Demand for Hospital Care and Private Health Insurance in a Mixed Public-Private System: Evidence from Australia

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Abstract

This paper develops a model of demand for private hospital insurance and hospital care in a mixed public and private hospital system. The model is applied to empirically analyse the determinants in the decision to purchase insurance, the choice of hospital admission as a public or private patient and the intensity of hospital care. The econometric model accommodates the count data nature of the length of hospital stay and simultaneity in the public-private admission and insurance decisions. Estimation is carried out via simulated maximum likelihood using microdata from the 2004 National Health Survey in Australia. The results suggest that individuals seek private care for hospital treatments that involve shorter hospital stays. Consistent with previous studies, there is evidence to suggest the presence of moral hazard in private hospital use.

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Keywords: Demand for Hospital Care, Private Hospital Insurance, Public Private Mix.

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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 experienced by most OECD countries from late 1990s has placed tremendous fiscal pressures on government budgets. A recent report published by the OECD projected that average public spending on health and long-term care across OECD countries will roughly double from 6.7% of Gross Domestic Product (GDP) in 2005 to 10-13% by 2050 (OECD 2006).[1] Population aging and longevity, technological advancement and increasing relative prices of health services are some key drivers of the growth in health care expenditures.

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 is a classic example in this regard.

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 insurers if individuals have private health insurance. 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.

[1] Variations in projections accrued from different underlying assumptions surrounding the rate of expenditure growth arising from non-demographic drivers of health expenditures such as technological change and price movements in the supply of health services.

Against the background of steadily declining private health insurance membership within the Australian population after Medicare was introduced in 1984, the Australian government implemented a series of policy changes between 1997 to 2000 with the aim of encouraging private health insurance purchase. These policies included a combination of tax subsidies, tax penalties and a modification of the community rating regulations which allowed private health insurance funds to vary premiums according to individuals' age at the time of purchase.[2] The prevailing policy stance within the government at the time these policies were implemented clearly supported a balanced public and private involvement in the delivery of health care to ensure both universal access and choice. The declining private health insurance 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 (CDHAC 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). 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 table insurance coverage.

Despite the prominence of private health insurance in Australia, the bulk of financing of hospital services still remained the responsibility of the government. In 2005-06, government sources of funding accounted for 81% of the recurrent expenditure on public and private hospitals with the remaining 19% accruing from non-governmental sources through out-of-pocket expenditures and private health insurers.[3] 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. Previous research that attempted to evaluate the effects of these policy interventions have largely relied on the use of aggregate level data. The evidence suggest that while utilisation of private hospital care increased after the expansion of private health insurance coverage in 2000, a significant

[2]The first of the series of three policies that were introduced was the Private Health Insurance Incentive Scheme (PHIIS) implemented in July 1997. The scheme involved the use of tax subsidies to encourage the purchase of private health insurance amongst lower income individuals and tax penalties for individuals who did not purchase insurance. The PHIIS was modified on 1 January 1998 by a non means-tested 30% rebate on health insurance premiums. The third policy is the Lifetime Community Rating (LCR) policy which came into effect on July 2000. LCR involved a modification of the community rating regulations and allowed private health insurance funds are allowed to vary insurance premiums according to individuals' age at the time entry into funds and the number of years individuals remained insured. See Butler (2002) for a more detailed description of the policy measures.

[3]The figures were derived by summing the level of government and non-government recurrent expenditures on public and private hospitals using expenditure statistics in Tables 15 and 16 in AIHW (2007).

fraction of the increase in private hospital activity was accounted for by admissions for elective surgical and medical procedures (Sundararajan et al. 2004). Patients suffering from severe medical conditions are less likely to seek private relative to public care, which leads to the public hospital system being increasingly burdened by patients with complicated, and potentially expensive medical needs (Hopkins and Frech 2001).

This paper seeks to contribute to the body of evidence on the effectiveness of private health insurance as health policy tool in health care systems like that of Australia where governments play a dominant role in the financing of medical care. The paper achieves this by investigating decision making processes individuals undertake in the decisions to purchase private health insurance and seek hospital care in a mixed public and private system.

The theoretical framework that underlies consumers' demand for health insurance and health care was developed by Cameron et al. (1988). The choice to purchase health insurance depends on the expected future consumption of health care. Individuals make decisions on whether to purchase health insurance when they are healthy. Upon the onset of illness, they decide on the level of medical care to consume, which is influenced *inter alia* by the net prices of medical care individuals face. In the context of private hospital insurance in Australia, the decision to purchase private hospital insurance will depend on the expected future consumption of private hospital care. Savage and Wright (2003) developed an model of demand for private health insurance and public-private hospital care where individuals may either choose to consume private care for a price or wait on hospital lists for a duration of time before accessing free public hospital care. In this paper, I propose an alternative formulation of the consumer's problem. In the model, individuals decide between obtaining public and private hospital care not solely on the basis that public care is delivered with a delay, but also on the account of other quality attributes associated with private hospital care as such the ability to choose one's doctor and access to better quality hospital facilities and amenities.

A thorough empirical examination of the demand for private hospital insurance and hospital care in the mixed public-private hospital setting should involve the investigation of the choice to purchase insurance and the decisions on the type and intensity of care within a simultaneous framework. This approach will enable us to isolate and identify the intertwining factors that motivate the three decisions. In the existing literature, there has not been any previous attempt to empirically examine the determinants that influence the three decisions simultaneously. For the empirical analysis, I develop a simultaneous equation regression model that accommodates the count data nature of the length of hospital stay and simultaneity in the public-private patient type and insurance decisions. Estimation is carried out via simulated maximum likelihood. The econometric model is applied to individual level data from the 2004 National Health Survey.

The paper is organised as follows. Section 2 describes the theoretical model and presents the solution to the consumer's resource allocation problem. Section 3 describes the 2004 National Health Survey data. The econometric model and estimation approach is discussed in Section 4. The results from the empirical analysis is presented in Section 5. Section 6 concludes with a discussion of the key contributions of the paper and presents some possible limitations and further extensions for future work.

2 Theoretical Framework

In this section, a theoretical model of demand for hospital care, care quality and private hospital insurance is developed. The model is introduced in Section 2.1, together with the solutions to the consumer's resource allocation problem where the choice sets of hospital care and quality attributes are characterised as continuous. In Section 2.2, I consider the case where the consumer chooses from one of W mutually exclusive quality 'bundles' or alternatives and present the full solutions to the consumer's optimisation problem. Section 2.3 concludes with a discussion of the theoretical results.

2.1 The General Model

Consider an individual with a two-period utility function

$$U = C_0 C_1^{\alpha+1} H^{\sigma+1} \tag{1}$$

with

$$H = m^{\alpha_m(s,A)} \prod_{l=1}^{L} q_l^{\alpha_{ql}(s,A)} \tag{2}$$

where C_0 and C_1 denotes current (period 0) and future (period 1) consumptions respectively. H denotes the health status of the individual which is determined by m, a one-dimensional[4] medical care input and $\tilde{q}$, a L-dimensional vector representing the L attributes of medical care quality and the uncertain health state s. A is a vector of attributes that describe the individual such as age, gender and health status.

H has the interpretation of a health production function. The incidence of illness (or the realisation of health state s) produces a loss in health which can be mitigated by using medical care m with quality $\tilde{q}$. Within the context of the role private health insurance play in the utilisation of medical care in Australia, medical care m pertains to hospital services. The quality attributes captured in $\tilde{q}$ include different grades or levels of hospital accommodations, the choice of treating physicians and waiting times for hospital care. We assume that the level of quality is increasing in q_l for each l-th attribute. We further assume for the moment that the choice set surrounding the quality attributes $\tilde{q}$ is continuous.

Uncertainty enters the model through the health state s where the individual's health in period 1 is unknown in period 0. Instead, the individual makes subjective evaluations on the likelihood of s occurring. We denote the subjective distribution of s by $\pi(s|A)$. As given in (2), s affects the production of health through α_m and α_q, which can be interpreted as the individual's subjective assessment of the marginal productivity of medical care and quality. An alternative interpretation of α_q is the individual's valuation of the benefits of medical care quality. Heterogeneity in individuals' taste for the quality attributes of care is reflected through variations in α_q across individuals. Finally, α is the intertemporal rate of substitution and σ the constant coefficient of relative risk aversion, where $-1 < \alpha < 0$ and $-1 < \sigma < 0$.

In terms of the budget constraint, the individual decides in period 0 to allocate P_j of current income Y_0 to purchase private health insurance, where P_j denotes the premium of insurance policy j. The decision to purchase insurance is undertaken before the true health state s is revealed in period 1. In addition to the expenditure on insurance, the individual further allocates Y_0 to current consumption C_0 and savings a_0. We assume that savings a_0 produces a return of ra_0 in period 1, where r is the rate of interest. When the true health state s is revealed in period 1, the individual allocates exogenous income Y_1 and $(1 + r)a_0$ to hospital services m at

[4]Cameron et al. (1988) considers the case where a multi-dimensional medical care vector enters into the utility function. For simplicity in exposition, we assume that m is a one-dimensional medical care input.

price p_j^m, quality $\tilde{q}$ at prices $\tilde{p}_j^q$ and the consumption C_1. The prices p_j^m and $\tilde{p}_j^q$ are the net prices that the individual faces if insurance policy j is purchased in period 0. Conditional on policy j, the net prices are the full prices of medical care and care quality less insurance reimbursement[5] and coverage under Medicare[6].

To solve the intertemporal allocation problem, the consumer chooses $C_0, C_1, m, \tilde{q}$ and a_0 to maximise expected utility for each insurance policy j:

$$\max_{\{j,C_0,C_1,m,\tilde{q},a\}} EU_j = \int_s C_0 C_1^{\alpha+1} H^{\sigma+1}\, d\pi(s|A) \tag{3}$$

subjected to the constraints

$$\begin{aligned} Y_{0j} + P_j = &\; Y_0 \\ C_0 + a = &\; Y_{0j} \\ C_1 + p_j^m m + \tilde{p}_j^q \tilde{q} = &\; Y_1 + (1+r)a_0 \end{aligned} \tag{4}$$

where H is given in (2). The solutions to the consumer's optimisation problem can be derived by taking the logarithms of the utility function in (1) to obtain

$$lnU = lnC_0 + (\alpha+1)lnC_1 + (\sigma+1)\alpha_m lnm + (\sigma+1)\sum_{l=1}^{L} \alpha_{ql} lnq_l \tag{5}$$

and substituting the constraints in (4) into (2.2) and differentiating the maximisation problem with respect to C_0 m and $\tilde{q}$, conditional on the realisation of each health state s. The first order conditions for the values of m and $\tilde{q}$ that maximises the individual's expected utility, conditional on policy j in health state s are

$$\frac{p_j^m}{Y_1 + (1+r)a_0 + p_j^m m + \tilde{p}_j^q \tilde{q}} = \frac{\alpha_m(\sigma+1)}{m} \tag{6}$$

[5]The effective prices of medical care and care quality faced by individuals is dependent on the attributes of insurance policies (e.g. cost sharing arrangements such as copayments, limits and deductibles) individuals purchase, as well as the choice of medical care providers. For the latter, health insurers in Australia maintain contracts with a network of medical practitioners and private hospitals. Insured individuals typically receive higher benefits and lower out-of-pocket costs when they utilise a health care provider that is within a particular insurers' network.

[6]For individuals admitted as private patients in public and private hospitals, Medicare covers 75% of the MBS fees for approved in-hospital services which includes physician services and medical procedures. Private health insurers are required to cover the remaining 25% of the MBS if patients have private health insurance. The difference between the actual amount charged to patients and the MBS fee is referred to as the gap. Individual may purchase additional private insurance cover to eliminate or reduce the gap expenses.

$$\frac{p_{jl}}{Y_1 + (1+r)a_0 + p_j^m m + \tilde{p}_j^q \tilde{q}} = \frac{\alpha_{ql}(\sigma+1)}{q_l} \tag{7}$$

where p_j^m is the net price of medical care and p_{jl}^q the net price of the l-th quality attribute, given insurance policy j. The first order conditions are interpreted as follows. Equation (6) states that at the optimal medical care m, the loss in utility from the decrease in consumption by increasing m by an additional unit equals the utility gain from health. Equation (7) states that at the optimal q_l, an additional unit of l-th quality attribute produces a loss in utility from the decrease in consumption that equals the utility gain from health through higher quality.

We can observe the effects of moral hazard on medical care use from equation (6). Differentiating the LHS of equation (6) with respect to p_j^m, we obtain

$$\frac{1}{A}\left[1 - \frac{p_j^m}{A}\right] \tag{8}$$

where $A = Y_1 + (1+r)a_0 + p_j^m m + \tilde{p}_j^q \tilde{q}$. Given that (8) is always positive, a decrease in p_j^m will always result in an decrease in the LHS of (6). For the equality condition in (6) to hold, the level of medical care m must increase. Hence, a decrease in the net price of medical care increases the utilisation of medical care.

2.2 Medical Quality as a Discrete Choice

Let us now consider the scenario where the choice of quality attributes is characterised as a discrete choice from W alternatives comprising of different combinations or 'bundles' of q_l where $l = 1, \ldots, L$. The solutions to the optimisation problem can be easily obtained through simultaneously solving for the choice variables via the application of the intuition that underlines the dynamic programming approach applied to the case where the choice sets are both continuous and discrete (Pakes 1994). The individual's optimisation problem may be solved as follows. As in (2.2) above, the logarithm of the individual's utility function is

$$lnU = lnC_0 + (\alpha+1)lnC_1 + (\sigma+1)\alpha_m lnm + (\sigma+1)\sum_{l=1}^{L}\alpha_{ql} lnq_l$$

and the constraints as outlined in (4) are

$$
\begin{aligned}
Y_{0j} + P_j &= Y_0 \\
C_0 + a &= Y_{0j} \\
C_1 + p_j^m m + \tilde{p}_j^q \tilde{q} &= Y_1 + (1+r)a_0
\end{aligned}
$$

Suppose the individual chooses from W alternatives comprising of different combinations or 'bundles' of q_l where $l = 1, \ldots, L$. We denote these bundles by $\tilde{q}_w$, where $w = 1, \ldots, W$. We further denote using q_{wl} the l-th quality attribute within the w-th bundle. The first step towards obtaining a solution to the optimisation problem involves deriving the optimal values of C_0, C_1 a_0 and m for each policy choice j and quality choice w, conditional on health state s. The optimal values are

$$
C^*_{0jw}(s) = \frac{Y_1 + (1+r)Y_{0j} - \tilde{p}_j^q \tilde{q}_w}{(1+r)[(2+\alpha) + \alpha_m(1+\sigma)]} \tag{9}
$$

$$
a^*_{jw}(s) = Y_{0j} - \frac{Y_1 + (1+r)Y_{0j} - \tilde{p}_j^q \tilde{q}_w}{(1+r)[(2+\alpha) + \alpha_m(1+\sigma)]} \tag{10}
$$

$$
C^*_{1jw}(s) = \frac{(1+\sigma)[Y_1 + (1+r)Y_{0j} - \tilde{p}_j^q \tilde{q}_w]}{[(2+\alpha) + \alpha_m(1+\sigma)]} \tag{11}
$$

$$
m^*_{jw}(s) = \frac{\alpha_m(1+\sigma)[Y_1 + (1+r)Y_{0j} - \tilde{p}_j^q \tilde{q}_w]}{p_j^m[(2+\alpha) + \alpha_m(1+\sigma)]} \tag{12}
$$

Note that solutions in (9) to (12) contains the term $\tilde{p}_j^q \tilde{q}_w$, which is the total expenditure on quality bundle w. Given health state s, the indirect utility function of the individual when policy j and quality bundle w is chosen can be obtained by substituting (9) to (12) into (2.2). We denote the indirect utility function by V_{jw} which is generally expressed as

$$
V_{jw}(s) = V_j\left[(1+r)(Y_0 - P_j), Y_1, p_j^m, \tilde{p}_j^q, \tilde{q}_w, \varphi, A\right] \qquad w = 1, \ldots, W \tag{13}
$$

where $\varphi = (\alpha, \alpha_m, \alpha_q, \sigma)$ the vector of parameters in the utility function. The decision rule on the optimal quality bundle across W alternatives can be expressed as follows: for every insurance policy j and health state s, the individual will choose quality bundle w^* where $V_{jw^*} \geq V_{jw}$ for all $w \neq w^*$. The individual quality attributes with the quality vector $\tilde{q}_j^*$ that corresponds to the optimal bundle w^* for each j and s can be substituted into the solutions (9) to (12) to obtain

$$C^*_{0j}(s) = \frac{Y_1 + (1+r)Y_{0j} - \tilde{p}^q_j \tilde{q}^*}{(1+r)[(2+\alpha) + \alpha_m(1+\sigma)]} \tag{14}$$

$$a^*_j(s) = Y_{0j} - \frac{Y_1 + (1+r)Y_{0j} - \tilde{p}^q_j \tilde{q}^*}{(1+r)[(2+\alpha) + \alpha_m(1+\sigma)]} \tag{15}$$

$$C^*_{1j}(s) = \frac{(1+\sigma)[Y_1 + (1+r)Y_{0j} - \tilde{p}^q_j \tilde{q}^*]}{[(2+\alpha) + \alpha_m(1+\sigma)]} \tag{16}$$

$$m^*_j(s) = \frac{\alpha_m(1+\sigma)[Y_1 + (1+r)Y_{0j} - \tilde{p}^q_j \tilde{q}^*]}{p^m_j[(2+\alpha) + \alpha_m(1+\sigma)]} \tag{17}$$

where the optimal consumption paths, savings and intensity of medical care is now conditional on policy j and health state s. Given that the decision on the choice of insurance is made prior to the realisation of health state s, the individual in period 0 chooses the insurance policy j which maximises his expected utility. Using the solutions from (14) to (17), we can derive the expected indirect utility function as given in (3) as

$$\begin{aligned} EV_j &= \int_s U[C^*_{0j}(s), C^*_{1j}(s), m^*_j(s), q^*_j(s)]\; d\pi(s|A) \\ &= EV[(1+r)(Y_0 - P_j), Y_1, p^m_j, \tilde{p}^q_j, \tilde{q}^*_j, \varphi, A] \qquad j = 1, \ldots, J \end{aligned} \tag{18}$$

where φ is a vector of parameters in the utility function. Using (18), the decision rule on the choice of insurance policy j can now be described. The individual will choose insurance policy j^* such that $EV_{j^*} \geq EV_j$ for all $j \neq j^*$.

2.3 Discussions

The solutions to the optimal level of consumptions, savings and medical care utilisation are presented in equations (14) to (17), while the decision rules surrounding the quality and insurance choices are described in equations (13) and (18) respectively. Using these solutions, we can examine how the demand for medical care and choices across quality and insurance alternatives varies with the parameters in the model. First and foremost, we observe from equation (17) a tradeoff between the optimal intensity of medical care and expenditure on quality. Individuals with illness conditions requiring more intensive medical care would allocate a lower share of the budget on the expenditure on care quality. Correspondingly, we can expect that individuals with serious medical conditions are be more likely to opt for free public hospital care.

Similarly from equation (17), we can observe that the intensity of demand for medical care increases as the price of care p^m decreases. This is the moral hazard effect briefly discussed in Section 2.1. It should be noted that the discussion of moral hazard in the utilisation of hospital care in Australia is relevant only to patients who choose to be admitted as private patients in public or private hospitals. This is because individuals who are admitted as a public or Medicare patient face zero prices for public hospital care. Individuals who purchase private health insurance is expected to utilise private hospital care services at a higher intensity than individuals without private health insurance because the former faces a lower net price for medical care. In addition to price of medical care, the price of medical quality affects the total expenditure on medical quality. Hence, we can expect that the intensity of medical care use decreases as prices of quality attributes increase. We can further observe from (17) that the demand for medical care is increasing in income of both periods and the market interest rate.

An increase in the marginal productivity of medical care α_m increases the demand for care for any given level of illness severity. This result can be easily verified by differentiating equation (17) with respect to α_m where we can observe that the sign of $\delta m/\delta\alpha_m$ is > 0. Alternatively, we can interpret α_m as the individual's subjective valuation on the benefits from medical care. Individuals who value medical care highly can be expected to utilise a greater intensity of care. We would expect that individuals' valuations depend on positively on illness severity. Hence, variations in medical care use across individuals can arise from heterogeneity in how individuals value the benefits of medical care and the types and severity of the prevailing medical conditions that individuals are seeking treatment for.

Individuals' taste for quality influence the quality choices through the parameter α_q. An example of a quality attribute associated with public hospital care in Australia is waiting times for publicly financed elective medical and surgical treatment. Consider the simple case where the quality vector is one-dimensional quality indicator q, and that waiting times for medical care is the sole dimension of care quality. Suppose the individual chooses between medical care as a public patient where the waiting times is a positive number t, or alternatively seek private medical care without having to wait, that is $t = 0$.[7] We further assume that q is equal to e^{-t}. From the assumptions, the benefits from medical care can be expressed as m^{α_m} if the individual chooses private care. If instead, the individual chooses to wait for medical care in the public sector, the benefits from medical care is $m^{\alpha_m} e^{-\alpha_q t}$. For any positive t, $m^{\alpha_m} > m^{\alpha_m} e^{-\alpha_q t}$. The benefits from public medical care is lower than that of private care because public care is delivered with a delay of time t. The parameter α_q may be interpreted as the decay factor that determines the extent benefits from medical care diminishes with the duration of the delay, where α_q can capture the pain, suffering and reduced quality of life associated waiting for care (Lindsay and Feigenbaum 1984). The parameter may also be perceived as the individual's valuation of time which is expected to depend on the individual's income and employment status (Propper 1990a). We can expect individuals' taste to be influenced by income, education and political attitudes. For example, Propper (2000) found that individuals with strong beliefs on the role of the state in the provision of health care are more likely to seek public care when required rather than private care.

Lastly, an increase in the degree of risk aversion $|\sigma|$ which leads to a decrease in $(1 + \sigma)$, increases first period consumption and reduces second period consumption and intensity of medical care use. We can verify these results by differentiating (14) to (17) with respect to $(1+\sigma)$ where we can observe that $\delta C_0/\delta(1+\sigma) < 0$, whereas $\delta C_1/\delta(1+\sigma)$ and $\delta m/\delta(1+\sigma)$ are > 0. The intuition underlying these results is as follows: due to the uncertainty surrounding the occurrence of ill health in the second period, individuals who are more risk averse discount to a larger degree the second period utility arising from health and consumption. Correspondingly, these individuals allocate a greater share of their budget to the first period relative to the second period[8].

The results from the theoretical model will form the basis of the structural econometric model to empirically examine the determinants of the demand for insurance, the choice of public or private care and the intensity of care. Before proceeding to the empirical strategy which will be discussed in Section 4, I will first provide a description of the data.

[7] For this scenario, the number of quality attributes L is equal to 1 and the number of quality alternatives W is 2.

[8] The equilibrium condition for an individual's intertemporal resource allocation problem is such that the marginal utility of consumption from each period is equal. As the second period is discounted to a larger degree given the uncertainty, the individual chooses to consume more in the first period relative to the second for the equality condition to hold.

3 Data

The empirical section for this paper uses microdata[9] from the National Health Survey (NHS) 2004-05 conducted by the Australian Bureau of Statistics (ABS) between August 2004 to July 2005. The survey collected information on 25,906 adults (age 18 years and over) and children (age 0 to 17) from 19,501 private dwellings randomly selected from across all states and territories in Australia. The data contains individual-level and household information such as demographic and socio-economic characteristics (age, gender, education attainment, employment, 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); household information (geography, family composition, household income).

Given that the primary focus of this study is to examine the determinants in the demand for health care and health insurance, we exclude from our sample 9,696 individuals who are under the age of 30 years at the time of the NHS was conducted. By doing so, we eliminate the possibility of the inclusion in our sample dependents covered under their parents' policy[10]. In addition, we further exclude 921 individuals from multiple family households, including only respondents from one family households consisting of either single persons or couple households with or without dependent children[11]. Observations with incomplete or ambiguous responses on key outcome measures and explanatory variables (e.g. choice of hospital admission as a public or private patient and types of private health insurance policies purchase) are dropped. Ambiguous or missing responses in all remaining variables will be imputed randomly wherever necessary[12].

[9]The microdata of the 2004-05 NHS is available in two formats: A *Basic* Confidentalised Unit Records Files (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.

[10]A dependent child may remain in his or her parent(s) policy if the child is unmarried and under the age of 21; or 25 years if the dependent child is undertaking full-time study.

[11]The exclusion of multiple family households is motivated by two main reasons. Firstly, eliminating multiple family households from the study would restrict the sample to family structures similar to the type of insurance policies available. Secondly, given that the only measure of household income available in the basic version of the data is the total equivalised household income, dropping multiple family household structures will avoid complications arising from the possibility of multiple income units residing within a given dwelling.

[12]The random assignment involves a two-stage procedure. At the first stage, observations containing missing or ambiguous responses are assigned an identifier constructed using a random number between 0 and 1 multiplied by the total number of observations in the remaining response categories. The random number is created using the random number generator command *uniform* in-built in `Stata` version 9.2. At the second stage, the observations are assigned by matching the identifiers with the lower and upper frequency cut-offs of each remaining category.

Table 1: Private health insurance status and coverage type: Sub-Sample

No private health insurance					1,093 (49.73%)
With private health insurance					1,105 (50.27%)
	Coverage Type				
	Hosp & Anci[a]	Hosp only	Anci only	Total	
Purchased PHI before Aug 1999	731 (79.0%)[b]	139 (15.0%)	55 (6.0%)	925 (100.0%)	
Purchased PHI after Aug 1999	133 (73.9%)	39 (21.6%)	8 (4.5%)	180 (100.0%)	
Total	864 (78.2%)	178 (16.1%)	63 (5.7%)	1,105 (100.0%)	
Total Sample					2,198 (100.0%)

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

After taking into account the dropped responses from the sample as described above, the size of the working sample is 12,990. From this working sample, the sub-sample consist of 2,198 observations for which the respondents had indicated that they have been hospitalised at least once in the last twelve months.

3.1 Private Health Insurance Coverage and Medical Care Use

The NHS captures information on whether individuals have private health insurance, and if applicable, insurance policy types (hospital, ancillary or both) and the duration[13] for which individuals have been insured. From the responses to questions on the duration of insurance coverage, we can identify if individuals purchased insurance prior to or after the series of private health insurance policies were introduced from 1997 to 2001[14]. We describe in Table 1 the distribution of individuals who reported having been hospitalised at least once in the past 12 months by insurance status, type and duration of coverage. In the sample of 2,198 individuals, 1,093 (49.7%) individuals do not have private health insurance. Of the 1,105 (50.3%) individuals with private health insurance, 925 (83.7%) individuals purchased coverage prior to August 1999 while 180 (16.3%) purchased insurance after August 1999. The distribution of coverage types

[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; (iii) 1 year to less than 2 years; (iv) 2 years to less than 5 years and (v) 5 years or more.

[14] 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.

is generally similar to the full sample. 78.2% of individuals owned both hospital and ancillary coverage while 16.1% and 5.7% of individuals have hospital only and ancillary only. As our study focuses on how private health insurance influences the decisions on the choice of public or private hospital care and the intensity of hospital care, we define insurance coverage as whether individuals have or do not have private hospital insurance.

On medical care use, we are primarily interested in two hospital care utilisation measures among individuals who reported to have been admitted to hospital at least once in the last one year. These measures are (a) whether individuals chose to be hospitalised as a public or private patient and (b) the number of nights in hospital[15]. As we will elaborate in the next section, because our econometric model requires that the length of hospital stay be of integer values, we replace interval values by their lower bound wherever appropriate. The frequencies in the choice of public or private hospitalisation and average length of hospital stay across individuals with and without private hospital insurance are illustrated by means of a decision tree in Figure 1. As seen in the decision tree, the utilisation of private hospital care is significantly higher among individuals with private hospital insurance. Of the 1,042 individuals with private hospital insurance, 82.5% (N=860) chose to be hospitalised as private patients while 17.5% (N=182) were hospitalised as private patients. Conversely, only 7.9% (N=91) of uninsured individuals chose private care, with overwhelming majority of 92.1% of individuals (N=1,065) opting to be admitted as Medicare patients. On length of hospital stay, uninsured individuals who were hospitalised as Medicare patients spent an average of 2.24 nights in hospital. In contrast, the average length of stay by publicly admitted individuals with private hospital insurance is 2 nights. Of those who chose private hospital care, individuals with hospital insurance spent an average 1.93 nights, as compared to 1.49 nights for the uninsured. For all 2,198 individuals in the sample, the mean length of hospital stay is 2.07 nights with a variance of 6.58.

The remaining explanatory variables are defined in Table 4. These variables can be classified into the following four categories: demographics, socioeconomic characteristics, health status and risk factors. We present in Table 5 the summary statistics describing these variables. Both tables are located at the end of this paper.

[15] Both the patient type and hospital length of stay questions refer to the last hospital admission. Responses on the length of hospital stay are recorded in the NHS as 0 (no nights), 1 to 2, 3 to 4, 5 to 7, 8 or more.

4 An Econometric Model of Demand for Medical Care, Quality and Private Health Insurance

Let the dependent variable m_i be the observed medical care use of individual i ($i = 1, \ldots, N$). We assume that conditional on the exogenous covariates X_i, the endogenous variables q_i and d_i, m_i follows a Poisson distribution with probability density function

$$f(m_i \mid X_i, q_i, d_i) = \frac{\exp^{-\mu_i} \mu_i^{m_i}}{m_i!} \tag{19}$$

where the conditional mean parameter μ_i is

$$\mu_i = \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i) \tag{20}$$

We introduce into the conditional mean equation μ_i a heterogeneity term which is a normally distributed random variable with mean 0 and variance σ^2. The heterogeneity term is standardised by the standard deviation σ and ξ_i, where ξ_i is distributed standard normal, that is $\xi_i \sim$ N$[0, 1]$. The conditional mean equation is rewritten as

$$\begin{aligned} \mu_i &= \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i + \sigma\xi_i) \\ &= \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i)\exp(\sigma\xi_i) \end{aligned} \tag{21}$$

Accordingly as in equation (19), m_i conditional on q_i, d_i and ξ_i is distributed Poisson. The decision rule surrounding the binary variable representing quality choice is given by q_i^* where

$$q_i^* = Z_i\alpha + \beta_1 d_i + v_i \tag{22}$$

where $v_i \sim$ N$[0, 1]$. Empirically, q_i^* is unobservable. Instead, we observe the indicator variable q_i where

$$q_i = 1\,[q_i^* > 0] \tag{23}$$

The decision rule surrounding the choice of insurance is given by d_i^* where

$$d_i^* = W_i\gamma + \eta_i \tag{24}$$

where $\eta_i \sim$ N[0, 1]. Again, d_i^* is not observable. Instead, we observe the indicator variable d_i where

$$d_i = 1\,[d_i^* > 0] \tag{25}$$

We allow the quality and insurance binary variables in equations (21) in (22) to be potentially endogenous assuming that ξ_i, v_i and η_i are correlated. More specifically, we assume that ξ_i, v_i and η_i are distributed bivariate normal where

$$[\xi_i, v_i] \sim N_2[(0,0),(1,1),\rho_{12}] \tag{26}$$

$$[\xi_i, \eta_i] \sim N_2[(0,0),(1,1),\rho_{13}] \tag{27}$$

$$[v_i, \eta_i] \sim N_2[(0,0),(1,1),\rho_{23}] \tag{28}$$

We use the notation $N_2[(\mu_1, \mu_2),(\sigma_1^2, \sigma_2^2), \rho]$, where μ denotes the mean, σ^2 the variance and the correlation parameter ρ. An equivalent expression for (26) to (28) is to specify that ξ, v and η are distributed multivariate normal (MVN) with mean vector zero and covariance Σ where

$$\Sigma = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix} \tag{29}$$

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

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

where $\Omega_i = (X_i, Z_i, W_i, q_i, d_i)$ 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 is expressed as

$$\int_{-\infty}^{\infty} \Big[(1-q_i)(1-d_i)\int_{-\infty}^{-Z_i\alpha}\int_{-\infty}^{-W_i\gamma} f(m_i \mid X_i, q_i = 0, d_i = 0, \xi_i)\; g(\xi_i, v_i, \eta_i \mid \Omega_i)\; d\eta_i\, dv_i\ +$$

$$(q_i)(1-d_i)\int_{-Z_i\alpha}^{\infty}\int_{-\infty}^{-W_i\gamma} f(m_i \mid X_i, q_i=1, d_i=0, \xi_i)\; g(\xi_i, v_i, \eta_i \mid \Omega_i)\; d\eta_i\, dv_i \;+$$

$$(1-q_i)(d_i)\int_{-\infty}^{-Z_i\alpha}\int_{-W_i\gamma}^{\infty} f(m_i \mid X_i, q_i=0, d_i=1, \xi_i)\; g(\xi_i, v_i, \eta_i \mid \Omega_i)\; d\eta_i\, dv_i \;+$$

$$(q_i)(d_i)\int_{-Z_i\alpha}^{\infty}\int_{-W_i\gamma}^{\infty} f(m_i \mid X_i, q_i=1, d_i=1, \xi_i)\; g(\xi_i, v_i, \eta_i \mid \Omega_i)\, d\eta_i\, dv_i\Big]\; d\xi_i \tag{30}$$

where $f(m \,|\, X, q, d, \xi)$ is the conditional pdf of m_i as defined in (19). An approach to estimate the model is to construct the overall log-likelihood function for the model by summating (30) for all $i = 1, \ldots, N$. An alternative approach is to decompose the trivariate normal density function into a series of conditional bivariate normal pdfs. This method is more tractable as it reduces the number of integrals that we are required to evaluate to compute the likelihood function. We will describe this approach in the following[16]. Let the joint density for the observed data $f(m_i, q_i, d_i \,|\, \Omega_i)$ be expressed as

$$f(m_i, q_i, d_i \,|\, \Omega_i) = \int_{-\infty}^{+\infty} f(m_i, q_i, d_i \,|\, \Omega_i, \xi_i)\phi(\xi_i)d\xi_i \tag{31}$$

where $\phi(\xi_i)$ is the standard normal density. We specified in (26) to (28) that m_i, q_i and d_i are related 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 we can express

$$f(m_i, q_i, d_i \,|\, \Omega_i, \xi_i) = f(m_i \,|\, X_i, q_i, d_i, \xi_i)\; \cdot g(q_i, d_i \,|\, Z_i, W_i, \xi_i) \tag{32}$$

where $f(m_i \,|\, X_i, q_i, d_i, \xi_i)$ is the conditional Poisson density function in (19) and $g(q_i, d_i \,|\, Z_i, W_i, \xi_i)$ is conditional density function of q_i and d_i given Z_i, W_i and ξ_i. By the assumption of joint

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

normality[17] in (26) and (27), $(v_i \,|\, \xi_i)$ and $(\eta_i \,|\, \xi_i)$ is distributed bivariate normal

$$\begin{pmatrix} v_i \,|\, \xi_i \\ \eta_i \,|\, \xi_i \end{pmatrix} \sim N_2 \left[\begin{pmatrix} \rho_{12}\xi_i \\ \rho_{13}\xi_i \end{pmatrix}, \begin{pmatrix} 1-\rho_{12} & \rho_{23}-\rho_{12}\rho_{13} \\ \rho_{23}-\rho_{12}\rho_{13} & 1-\rho_{13} \end{pmatrix} \right] \tag{33}$$

and

$$v_i \,|\, \xi_i = \rho_{12}\xi_i + \epsilon_{1i}(1-\rho_{12}^2)^{1/2}, \quad \epsilon_{1i} \sim N[0,1] \tag{34}$$

$$\eta_i \,|\, \xi_i = \rho_{13}\xi_i + \epsilon_{2i}(1-\rho_{13}^2)^{1/2}, \quad \epsilon_{2i} \sim N[0,1] \tag{35}$$

By substituting (34) into (22) and using the decision rule for q_i, we obtain

$$\begin{aligned} P(q_i = 1) = \;& P\left(\epsilon_{1i} > -\frac{Z_i\alpha + \beta_1 d_i + \rho_{12}\xi_i}{(1-\rho_{12}^2)^{1/2}} \right) \\ = \;& P\left(\epsilon_{1i} < \frac{Z_i\alpha + \beta_1 d_i + \rho_{12}\xi_i}{(1-\rho_{12}^2)^{1/2}} \right) \end{aligned} \tag{36}$$

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

$$P(q_i = 0) = \; P\left(\epsilon_{1i} > \frac{Z_i\alpha + \beta_1 d_i + \rho_{12}\xi_i}{(1-\rho_{12}^2)^{1/2}} \right) \tag{37}$$

Similarly, by substituting (35) into (24), the probability of observing $d_i = 0, 1$ are

$$P(d_i = 1) = P\left(\epsilon_{2i} < \frac{W_i\gamma + \rho_{13}\xi_i}{(1-\rho_{13}^2)^{1/2}} \right)$$

$$P(d_i = 0) = P\left(\epsilon_{2i} > \frac{W_i\gamma + \rho_{13}\xi_i}{(1-\rho_{13}^2)^{1/2}} \right)$$

Given our assumption in (33) that $(v_i \,|\, \xi_i)$ and $(\eta_i \,|\, \xi_i)$ are distributed bivariate normal, we can write the joint conditional density for q_i and d_i. Let $y_{1i} = 2q_i - 1$ and $y_{2i} = 2d_i - 1$. Hence,

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

$$g(q_i, d_i \,|\, Z_i, W_i, \xi_i) = \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*] \tag{38}$$

where

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

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

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

and Φ_2 denote the bivariate normal cumulative density function. Finally, we obtain the joint density function for the data by substituting (38) and (32) into (31) to obtain

$$f(m_i, q_i, d_i \,|\, \Omega_i) = \int_{-\infty}^{+\infty} f(m_i \,|\, \Omega_i, \xi_i) \cdot \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*]\, \phi(\xi_i) d\xi_i \tag{39}$$

Equation (39) will be used to construct the log-likelihood function which we will use to estimate the model. We will devote the next section to the discussion of our estimation strategy.

4.0.1 Estimation Strategy

A solution to the joint conditional density function in (39) requires the evaluation of an integral. Given that (39) does not have a closed-form expression, we approximate the integral using simulation methods (Gouriéroux and Trognon 1996). As in (39), the joint conditional density function for the i-th observation in our sample is

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

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

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

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

$$\widehat{\mathrm{L}}(\Theta) = \prod_{i=1}^{N} \frac{1}{S} \sum_{1}^{S} f(m_i \,|\, \Omega_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*] \tag{40}$$

$$\ln \widehat{\mathrm{L}}(\Theta) = \sum_{i=1}^{N} \frac{1}{S} \sum_{1}^{S} f(m_i \,|\, \Omega_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*] \tag{41}$$

Estimation is implemented in `Stata` using numerical derivatives.

5 Results

In the following section, I discuss the findings from the simultaneous equation regression model of demand for private hospital insurance, the choice of hospital admission as a public or private patient and the intensity of hospital care utilisation. The discussion is organised as follows: Section 5.1 reports on the findings on the determinants of the demand for private hospital insurance. Section 5.2 discusses how private hospital insurance influences the choice of public or private hospital care. The section examines how the intensity of hospital care, vis-à-vis the length of hospital stay, varies by patient type and insurance status. Finally, Sections 5.3 and 5.4 elaborate on how socioeconomic, demographic and health factors affect the choice of patient type and the intensity of care. The paper concludes with a discussion in Section 6.

5.1 Demand for Hospital Insurance

Table 2 presents the coefficients, marginal effects and their respective standard errors[18] in the regression analysis on 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, our discussion focuses on the marginal effects, which is interpreted as the increase in the probability of being insured given a change in the explanatory variable[19].

As reported in Table 2, married individuals or those who are in a defacto relationship have a higher probability of purchasing private hospital insurance. More specifically, these individuals are 12% more likely to be privately insured relative to their single counterparts. We do not observe any statistically significant differences in the propensity to insure between households

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

[19] 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 2: Demand for Private Health Insurance: Hospital Table

Explanatory Variables	Coeff	S.E	dF/dX	S.E
Maristat	0.309***	0.072	0.122***	0.035
Depchild	-0.007	0.103	-0.003	0.041
Female	0.227***	0.076	0.090***	0.003
Age[b]	1.350***	0.370	0.009***	0.000
Age-squared	-0.987***	0.340		
Childbearing	-0.124	0.154	-0.049	0.060
Country of Birth:				
Main English	-0.342***	0.094	-0.133***	0.035
Others	-0.182*	0.100	-0.071*	0.038
Education				
Vocational	0.114	0.083	0.045	0.033
Diploma	0.368***	0.110	0.146***	0.043
Degree	0.507***	0.118	0.199***	0.044
Health Card	-0.429***	0.104	-0.170***	0.041
Household Inc	0.634***	0.161	0.052***,[a]	0.006
Household Inc-Sq	-0.193	0.154		
Occupation:				
Manager/Admin	0.417**	0.173	0.165**	0.066
Professional	0.187	0.152	0.075	0.061
Asc Professional	0.277*	0.147	0.110*	0.058
Tradesperson	-0.054	0.187	0.022	0.075
Adv Clerical/Service	0.372	0.269	0.147	0.103
Int Clerical/Service	0.109	0.147	0.043	0.058
Production/Transport	-0.174	0.201	-0.068	0.078
Ele Clerical/Service	-0.070***	0.024	-0.028***	0.010
Labourer	-0.420**	0.197	-0.160**	0.070
Alcohol 3-day Risk	-0.141	0.107	-0.056	0.042
Smoker Regular	-0.516***	0.099	-0.197***	0.035
Walk	0.121*	0.068	0.048*	0.027
Overweigh	-0.012	0.078	-0.026	0.031
Regions:				
VIC	0.181*	0.110	0.072*	0.044
QLD	0.380***	0.107	0.151***	0.042
SA	0.345***	0.108	0.137***	0.042
WA	0.421***	0.113	0.166***	0.043
TAS	0.536***	0.132	0.201***	0.049
NT	-0.091	1.415	0.036	0.564
ACT	-0.108	0.160	-0.043	0.062
Remoteness:				
Inner Australia	-0.212**	0.088	-0.083**	0.034
Others	-0.330***	0.100	-0.128***	0.038
Constant	-3.723***	0.682		
Number of observations:	2198			
LogL value:	-6037.4676			

***, **, * denote significance at 1%, 5% and 10% respectively.
Note: ICD10-AM diagnostic categories for long-term chronic conditions are not reported.
a. The change in probability of insurance given a $100 increase in weekly household income.

with or without dependent children although the price of insurance is comparatively lower for families relative to non-families due to community rating regulations on private health insurance premiums in Australia[20].

The purchase of hospital insurance is positively associated with age. An increase in the individual's age by one year increases the probability of purchasing insurance by 0.9%. We observed that the coefficient on regressor age-squared has a negative sign. This result is consistent with what would be observed if one were to examine how private hospital insurance status varies across age groups, which showed that while the proportion of individuals with private hospital insurance increases with age, this relationship is reversed beyond the 50-59 years age group. The propensity to insure differs across genders, as females are approximately 9% more likely to have hospital insurance as compared to males. This is not unexpected given that females generally consumes more medical care than their male counterparts, particularly during the childbearing years[21]. We include a binary variable to examine the impact of childbearing on the purchase of hospital insurance but the effect is not statistically significant. Individuals' country of birth have a significant effect on the likelihood to purchasing insurance, with individuals not born in Australia being less likely to have purchased private health insurance than those born in Australia.

Post-school education is positively associated with hospital insurance purchase. Compared to individuals with no post-school education qualifications, individuals with diplomas are 14.6% more likely to have private hospital insurance while those with a bachelor degrees and above are 20% more likely to be privately insured. These results may be due to individuals who are more educated having a better understanding of the purpose of private hospital insurance. The level of household income has a strong positive effect on the probability of purchasing private hospital insurance. An increase of $100 in the weekly equivalised cash household income increases the probability of insurance purchase by 5.2%. The result is expected given that high income individuals have the incentive to purchase private health insurance to avoid paying the

[20]Community rating regulations on private health insurance premiums in Australia requires that family policies (single or couple insurees with dependent children) are charged the same premium as that of non-family policies. Butler (1999) argues that as a result of the community rating requirement, cross-subsidisation in favour of families with children may occur. The author showed that the estimated price of insurance, which is calculated as a ratio of the premium to the expected benefits, is lower for family as compared to singles policies for all ages up to age 50-54 years.

[21]Butler (1999) showed that the estimated hospital insurance benefits received by females is significantly higher than that for males for age groups between 20 to 54 years.

Medicare Levy Surcharge. Individuals holding government health concession cards are less likely to purchase private health insurance. Cardholders have a lower incentive to purchase private insurance as they generally face a lower net price for medical care[22]. To examine if individuals' occupation has an impact on the propensity to insure, we include in the regression a set of occupational dummy variables. In comparison with unemployed individuals and those who are not in the labour force, individuals in professional and related occupations such as managers and administrators are more likely to purchase private health insurance. In contrast, individuals who are in the elementary workers and labourers occupation group are less likely to purchase private health insurance[23].

A key insight from the results of the theoretical model described in Section 2 is that the decision to insure depends on the expected net expenditure on medical care and quality, which in turn depends on individuals' expectations on his or her health states in the future. We included a set of dummy variables representing the sixteen ICD10-AM disease categories[24] of long-term chronic conditions reported by survey respondents to further capture individual heterogeneity in current and expected health status. We obtained significant coefficient estimates for three of the sixteen disease categories. Mental and behavioral problems and diseases of the circulatory system as negatively associated with insurance purchase. We observe a negative association between medical conditions of the circulatory system and private hospital insurance purchase. This result is particularly surprising given that this disease category includes conditions such as ischaemic heart diseases, haemorrhoids and varicose veins which are medical conditions that require hospital treatments associated with high volumes and long waiting lists in public hospitals. Having a chronic medical condition of the genito-urinary system is positively associated with insurance purchase. We experimented with two other health proxy measures but none of

[22]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.

[23]An alternative variable that may be used to examine the effect of occupation or employment on insurance purchase is the individuals' employment status. We found no difference in the propensity to purchase insurance among individuals who are in either full-time or part-time employment as compared with the individuals who are unemployed or not in the labour force.

[24]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.

which produces significant results. The first health measure 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[25]. We expect that the presence of medical conditions for which treatment is associated with long waiting times in public hospitals to be positively associated with private hospital insurance purchase. The second health measure is a count variable denoting the number of long-term chronic conditions reported by individuals. This measure reflects the health status of individuals, where a higher number of chronic conditions implies a lower health status. Contrary to expectations, we found the coefficient on the number of long term conditions to be negative and statistically insignificant.

Health risk factors such as alcohol risk and regular smoking generally decrease the propensity to purchase private hospital insurance[26]. Regular smokers are 20% less likely be privately insured compared to non-smokers, non-regular smokers and ex-smokers. Exercise habits such as walking for sports, recreation and fitness is positively associated with private insurance purchase. These variables behave as proxies for individuals' health status, risk aversion and attitudes towards good health. Finally, we included regional dummies to capture the geographical effects on the propensity to purchase insurance. Individuals living in Victoria, Queensland, South Australia and Western Australia have a higher probability of purchasing private hospital insurance relative to those living in New South Wales. This result is in contrast with previous studies by Cameron and Trivedi (1991) and Savage and Wright (2003), which both found that living in Queensland has a negative effect on insurance purchase. The observed differences may be due to differences in the versions of National Health Survey data used in this study compared to the other two studies. Individuals residing in more remote parts of Australia are less likely than their counterparts living in major cities to purchase private hospital insurance.

[25]These conditions are referred to as *indicator procedures* (AIHW 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.

[26]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.

Table 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	2.223***	0.559	0.713***[b]	0.124	2.227***	0.083	0.714***	0.018
				Hospital Length of Stay				
Patient-Type	-1.430***	0.485	-1.616***	0.587	-0.469***	0.090	-0.877***	0.166
Insurance	0.294	0.507	0.340	0.596	0.020	0.058	0.039	0.112
Insurance*P_Type	0.523**	0.218	0.641**	0.287	0.430***	0.107	0.867	0.229
Moral Hazard Effect[d]			0.455**	0.226			0.697***	0.118
Insurance on Pub_Pat[c]			0.514	0.989			0.040	0.116

Correlation Parameters

	ρ	S.E
$\text{Corr}_{(\text{LOS,PAT})}$	0.453***	0.218
$\text{Corr}_{(\text{LOS,INS})}$	0.179	0.168
$\text{Corr}_{(\text{PAT,INS})}$	-0.009	0.374

***, **, * denote significance at 1%, 5% and 10% respectively.
a. Regression models under the exogenous assumptions are the 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, $\bar{X}$)

5.2 Insurance and Patient Type Effects

Table 3 presents the coefficients and 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, each obtained under the endogeneity and exogeneity assumptions respectively. The results presented under the endogeneity assumption are those obtained from the structural econometric model. Under the exogeneity assumption, we apply the reduced form Probit and Poisson regression models to estimate the patient choice and hospital length-of-stay equations respectively. Estimates of the correlation parameters from the structural model are presented at the bottom of Table 5.2. These estimates reflect the degree of correlation between the unobservables in the insurance, patient choice and hospital care intensity equations which provide evidence on the presence of endogeneity of the insurance and patient-type binary variables. The following discussion focuses on the estimates from the structural model and where appropriate contrasts these results with that obtained under the exogeneity assumption.

In the patient choice equation, the coefficient on the insurance binary variable is positive and statistically significant. From the estimates of the marginal effects, individuals with private hospital insurance are 71% more likely to admit into hospital as a private patient relative to a public patient. This result is logical and consistent with the predictions from the theoretical model given that individuals with private hospital insurance face lower net prices for private hospital care relative to individuals who are not privately insured. We may hypothesise that unobserved heterogeneity such as individuals' taste for private care influence both the propensity to purchase private health insurance and the choice of private hospital care. In this case, the insurance variable in the patient type equation is endogenous and the marginal effect of insurance on the propensity to seek private hospital care will be biased upwards. However, the results do not support this hypothesis given that that the estimate of the correlation parameter $\text{Corr}_{(\text{PAT, INS})}$ between the unobservables in the patient choice and the insurance equations is not statistically significant. Correspondingly, we can observe that the coefficients and marginal effects on the insurance variable under the endogeneity and exogeneity assumptions do not differ by much.

Moving on to the hospital length-of-stay equation, the coefficient on the patient-type variable is -1.43. The marginal effect on the expected length of stay when the patient-type binary variable changes from 0 to 1 is -1.62. Both of these estimates are highly statistically significant. The marginal effects of a change in the patient-type variable can be 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 shorter by 1.62 nights compared to publicly admitted (Medicare) patients. There is strong evidence that the patient-type variable is endogenous, given that the estimate of the correlation parameter $\text{Corr}_{(\text{LOS, PAT})}$ is 0.453 and statistically significant. It is likely that the endogeneity arises unobserved heterogeneity in individuals' medical conditions for which hospital care was obtained and the nature of the hospital treatments. These information are not available in the data. Patients who opt for private hospital care generally seek medical and surgical treatment for conditions that are elective in nature. Admissions for elective surgery typically involved shorter hospital stays where many are performed on a day-admission basis[27]. From an omitted variable perspective, if individuals seek private hospital care for treatments that generally involve shorter length of hospital stays, the omission of information on the type of hospital care leads to a

[27]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

bias towards zero in the estimate of the coefficient on the patient type variable[28]. We can observe that under exogeneity assumption, the estimate of the marginal effect of the patient type binary variable is -0.88, which is roughly half the value of the estimate obtained in the structural model. This result supports the hypothesis that individuals sought private hospital care for elective treatment that are associated with shorter length of stay.

We included in the length of stay equation a binary variable indicating insurance status and an interaction term combining insurance status and patient-type to examine the insurance effects on hospital care intensity for private and public patients separately. Here, we will not discuss the coefficients and marginal effects of these variables individually as they do not have meaningful interpretations[29]. Instead, we examine the marginal effects of a 0 to 1 change in the insurance binary variable on the expected length of stay among individuals who were admitted as private patients (termed as *moral hazard effects*[30]) and public patients (*insurance on public patients*[31]). The estimate of the moral hazard effect is 0.46 and highly statistically significant from zero. Amongst individuals who obtained private hospital care, those with private hospital insurance stay on average 0.46 nights longer than uninsured individuals. The estimate of the insurance effect on individuals hospitalised as public patients is not statistically significant from zero. This result is logical given that private hospital insurance does not apply to public hospital care. Overall, the results do not suggest that the insurance variable in the length-of-stay equation is endogenous. This follows from the statistically insignificant estimate of the correlation parameter $\text{Corr}_{(\text{LOS, INS})}$.

[28]This result follows the consequences of ignoring omitted variables in estimation via ordinary least squares (OLS). The probability limits of the OLS estimator when omitted variable is ignored can be expressed as: plim $\hat{\beta}_k = \beta_k + \gamma[\text{Cov}(x_k, q)/\text{Var}(x_k)]$. See Page 62 of Wooldridge (2002). In our case, $\hat{\beta}_k$ is the coefficient on patient-type variable, q is the elective care variable that is omitted and γ is the partial effect of q on length of stay. Given that $\text{Cov}(x_k, q)$ is positive and γ is negative, the estimate on patient-type is asymptotically biased downwards.

[29]The estimates of the marginal effects for a $0 \rightarrow 1$ change in the insurance or insurance-patient interaction term are each calculated with all other explanatory variables held at their mean value. As we will see elaborate further on, these computations are different from the marginal effects of insurance given a public or private hospital admission.

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

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

5.3 The Choice of Public or Private Patient

The regression results on the choice of hospital admission as a public or private patient is presented in columns 2 to 5 of Table 6. Marital status has a significant positive effect on the choice of patient type, with married individuals being 8.2% more likely to be hospitalised as a private patient. The marginal effect on one year increase in the respondent age increases the probability of seeking private care by 0.7%. The propensity to obtain private hospital care does not differ between males and females and whether or not individuals have dependent children. In addition, we would expect that females in the childbearing ages of 25 to 40 years are more likely to seek private hospital care but found no strong statistical evidence to support this view. There is some evidence that individuals who were born in Australia are more likely to obtain private care relative to those not born in Australia.

Educational attainment appears to have a limited effect on patient type choice as only individuals with diplomas have a significantly higher probability of choosing hospital care as private patients as compared to individuals without post-school education. This result is similar to Propper (2000) who found that higher education does not have any significant effect on both public and private inpatient hospital stay for the case of the UK. Household income is positively associated with the choice of private care. A $100 increase in the weekly equivalised cash household income increases the probability of being hospitalised as a private patient by 3.1%. This result is consistent with previous studies that examines waiting on lists in the UK National Health Service which found that the monetary valuation of time is larger for individuals with higher household income and individuals engaging in full or part-time employment (Propper 1990b, 1995). In contrast with these results, we observed no significant evidence that the choice of patient type is associated with employment status. Also, whether or not individuals have health care concession cards does not affect the propensity to seek private care.

One of the key factors 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, we would expect that individuals are more likely to seek private care for elective treatments that are associated with long waiting times in the public sector. Unfortunately, information on types of medical conditions are not available in data set that we use in this study. As proxies for individuals' health status, we experimented with two sets of health status indicators. The first indicator, which is reported in Table 6, is a set of binary variables which indicates whether or not the respondent has long-term and chronic medical conditions by the ICD10 categories. Having diseases of the endocrine or nervous system decreases the propensity to seek private hospital care. On the other hand, individuals suffering from diseases of the musculoskeletal system are more likely to have obtained private care. The second indicator is a count variable describing the number of long-term chronic conditions individuals' suffer from. This indicator reflects the degree of ill-health, with a higher count connoting poorer health. With this measure of health status, we not find any evidence to suggest that individuals' health status affects the choice of patient type. We included information on whether the respondent is a regular smoker or whether the individual is overweigh to capture the effects of health risk and attitudes on health on the choice of public and private care. The results showed that individuals who reported having undertaken some exercise through walking are more likely to have obtained private care. There is no evidence that the health risk measures have a significant impact on hospitalisation choice.

Finally, we found evidence of a geographical effect on the patient type choice on hospital admission. Comparative to respondents from New South Wales, individuals from Queensland and Tasmania are more likely to seek hospital care as a private patient. There is however no evidence to suggest that hospitalisation choices are influenced by the remoteness of individuals' residences.

5.4 Length of Inpatient Stay

We present in columns 6 to 9 of Table 6 the regression results for patients' 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 suggest the presence of overdispersion[32] in the data, which indicates the inappropriateness of the Poisson regression model.

Moving on to the explanatory variables, age and marital status has a small positive and statistically significant effect on patients' length of stay. There is strong evidence linking a higher intensity of inpatient stay for childbirth given that women in the childbearing years stay in

[32]For 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 $\sigma > 0$.

hospital for an average 0.86 days more. Individuals' educational attainment, household income and whether or not individuals have a government health care card do not have a significant influence on the duration of hospital stay. Individuals engaging in full-time employment spend an expected 0.24 days shorter in hospital as compared to those who are unemployed. This result may be attributable to employed individuals being unable to take significant amount of time away from work. We observe some variations in the length of stay across geographical regions that may be indicative of differences in medical norms and practices surrounding the treatment of hospital patients.

As in the patient type equation, we experimented with two sets of variables that serves as proxies for individuals' health status. A priori, we expect that individuals with poorer health should on average require a greater intensity of care when hospitalised. Furthermore, we expect that the medical conditions for which hospital treatment was obtained differ for public and private patients. For example, if patients who seek private care generally do so for elective treatment which is associated with short stays in hospitals, the role of health status in explaining variations in private hospital days may be limited and different from that of public hospital care. As presented in Table 6, except for mental & behavioural conditions and diseases of the musculoskeletal system, the presence of long-term conditions is not associated with the length of hospital stay. The inclusion of a count variable representing the number of long-term chronic conditions individuals have as a measure of health does not produce any significant results. Using available information in the data as proxies for the health state of individuals, our results suggest that health status does not play a significant role in influencing either public/private hospitalisation choices or the length of hospital stay.

6 Discussion and Concluding Remarks

Individuals' decision-making on the utilisation of hospital services in the mixed public-private hospital system in Australia involves 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 UK-based studies have investigated the determinants that influence the choice of public or private health care. To our 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 us to isolate and identify the intertwining factors that motivate the three decisions surrounding the use of hospital care. To achieve this, we developed a simultaneous equation regression model that accommodates the count data nature of hospital stay and binary outcomes in the decisions to insure and the choice of public or private care.

The results on the demand for private health insurance is largely consistent with similar studies by Cameron and Trivedi (1991) and Savage and Wright (2003). Demographic and socioeconomic factors such as age and gender, marital status, education attainment, household income and the availability of government concession cards have significant influence 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 insured 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. On the decision of public or private hospital care, the results indicate that private health insurance is the most significant factor that influences the decision to seek private hospital care[33]. Age, marital status and household income are important determinants that influence the probability of obtaining private hospital care. Consistent with Cameron and Trivedi (1991) and Savage and Wright (2003), we found evidence on the presence of moral hazard in private hospital use.

The results also indicate that individuals seek private care for medical and surgical treatments that involve short hospital stays and day admissions. The length of hospital stay for privately admitted patients is on average 1.6 nights shorter than that for public (Medicare) patients. This finding is consistent with the evidence presented in Sundararajan, Brown, Henderson, and Hindle (2004) and Hopkins and Frech (2001) which suggest that while the increase in private health insurance coverage in the Australian population in 2001 is associated with higher use of private hospital care, the public hospital system has been burdened by patients with more severe medical conditions that require a higher intensity of treatment than that in

[33]In a similar study for the case of Jamaica, Gertler and Strum (1997) 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. Unlike curative care where insurance shifted demand from public to private care, insurance increases the total (public and private) demand for preventive services.

private hospitals. This result has significant policy implications. In particular, it calls into question whether private health insurance is regarded as an effective tool to help alleviate the burden on the public hospital system. Clearly, the findings of this paper indicate that the effectiveness of private health insurance on this regard is limited.

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Figure 1: Decision Tree: Insurance, Patient Type and Average Length of Stay

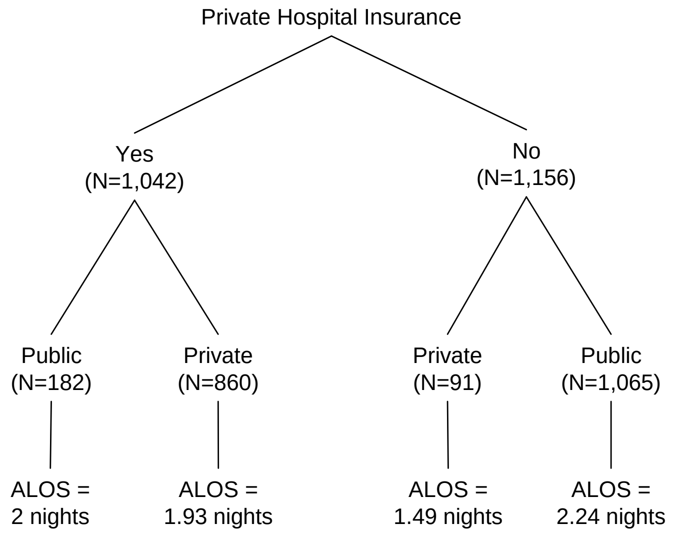

Table 4: Variable names and description

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
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
Ear	=1 Diseases of the ear and mastoid
Circulatory	=1 Diseases of the circulatory system
Respiratory	=1 Diseases of the respiratory system

Table 4: Variable names and description: Cont.

Variable	Description
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 5: Means of explanatory variables

Sample Size N=2,198

Binary explanatory variables

Variable	Mean	Variable	Mean
Female	0.582	SAH-Very Good	0.260
Childbear	0.148	SAH-Excellent	0.107
Maristat	0.559	ICD10-Infectious/Parasitic	0.017
Depchild	0.282	ICD10-Neoplasm	0.075
IU-Couple	0.355	ICD10-Blood	0.032
IU-Couple_Dep	0.227	ICD10-Endocrine	0.274
IU-One_Parent	0.055	ICD10-Mental/Behavioural	0.158
IU-One_Person	0.364	ICD10-Nervous	0.121
COB-Aust	0.737	ICD10-Eye	0.794
COB-Main_Eng	0.136	ICD10-Ear	0.251
COB-Others	0.128	ICD10-Circulatory	0.431
Edu-School	0.507	ICD10-Respiratory	0.347
Edu-Voc	0.235	ICD10-Digestive	0.188
Edu-Dip	0.103	ICD10-Skin	0.051
Edu-Degree	0.155	ICD10-Muscular	0.578
Hconcard	0.570	ICD10-Genitourinary	0.091
Occup-N_Emloy	0.565	ICD10-Congenital	0.012
Occup-Mgmr/Adm	0.052	ICD10-Others	0.183
Occup-Prof.	0.091	Alcohol 3-day	0.124
Occup-A/Prof.	0.068	Smoker Reg	0.183
Occup-TradesP	0.042	Walk	0.494
Occup-Adv Clr/Svc	0.012	Overweigh	0.234
Occup-Int Clr/Svc	0.069	NSW	0.207
Occup-Prod/Trans	0.034	VIC	0.165
Occup-Ele Clr/Svc	0.244	QLD	0.155
Occup-Labour	0.036	SA	0.172
Employ-FT	0.277	WA	0.129
Employ-PT	0.158	TAS	0.106
Employ-Not	0.014	NT	0.003
Employ-NILF	0.551	ACT	0.067
SAH-Poor	0.139	ASGC-Major Cities	0.600
SAH-Fair	0.203	ASGC-Inner Region	0.243
SAH-Good	0.291	ASGC-Others	0.157

Continuous and Count explanatory variables

	Mean	Std. Dev.	Min	Max
AGE	55.91	16.21	32	85
HHINC	533.11	372.55	119.00	1279.00
LTCOND	3.66	1.57	0	5

Table 6: Regression Results - Public/Private Choice and Hospital Length of Stay

	Public Private Patient				Length of Hospital Stay			
	Coeff	S.E	dF/dX	S.E	Coeff	S.E	dF/dX	S.E
Heterogeneity σ					1.104***	0.061		
Maristat	0.228**	0.113	0.085**	0.042	0.162**	0.078	0.184**	0.087
Depchild	0.134	0.117	0.051	0.045				
Female	0.155	0.106	0.058	0.039	0.032	0.079	0.037	0.089
Age	-0.197	0.504	0.007***	0.003	-0.553	0.370	0.028***	0.005
Age-squared	0.520	0.451			0.972***	0.342		
Childbearing	0.152	0.182	0.058	0.070	0.599***	0.154	0.859***	0.275
Country of Birth:								
Main English	-0.140	0.142	-0.052	0.051				
Others	-0.268**	0.136	-0.096**	0.047				
Education:								
Vocational	0.019	0.104	0.007	0.039	0.045	0.082	0.052	0.096
Diploma	0.294*	0.162	0.114*	0.064	-0.040	0.082	-0.045	0.138
Degree	0.083	0.147	0.031	0.056	0.101	0.117	0.119	0.143
Health Card	0.104	0.149	0.039	0.056	0.036	0.117	0.041	0.134
Household Inc[a]	0.746***	0.242	0.031***	0.012	0.065	0.177	0.020	0.020
Household Inc-Sq	-0.560***	0.190			-0.018	0.154		
Employment:								
Full-Time	0.205	0.147	0.078	0.056	-0.116*	0.103	-0.229**	0.122
Part-Time	0.134	0.141	0.051	0.054	-0.110	0.099	-0.110	0.117
ICD10:								
Infectious/Parasitic	0.289	0.353	0.112	0.140	-0.071	0.243	-0.078	0.260
Neoplasm	-0.226	0.159	-0.081	0.055	-0.071	0.121	-0.079	0.130
Blood	-0.150	0.225	-0.055	0.079	0.033	0.174	0.038	0.205

Table 6: Regression Results - Public/Private Choice and Hospital Length of Stay (Cont.)

	Public Private Patient				Length of Hospital Stay			
	Coeff	S.E	dF/dX	S.E	Coeff	S.E	dF/dX	S.E
Endocrine	-0.180*	0.106	-0.065*	0.039	-0.034	0.079	-0.039	0.089
Mental/Behavioural	-0.357	0.138	-0.013	0.051	0.173*	0.097	0.211*	0.124
Nervous	-0.265*	0.138	-0.095**	0.047	-0.078	0.106	-0.087	0.114
Eye	0.173	0.128	0.064	0.046	0.037	0.104	0.042	0.117
Ear	-0.483	0.103	-0.018	0.039	-0.043	0.078	-0.048	0.087
Circulatory	-0.138	0.099	-0.051	0.037	-0.013	0.074	-0.015	0.084
Respiratory	0.446	0.085	0.017	0.032	-0.009	0.071	-0.010	0.081
Digestive	-0.133	0.108	-0.049	0.039	0.018	0.821	0.021	0.095
Skin	-0.178	0.178	-0.065	0.062	-0.762	0.155	-0.084	0.166
Muscular	0.180*	0.094	0.067*	0.035	-0.138	0.071	-0.160*	0.083
Genitourinary	-0.029	0.158	-0.011	0.059	-0.007	0.115	-0.008	0.131
Congenital	0.219	0.473	0.084	0.187	0.440	0.295	0.630	0.520
Others	-0.039	0.103	-0.014	0.038	0.142*	0.085	0.170	0.106
Alcohol 3-day Risk	0.0845	0.136	0.032	0.052				
Smoker Regular	-0.129	0.170	-0.048	0.062				
Walk	0.200**	0.085	0.075**	0.032				
Overweigh	-0.061	0.091	-0.023	0.034				
Region								
VIC	0.023	0.139	0.009	0.053	0.145	0.106	0.174	0.134
QLD	0.385***	0.148	0.149***	0.058	0.230**	0.116	0.286	0.157
SA	0.035	0.149	0.012	0.056	0.193*	0.111	0.235*	0.144
WA	-0.060	0.167	-0.022	0.061	0.350***	0.117	0.460***	0.174
TAS	0.466	0.193	0.182**	0.076	0.372***	0.137	0.495**	0.211
NT	0.266	2.616	0.103	1.040	0.296	0.797	0.394	1.225
ACT	0.150	0.165	0.057	0.064	-0.114***	0.149	-0.124	0.155
Remoteness								
Inner Aus	-0.100	0.115	-0.037	0.042	0.103	0.086	0.121	0.104
Others	-0.217	0.143	-0.079	0.050	0.070	0.102	0.083	0.122
Constant	-3.071***	0.886			0.084	0.668		

***, **, * denote significance at 1%, 5% and 10% respectively.
a. The change in probability of insurance given a $100 increase in weekly household income.