
Main English	-0.303***	0.091	-0.117***	0.034
Others	-0.178*	0.093	-0.069*	0.036
Household Inc	0.607***	0.148	0.049***,[a]	0.006
Household Inc-Sq	-0.175	0.139		
Health Card	-0.484***	0.095	-0.190***	0.037
Education				
Vocational	0.129*	0.074	0.051*	0.029
Diploma	0.435***	0.106	0.172***	0.041
Degree	0.551***	0.100	0.217***	0.038
Occupation:				
Manager/Admin	0.362**	0.159	0.144**	0.062
Professional	0.106	0.137	0.042	0.054
Asc Professional	0.344**	0.138	0.137**	0.054
Tradesperson	-0.006	0.159	0.002	0.063
Adv Clerical/Service	0.466*	0.274	0.183*	0.103
Int Clerical/Service	0.135	0.126	0.054	0.050
Production/Transport	-0.175	0.180	-0.068	0.069
Ele Clerical/Service	-0.056**	0.023	-0.022**	0.009
Labourer	-0.438**	0.172	-0.164***	0.059
Alcohol 3-day Risk	-0.123	0.103	-0.048	0.040
Smoker Regular	-0.496***	0.082	-0.189***	0.029
Regions:				
VIC	0.159	0.098	0.063	0.039
QLD	0.301***	0.100	0.119***	0.039
SA	0.330***	0.096	0.131***	0.038
WA	0.368***	0.105	0.146***	0.041
TAS	0.425***	0.118	0.168***	0.046
NT	0.089	0.533	0.036	0.212
ACT	-0.115	0.135	-0.045	0.052
Remoteness				
Inner Aus	-0.183**	0.080	-0.072**	0.031
Others	-0.267***	0.091	-0.104***	0.035
Constant	-3.277***	0.395		

a. The change in probability of insurance given a $100 increase in weekly household income.