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Abstract

This paper examines the determinants of hospital stay intensity, the decision to seek hospital care as a public or private patient and the decision to purchase private hospital insurance. We describe a theoretical model to motivate the simultaneous nature of these decisions. For the empirical analysis, we develop a simultaneous equation econometric model that accommodates the count data nature of length of stay and the binary nature of the patient type and insurance decisions. The model also accounts for the endogeneity of the patient type and insurance binary variables. The results suggest that there is some weak evidence of endogeneity between the decision to purchase insurance and the intensity of hospital use. We do not find significant moral hazard effects of private hospital insurance on the intensity of private hospital care. The results also indicate that the length of hospital stay for private patients is shorter than for public patients.

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1 Introduction

In many developed countries including Australia and the UK, the public sector plays a dominant role in the financing of medical care. In these health systems, public hospital services are provided free at the point of use and waiting lists feature predominantly as resource allocation mechanisms to control access to services. Usually, a private hospital market coexist alongside the public sector, and it delivers private care that is financed either through direct payments or private health insurance. With the rapidly growing public expenditure on health and long-term care predicted to escalate further in the future, governments have sought to identify and implement alternative mechanisms to finance the health care demands of their populace. Among the strategies explored, the expansion of private health care markets through greater reliance of private health insurance have generated considerable attention among policy makers (Colombo and Tapay 2004). The effects of private markets for health care on the public health care system have been the subject of extensive debate. It is often argued that a private health care market can relieve pressures off the public system in an environment of budget and capacity constraints which leads to faster access and higher quality care in the public sector. Private health care is also perceived to enhance consumers' choice and the responsiveness of health systems to the diversity of tastes and needs. However, questions have been raised on whether a mixed public-private approach to the provision of health care diverts resources away from the public sector particularly in a regime where doctors are allowed to practice in both sectors. Issues surrounding the equity of access arise as individuals with private health insurance, who usually have high incomes, can gain faster access to elective surgeries which in the public sector would involve significant waiting times.

In this paper, we empirically investigate the relationships between the intensity of health care use, the choice to seek public or private health care and the decision to purchase private health insurance within a simultaneous framework. Previous studies have examined each of these either separately or in combination with one other theme. Within the literature on the demand for public and private care, the main subject of interest is how 'prices', viz-á-viz waiting times and private health insurance, influence the demand for public and private medical care. In the absence of explicit monetary prices for public health care, the cost of waiting on waiting lists perform 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). With this framework in mind, Martin and Smith (1999) empirically investigated the determinants of demand and supply for elective surgery in the UK National Health Service (NHS) using ward level data. These authors found that the demand for NHS care is negatively associated with NHS waiting times. This result is consistent with McAvinchey and Yannopoulos (1993) who showed that higher NHS waiting times and lower private medical insurance premiums are associated with lower expenditures on public health care. Private health insurance has been found to be associated with higher use of private health care services. Srivastava and Zhao (2008) found that individuals with private health insurance are more likely to seek private hospital services in Australia. Also, in the context of a developing country, Gertler and Strum (1997) showed that individuals with private health insurance switch from public to private providers for both curative and preventive care in Jamaica. On the dynamics of the public and private choice, Propper (2000) observed that individuals have a tendency to be persistent in their choices over time.

The relationship between health care use and private health insurance, particularly in health systems where the public sector plays a dominant role have been examined by a number of studies. The interdependence between health care use and health insurance is highlighted in Cameron et al. (1988). The demand for health care is influenced by the availability of insurance, and the decision to purchase health insurance depends on the expected utilisation of health services in the future. As a result of the simultaneity between the utilisation of health care and the decision to insure, careful attention is required to address the problem of self-selection when one attempts to quantify the effects of insurance on the intensity of health care use. Using the 1977-1978 Australian Health Survey, Cameron et al. (1988) found that individuals with insurance utilised more doctor visits and prescribed medicine but insurance does not have a significant impact on the frequency of hospital admissions and hospital days. Savage and Wright (2003) used the 1989-1990 Australian National Health Survey and found that the duration of stay in private hospital is higher for individuals with private health insurance. Riphahn et al. (2003) analysed data from the German Socioeconomic Panel and showed that after controlling for self-selection effects, add-on insurance is not associated with a higher number of hospital and doctor visits. Harmon and Nolan (2001) found for the case of Ireland that the insured individuals have a higher probability of having an hospital inpatient stay.

This paper distinguishes from previous studies in that we empirically investigate the determinants of hospital stay intensity and the choices between public or private care and private hospital insurance using a simultaneous framework. We develop a simultaneous equation econometric model that accommodates the count data nature of the hospital length of stay and accounts for the potential endogeneity in the binary variables that represent the outcomes of the patient type[1] and insurance decisions. This econometric model is novel and contributes to the literature on simultaneous equation count data models. Although a variety of methods have been developed to analyse count data models with endogenous regressors (e.g. Terza 1998, Greene 2007), there has been to date only a handful of studies that attempt to extend these models to a system of simultaneous equations. Some examples are Atella and Deb (2008) who examined the utilsation of primary care and specialists services with a multivariate count data models in a system of equations. Also, Deb and Trivedi (2006) developed a count data model with endogenous multinomial treatment outcomes using a Negative Binomial and multinomial mixed logit mixture with latent factors.

The remaining of the paper is organised as follows. Section 2 describes a model of demand for hospital care, the choice of admission as a public or private patient and the decision to purchase insurance. Section 3 presents the econometric model and estimation strategy. Section 4 describes how hospital care is financed in Australia and the data used in the empirical analysis. The results are discussed in Section 5. Finally, Section 6 concludes with a discussion of the key findings in the paper.

2 Economic Model

In this section, a simple theoretical model is developed to describe how individuals make decisions on the demand for hospital care, the choice between admission as a public or private patient, and the decision to purchase insurance. We use this theoretical model to elaborate the simultaneous nature of these decisions.

We consider an individual whose utility is directly influenced by his or her health. The individual's health is adversely affected by the incidence of illness, and although the individual can

[1] "Patient type decision" refers to the decision to use medical services as a private or a public patient. A person without private insurance can still choose to pay the full fee out of pocket to use medical facilities as a private patient in order to see a particular doctor or avoid the waiting time. More importantly in the case of Australia, a person with private insurance may choose to use medical services as a public patient if he or she thinks that for his or her particular illness there is no advantage in paying the co-payment to be a private patient.

influence his or her health by life style choices and health related expenditures to some extent, it is assumed that the individual cannot reduce the probability of illness to zero. Specifically, the random variable S (denoting the severity of illness) can take any integer value from 0 to N where 0 corresponds to the situation where the individual is well or in perfect health and $1, \ldots, N$ represent health states that are associated with the incidence of progressively more serious medical conditions. The probability of any outcome s of S is denoted by $\pi(s)$ which is assumed to be positive for all s and for all individuals. While we do not index π (and other variables) by i to simplify the notation, it is understood that these probabilities can depend on individual characteristics such as age, gender and life habits.

We assume that the utility function of the individual in each state s is given by the following general form

$$U = U(C, h(s)) \tag{1}$$

where C denotes the level of consumption and h is the individual's health. It is assumed that conditional on s, $U(\cdot)$ is a strictly concave function of C and h. The health function h has its maximum value when the individual is in perfect health (i.e., when $s = 0$). In the presence of illness (i.e., when $s > 0$), the individual can mitigate the reduction in health by using hospital care at intensity m and quality q. The relationship between health h and hospital care m, q in health state s is characterised by the health production function

$$h(s) = h(m, q \,|\, S = s) \tag{2}$$

where

$$\frac{\partial h(s)}{\partial s} < 0, \frac{\partial^2 h(s)}{\partial s^2} > 0, \tag{3}$$

$$\frac{\partial h(s)}{\partial m}, \frac{\partial h(s)}{\partial q} > 0, \frac{\partial^2 h(s)}{\partial m^2}, \frac{\partial^2 h(s)}{\partial q^2} \leq 0 \text{ for all } s > 0. \tag{4}$$

The utilisation intensity measure m can be characterised as a vector of health care inputs (e.g. doctor/surgeon time, bed days, number of diagnostic tests) or aggregate measures such as the number of hospitalisation episodes over a predetermined duration of time and the length of hospital stay. The quality indicator q, on the other hand, is a composite index function that describes the quality attributes of hospital care. These include the length of waiting time on hospital waiting lists, amenities such as private hospital rooms and the choice of treatment doctor. We impose two assumptions on m and q to make the theoretical model consistent with the available data used in the empirical analysis. Firstly, given that the observed measure of hospital care intensity examined in the empirical analysis is an aggregate measure (namely the length of hospital stay), we assume here that m is one-dimensional. Secondly, we observe in the data a binary outcome variable whether individuals chose to seek publicly (Medicare) funded hospital care or obtain care as a private patient. Hence, we assume that the quality indicator $q \in \{0, 1\}$, with $q = 0$ if the individual chooses to receive public care, and $q = 1$ otherwise.

Public hospital care is provided free at the point of demand but public patients may experience lengthy waiting times, are not entitled to private accommodations and do not have the choice of treating doctor. An alternative to public hospital care is private care that involve shorter length of time waiting and higher quality amenities. Suppose each unit of private hospital care is supplied at an average price of P^m. This includes the price of quality goods that a private patient can choose, such as a private room or a reputable doctor. Since our data set only contains information about whether a patient chooses to use the hospital services as a private or public patient and does not provide information about what exact services the private patients use during their hospital stay, we use the average price rather than a disaggregated price vector for a menu of services available to private patients. Suppose both public and private patients face an indirect price P_{ind} associated with each unit of hospital care that arises from the cost of traveling to hospitals and loss of income as a result of hospitalisation. The total direct and indirect costs of private and public hospital care are $(P^m + P_{ind})m$ and $(P_{ind})m$ respectively.

Prior to the realisation of the health state s, the individual can purchase private hospital insurance at a fixed premium of P which reduces the direct cost of private care to $\alpha P^m m$ where $\alpha \in [0, 1)$ is the cost sharing parameter. Let the choice to purchase insurance be denoted by d, where $d \in \{0, 1\}$, where $d = 1$ when the individual purchases insurance and $d = 0$ otherwise. Suppose, the expenditures on consumption, insurance premium and private hospital care are afforded through income Y that is derived from both labour and non-labour sources. Based on the above assumptions, the individual faces a budget constraint

$$Y = C + dP + [1 - d(1 - \alpha)]qP^m m + P_{ind}m \tag{5}$$

which is dependent on the choice to purchase insurance d and the decision to obtain hospital care as a public or private patient q. We assume that the individual is an expected utility maximiser who solves the following resource allocation problem

$$\max_{m,\, q,\, d} \sum_s \pi(s)\, U[C, h(m, q \,|\, s)] \tag{6}$$

given the budget constraint in (5). The solutions to the resource allocation problem is obtained iteratively by first solving the optimal intensity of hospital care $\tilde{m}_{d,q}(s)$ for each insurance d and patient type strategy q, conditional on health state s. Conditional on insurance strategy d and health state s, the optimal intensity of hospital care if the individual chooses to obtain medical services as a public patient $(q = 0)$ is

$$\tilde{m}_{d,0}(s) = m[P_{ind}, Y - dP, s] \tag{7}$$

and private care $(q = 1)$ is

$$\tilde{m}_{d,1}(s) = m[(1 - d(1 - \alpha))P^m, P_{ind}, Y - dP, s] \tag{8}$$

Equation (7) shows that the optimal intensity of public hospital care is a function of the indirect unit cost of obtaining care, income minus the outlay for insurance premiums and the severity of illness. Equation (8) shows the optimal intensity of private hospital care depends on the effective price of private care which is a function of the availability of insurance, in addition to the similar set of factors that influence the intensity of public care. One result that can be expected from (8) is that the optimal intensity of private hospital care is increasing in the generosity of insurance (given by a lower cost sharing parameter α). This effect is referred to as *ex post* moral hazard where insurance lowers the effective price of medical care and hence increasing utilisation and medical expenditures (Pauly 1986).

The solutions $\tilde{m}_{d,q}(s)$ for all possible values of d, q and s are used to obtain the decision rule on the choice of admission into hospital as a public or private patient by substituting (7) and (8) into the health production function (2) and the utility function (1). Let $V_{d,q}(s)$ denote the individual's indirect utility associated with insurance strategy d and patient type strategy q. Conditional on insurance choice d and health state s, the individual will choose private care if

$$V_{d,1}(s) > V_{d,0}(s) \tag{9}$$

and will choose public care otherwise. These binary comparisons for every possible values of d and s determine the optimal choice of admission into hospital as a public or private patient, i.e. they define

$$\tilde{q}(d,s) = \underset{q\in\{0,1\}}{\arg\max}\ V_{d,q}(s). \tag{10}$$

The pair $\{\tilde{q}(d,s), \tilde{m}_{d,\tilde{q}(d,s)}(s)\}$ characterises the type of care and the intensity of care that the individual would optimally choose at each possible value of d and s, i.e. with and without private insurance and facing every possible severity of illness. Substituting these choices in the utility function, we obtain $V_d^*(s)$ for $d = \{0,1\}$ and $s = 1,\ldots,N$, which are the highest utility that the individual can obtain by making optimal decisions at every contingency with and without health insurance. These utility values together with the known probability distribution of illness severity determine the expected utility with and without health insurance. The expected utility associated with the purchase of insurance ($d = 1$) is given as

$$EV_1 = \sum_s \pi(s)\left[V_1^*(s)\right] \tag{11}$$

Correspondingly, the expected utility associated with not purchasing private hospital insurance ($d = 0$) is

$$EV_0 = \sum_s \pi(s)\left[V_0^*(s)\right] \tag{12}$$

The individual will decide to purchase or not to purchase private hospital insurance to maximise expected utility before the health state s is known. The optimal choice is therefore given by

$$\tilde{d} = \underset{d\in\{0,1\}}{\arg\max}\ EV_d. \tag{13}$$

The triplet $\{\tilde{d}, \tilde{q}(\tilde{d},.), \tilde{m}_{\tilde{d},\tilde{q}(\tilde{d},.)}(.)\}$, in which $\tilde{d}$ is a constant but the other two elements are functions of illness severity, completely characterises the insurance choice and also type of care and the intensity of care that the individual will optimally choose in every possible illness contingency. It should be clear from the above that after the insurance purchase decision is made and a certain health status is observed, the individual does not benefit from deviating from the plan dictated by this triplet. It should also be clear from this analysis that any unobserved individual specific effects in preferences or in health production that, all else constant, cause one individual to be on the right tail of the distribution of hospital care intensity and/or to have preference for a particular form of care (public versus private) will affect the insurance choice decision. At the same time, the decisions of what form of care to choose and at what intensity are influenced by the insurance choice. This analysis shows the simultaneous nature of these decisions, i.e. although chronologically the insurance decision is observed first and the care type and care intensity decisions are observed only after an illness, these decisions are made according to a complete contingent plan that was determined at the time of making the decision to purchase or not to purchase private health insurance.

The model can be extended to make it more realistic. For example, in the model presented above the difference between waiting times for receiving public and private care is captured only through the dependence of the health production function on q. This assumes that waiting times only influence individuals through affecting their capacity to enjoy life as healthy persons, and waiting times do not affect their budget constraint (recall that the loss of income in the budget constraint is bundled in $P_{ind}m$ that is proportional to the actual time spent in the hospital and does not change with the type of care). If this assumption is not correct and some individuals actually loose part of their income while waiting for an elective surgery, and if this information is available in a data set, then the model can and should be modified. Also, there are income tax incentives associated with the purchase of health insurance in Australia that can also be accommodated.

We have presented this bare-bone theoretical model to highlight that none of the three decisions – insurance choice, care type and care intensity – can be taken as exogenous for the other two. The model that we specify in the subsequent sections takes endogeneity seriously and is congruent with the count data nature of hospital length of stay and binary nature of care type and insurance choice variables. However, the exact mapping between the parameters of this model and the parameters of any particular utility function and health production function is not explored. Hence, our model is not a fully structural model in the sense of Keane (2010).

3 Econometric Methods

Let the m_i be the observed duration of hospital stay for the ith individual and q_i the patient type binary variable which takes the value of 1 when private care was chosen and 0 otherwise. The binary variable d_i denotes insurance status which assumes a value of 1 if individual i has private health insurance. Suppose 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

$$f(m_i \mid X_i, q_i, d_i, \xi_i) = \frac{\exp^{-\mu_i} \mu_i^{m_i}}{m_i!} \tag{14}$$

with the conditional mean parameter μ_i

$$\mu_i = \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i + \sigma\xi_i) \tag{15}$$

where ξ_i is a standardised heterogeneity term which is distributed standard normal, that is $\xi_i \sim \mathrm{N}(0,1)$. The decision rules to obtain hospital care as a public patient and to purchase private health insurance are related to two continuous latent variables q_i^* and d_i^* respectively where

$$\begin{aligned} q_i^* &= Z_i\alpha + \beta_1 d_i + v_i \\ d_i^* &= W_i\gamma + \eta_i \end{aligned} \tag{16}$$

and v_i, $\eta_i \sim \mathrm{N}(0,1)$. These latent variables correspond to $V_{d,1} - V_{d,0}$ in equation (9) and to $EV_1 - EV_0$ from equations (11) and (12) respectively. Considering these latent variables as utility differentials, it becomes apparent that they are related to the observed care type and insurance choices via the following dichotomous rules

$$\begin{aligned} q_i &= 1\,[q_i^* > 0] \\ d_i &= 1\,[d_i^* > 0] \end{aligned} \tag{17}$$

The RHS variables q_i and d_i in equation (15) and d_i in (16) are allowed to be endogenous by assuming that ξ_i, v_i and η_i are correlated. More specifically, it is assumed that each pair of ξ_i, v_i and η_i are distributed bivariate normal where

$$
\begin{aligned}
\xi_i, v_i &\sim N_2[(0,0),(1,1),\rho_{\xi v}] \\
\xi_i, \eta_i &\sim N_2[(0,0),(1,1),\rho_{\xi \eta}] \\
v_i, \eta_i &\sim N_2[(0,0),(1,1),\rho_{v \eta}]
\end{aligned} \tag{18}
$$

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

$$
\begin{pmatrix} v_i \,|\, \xi_i \\ \eta_i \,|\, \xi_i \end{pmatrix} \sim N_2 \left[\begin{pmatrix} \rho_{\xi v} \xi_i \\ \rho_{\xi \eta} \xi_i \end{pmatrix}, \begin{pmatrix} 1 - \rho_{\xi v} & \rho_{v\eta} - \rho_{\xi v}\rho_{\xi\eta} \\ \rho_{v\eta} - \rho_{\xi v}\rho_{\xi\eta} & 1 - \rho_{\xi\eta} \end{pmatrix} \right] \tag{19}
$$

Extending the framework outlined in Terza (1998), the joint conditional density for the observed data $f(m_i, q_i, d_i \,|\, \Omega_i)$ for individual i who has been hospitalised can be expressed as

$$
\begin{aligned}
\int_{-\infty}^{\infty} \Big[&(1-q_i)(1-d_i) f(m_i \mid X_i, q_i = 0, d_i = 0, \xi_i)\ P(q_i = 0, d_i = 0 \mid \Omega_i, \xi_i) + \\
&(q_i)(1-d_i) f(m_i \mid X_i, q_i = 1, d_i = 0, \xi_i) P(q_i = 1, d_i = 0 \mid \Omega_i, \xi_i) + \\
&(1-q_i)(d_i) f(m_i \mid X_i, q_i = 0, d_i = 1, \xi_i) P(q_i = 0, d_i = 1 \mid \Omega_i, \xi_i) + \\
&(q_i)(d_i) f(m_i \mid X_i, q_i = 1, d_i = 1, \xi_i)\ P(q_i = 1, d_i = 1 \mid \Omega_i, \xi_i) \Big]\ d\xi_i
\end{aligned} \tag{20}
$$

where $\Omega_i = (X_i \cup Z_i \cup W_i)$. From (15), (16), (19) and (20), 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

$$
g(q_i, d_i \,|\, Z_i, W_i, \xi_i) = \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*] \tag{21}
$$

where

$$
\begin{aligned}
\Theta_1 &= \frac{Z_i\alpha + \beta_1 d_i + \rho_{12}\xi_i}{(1-\rho_{12}^2)^{1/2}} \\
\Theta_2 &= \frac{W_i\gamma + \rho_{13}\xi_i}{(1-\rho_{13}^2)^{1/2}} \\
\rho^* &= y_{1i} \cdot y_{2i} \cdot \frac{(\rho_{23} - \rho_{12}\rho_{13})}{\sqrt{1-\rho_{12}^2}\sqrt{1-\rho_{13}^2}}
\end{aligned}
$$

In the above, $y_{1i} = 2q_i - 1$ and $y_{2i} = 2d_i - 1$. Φ_2 denotes the bivariate normal cumulative density function. Hence, $f(m_i, q_i, d_i \,|\, \Omega_i, \xi_i)$ in (20) may be expressed as

$$
f(m_i, q_i, d_i \,|\, \Omega_i, \xi_i) = f(m_i \,|\, X_i, q_i, d_i, \xi_i) \cdot g(q_i, d_i \,|\, Z_i, W_i, \xi_i) \tag{22}
$$

We emphasise again that the above applies only to those individuals who have been hospitalised in the observation period. For non-hospitalised individuals we only observe d_i and Ω_i, but the probability density of d_i conditional on Ω_i can be conveniently deduced from equations (16), (17) and (18). Hence, if we define the indicator variable H_i where $H_i = 1$ if the i-th individual has been hospitalised and 0 otherwise, then the contribution of every observation to the likelihood function can be succinctly expressed as

$$\ell_i(\Theta) = H_i \cdot \int_{-\infty}^{+\infty} f(m_i \mid \Omega_i, q_i, d_i, \xi_i) \cdot \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*]\, \phi(\xi_i) d\xi_i + (1 - H_i) \cdot \Phi[y_{2i}(W_i\gamma)] \quad (23)$$

where Θ is the set of all unknown parameters in equations (15), (16) and (18). Equation (23) will be used to construct the log-likelihood function which we will use to estimate the model. The estimation strategy for the three equation econometric model outlined above will be discussed in the next section.

3.1 Estimation

Evaluation of the joint conditional density function in (23) requires the evaluation of an integral. Given that this integral does not have a closed-form expression, it is approximated using simulation methods (Gouriéroux and Monfort 1996). Suppose ξ_i^s denote the s-th draw of ξ from the standard normal density $\phi(\xi_i)$. The simulated likelihood contribution for the i-th observation is

$$\widehat{\ell}_i(\Theta) = H_i \cdot \frac{1}{S} \sum_{1}^{S} f(m_i \mid \Omega_i, q_i, d_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*] + (1 - H_i) \cdot \Phi[y_{2i}(W_i\gamma)] \quad (24)$$

Correspondingly, the simulated log-likelihood function is

$$\ln\widehat{\mathrm{L}}(\Theta) = \sum_{i=1}^{N} \ln\left\{ H_i \cdot \frac{1}{S} \sum_{1}^{S} f(m_i \mid \Omega_i, q_i, d_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*] + (1 - H_i) \cdot \Phi[y_{2i}(W_i\gamma)] \right\} \quad (25)$$

The maximum simulated likelihood estimator (MSL) maximises the simulated log-likelihood in (25). Quasi-Monte Carlo draws based on the Halton sequence was used in the simulations which have been demonstrated to be faster and more accurate as compared the conventional random number generator (Bhat 2001, Train 2003). In choosing a practical number of simulations, S was increased stepwise by a factor of 2 from a minimum of 50 to a maximum of 3000. Thereafter, the estimates were examined to determine if the results vary significantly with increasing values of S. We used S=2000 in our study, beyond which the results obtained were very similar.

The Berndt, Hall, Hall and Hausman (BHHH) quasi-Newton algorithm was used to maximise the simulated likelihood using numerical derivatives. The variance of the MSL estimates were computed post convergence using the robust sandwich formula. Compared with the sandwich formula, the information matrix and outer product formula are inappropriate as they do not take into account the influence of simulation noise (Mcfadden and Train 2000).

The marginal effects for the Poisson model is calculated in two ways. For a continuous explanatory variable x_j, the coefficient β_j is a semi-elasticity.[2] Therefore, an increase in x_j by 0.01 changes the expected length of stay $E(m \mid X)$ by β_j percent. In the case of a binary explanatory variable x_j, this is expressed as a proportional change in the expected length of stay from changing x_j from 0 to 1 is calculated as

$$\frac{E(m \mid x_j = 1, X)}{E(m \mid x_j = 0, X)} = \frac{e^{\beta_j + \sum_{i \neq j} \beta_i x_i}}{e^{\sum_{i \neq j} \beta_i x_i}} = e^{\beta_j} \quad (26)$$

The standard errors of the marginal effects for binary variables are calculated using the delta method.

[2]See Riphahn et al. (2003) for a derivation of this property.

4 Australia's hospital care system and data

4.1 Financing hospital care and private health insurance in Australia

In Australia, health care is financed predominantly through a compulsory tax-funded universal health insurance scheme known as Medicare. Introduced in 1984, Medicare subsidies medical services and technologies according to a schedule of fees referred to as the Medicare Benefit Schedule (MBS). For hospital care, individuals who choose to be admitted as public or Medicare patients in public hospitals receive free treatment from doctors and health practitioners nominated by hospitals as well as free hospital accommodations and meals. Alternatively, individuals may choose to obtain private care in either private or public hospitals. Private patients are charged fees by doctors and are billed by hospitals for accommodations, theatres fees, diagnostic tests and medical supplies such as medications, dressings and other consumables. The fees charged by doctors to private patients attract a subsidy amounting to 75% of the scheduled fee under the MBS. The difference between doctors' fees and the Medicare subsidy is afforded either as out-of-pocket expenditure or covered by insurers if individuals have private health insurance. Private hospital charges however do not attract any Medicare subsidy but may be claimed through private health insurance. In addition to hospital insurance, individuals can purchase ancillary insurance to cover expenditures on general health services such as dental care, allied health (physiotherapy, podiatry) and items such as eye glasses which are not covered under Medicare.

The private health insurance market in Australia is a heavily regulated industry. A key feature is the community rating requirement on private health insurance premiums which stipulates that insurers must charge the same price for a given insurance contract regardless of individuals' age, gender and health status. This requirement also prohibits insurers from setting premiums using information on individuals' utilisation and claims history. Between 1997 and 2000, significant policy changes were introduced in the private health insurance market in Australia. These changes followed active public debate on the appropriate role of public and private health insurance in the financing of health care in Australia amidst the steadily declining private health membership after the introduction of Medicare. The then prevailing policy stance within the government 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). In response, the government introduced a series of policy changes with the aim of encouraging the uptake of private health insurance. 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.[3] 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.

[3] 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. This scheme was replaced in early 1998 by a non means-tested 30% rebate on health insurance premiums. The third policy introduced in July 2000 is the Lifetime Community Rating (LCR) which involved a modification of the community rating regulations and allowed private health insurance funds to vary insurance premiums according to individuals' age at the time of entry into funds and the number of years individuals remained insured. See Butler (2002) for more details.

4.2 Data

The empirical analysis used microdata from the 2005 National Health Survey (NHS) collected by the Australian Bureau of Statistics (ABS 2006b). The survey collected information on 25,906 adults (age 18 years and over) and children (age 0 to 17) from 19,501 private dwellings selected from across all states and territories in Australia except those in very remote areas. In the analysis sample, observations where the respondents' age is below 25 years and those from multiple family households were excluded.[4] After excluding observations with missing or ambiguous responses, 14,049 observations remained in the sample of which 2,406 individuals indicated that they have been hospitalised at least once in the last 12 months.

4.3 Hospital utilisation measures and insurance status

[Insert Table 1 about here]

The survey collects information on whether individuals have private health insurance and the type of insurance coverage. The three coverage types include hospital, ancillary, or both. We focus on whether individuals have private hospital insurance, that is if they possessed either hospital only or combined cover. In the full sample of 14,049 observations, 6,467 (46.0%) individual have private hospital insurance. Table 1 shows the frequency of hospital nights by insurance status and patient type for the 2,406 individuals who have been hospitalised. The number of hospital nights are recorded as 0 (which corresponds to a day admission), 1 night, 3, 5 and 8 nights.[5] Amongst the hospitalised individuals, 1,117 (46.4%) individuals have private hospital insurance. Three observations from the descriptive statistics in the Table 1 are noteworthy. Firstly, the utilisation of private hospital care is significantly higher among individuals with private hospital insurance. Of the 1,117 insured individuals, 82.3% (N=919) chose to be hospitalised as private patients while 17.7% (N=198) were public patients. Conversely, only 7.5% (N=97) of 1,289 uninsured individuals chose private care, with 92.5% (N=1,192) opting to be public patients. Secondly, uninsured individuals who chose public hospital care stayed the highest number of nights – an average of 2.2 nights. In addition, among individuals who chose to obtain private hospital care, those who are privately insured were admitted for a longer duration compared with those without insurance (1.98 vs. 1.48 nights). Thirdly, the data on length of stay exhibits overdispersion, in that the unconditional variance is larger than the mean.

4.4 Exogenous covariates

The explanatory variables that are used in this study can be classified into the following categories: demographics and socioeconomic characteristics (e.g. age, gender, household income), health status measures (presence of chronic conditions), health risk factors (alcohol risk, smoker) and geographical information (state/territories, remoteness). The choice of explanatory variables is similar to that in Cameron et al. (1988), Cameron and Trivedi (1991), Savage and Wright (2003) and Propper (2000). The variables names and description of these explanatory variables are presented in Table 2.

[Insert Table 2 and 3 about here]

[4] By the former, we include only individuals who bear the financial responsibilities on decisions pertaining to their medical and insurance needs. In Australia, a dependent child may remain on the parent's policy if the child is below 21 years of age and unmarried or 25 years if undertaking full-time study.

[5] Data on length of hospital stay is available in the following categories: 0 (no nights), 1 to 2, 3 to 4, 5 to 7, 8 or more. The lower bound in each of these categories was selected as the indicative value for the analysis. The sensitivity of the results to this assumption is examined in the discussion of the results.

The summary statistics in Table 3 presents the means of the explanatory variables for the sample analysed. The descriptive statistics for the hospitalised and non-hospitalised subgroups are also presented for comparison. Females make up roughly 54% of the sample. Roughly 60% of individuals are from couple income units and 34% have dependent children. The average age of individuals in the sample is 50.8 years, with those hospitalised (53.4 years) being slightly older than non-hospitalised individuals (50.2 years). Approximately half do not have any post-school educational qualifications. The average equivalised weekly household income is $610, and is considerably lower for hospitalised ($543) compared with the non-hospitalised ($625) subgroups.[6] Three indicators related to individuals' labour force characteristics are available in the data. These are employment status, sector and occupation types. 41% of individuals are either not in the labour force or are unemployed. By occupational types, the categories of "Professionals" and "Intermediate Clerical Services" are the two largest occupational groups.

Measures of health status are given by a set of 16 binary variables that indicate the presence of medical conditions.[7] These indicators are the International Statistical Classification of Diseases, 10th Revision, Australia Modification (ICD10-AM) disease categories of the long-term chronic conditions that individuals indicated they suffer from.[8] Indicators of health risk factors include whether individuals are consuming excessively high levels of alcohol and are regular smokers. Geographical information include state/territory indicators as well as remoteness categories. Approximately 60% of individuals reside in major cities in Australia.

The exogenous covariates described above do not enter as regressors in all three equations of the simultaneous equation model. We include employment status, i.e. whether individuals are in part-time, full-time or not in employment, and the childbearing binary variables only in the length of stay equation. We expect the former to capture the effect of the indirect cost of obtaining hospital care that is described in the theoretical model. On the latter, one could argue that pregnancy is one reason why individuals purchase private health insurance given that a significant proportion of obstetrics and gynaecological services are provided in the private sector. However, age and gender are included in the insurance equation and these variables would have already accounted for the effect of pregnancy on the propensity to purchase insurance.[9] We include the sector of employment only in the public-private patient choice equation as there is some evidence in Propper (2000) that public sector workers are more likely to seek public inpatient care. Following Cameron and Trivedi (1991), education attainment, the availability of a health concession card and occupational types are included only in the insurance equation. From the perspective of econometric modeling, because the three equations do not all contain the same set of exogenous covariates, there is more power in identifying the parameters of the econometric model.

[6]The only measure of household income in the data is the gross equivalised weekly income of the household that is made available as income deciles instead of actual values. Indicative values were constructed using information published in ABS (2006a).

[7]The 16 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.

[8]These variable do not represent the health states or illness severity (i.e. given by S in the theoretical model) for which hospital care was obtained. But rather, these variables influence individuals' perceptions of the probability of illness $\pi(S)$.

[9]The childbearing variable was included as a regressor, in addition to age and gender, in the insurance equation and the coefficient on insurance had a very high p-value (0.83).

5 Results

We estimated a variety of models with different combinations of the correlation parameters $\rho_{\xi v}, \rho_{\xi\eta}$ and $\rho_{v\eta}$ being restricted to zero. In a model specification where all three correlation parameters are set equal to zero, the length of stay is estimated using a lognormal random effects Poisson and the patient type and insurance equations are estimated using separate probit regressions. Of the three correlation parameters, $\rho_{\xi\eta}$ and $\rho_{\xi v}$ – which measure the correlations between the unobservables in the length of stay and patient type equations with that of the insurance equation – are weakly significant across the different models specifications. This result indicate that there is some evidence that the insurance variable, particularly in the length of stay equation, is endogenous. In view of this, the discussion in the remaining sections of this paper will be based on simultaneous equation model where $\rho_{\xi\eta}$ and $\rho_{\xi v}$ are not restricted to zero. For the discussion of the insurance and private patient effects in Section 5.1, the results from this model will be compared with that obtained under separate single equation models to examine how they differ under the endogeneity and exogenous assumptions.

5.1 Marginal effects of insurance and patient type

[Insert Table 4 about here]

Table 4 presents the marginal effects 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, with each obtained under the endogeneity and exogeneity assumptions. In the public/private choice equation, the estimate of the marginal effect of the insurance binary variable is positive and significant. All else being equal, individuals with private hospital insurance are 72.3% more likely to be admitted into hospital care as a private patient. This result is expected given that the availability of private hospital insurance reduces the effective monetary price of 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 insurance and patient type binary variables, combined with their interaction, reveal the effect of insurance on length of hospital stay for private and public patients separately. Here, two effects are of interest. The first is the *moral hazard effect*[10] which is the difference in the expected length of stay between privately admitted individuals with or without private hospital insurance. From the theoretical model described in Section 2, we observe that individuals who are privately insured face a lower effective monetary price for private care, and are expected to use private care at a greater intensity. An estimate that is larger than 1 implies that private patients with insurance have a proportionally longer expected length of stay than those without insurance. The results from the simultaneous equation model suggest that there is no evidence of moral hazard in the use of private hospital care. This is in contrast with the estimates from the random effects Poisson model which indicate that the expected length of private hospital stay by privately insured individuals is 1.62 times higher than that for the uninsured.

The second result of interest is the effect of insurance on the length of stay for publicly admitted patients. This is termed as the *insurance on public patient effect*.[11] Insofar as the insurance variable reflect the incentive effects of insurance, we would expect that private hospital insurance would have no impact on the intensity of public hospital care use. The estimates of

[10] The moral hazard effect is calculated as $\mathrm{E}(LOS \,|\, insurance = 1,\ private\,patient = 1,\ X)$ / $\mathrm{E}(LOS \,|\, insurance = 0,\ private\,patient = 1,\ X)$.

[11] The insurance on public patient effect is calculated as $\mathrm{E}(LOS \,|\, insurance = 1,\ private\,patient = 0,\ X)$ / $\mathrm{E}(LOS \,|\, insurance = 0,\ private\,patient = 0,\ X)$.

the public patient effect are significantly smaller than 1 which indicate that the expected length of hospital stay by privately insured public patients is shorter than that for non-insured public patients. The third outcome of interest is the difference in the expected length of stay between publicly and privately admitted patients. This is referred to in Table 4 as the *patient type effect*. The result indicates that the length of hospital stay by private patients individuals is on average 0.57 times shorter than that for publicly admitted patients.

We examine the sensitivity of the insurance and patient effects on length of stay to the stipulation of the lower bound values by using instead the upper bound of each length of stay interval.[12] The results obtained using the upper bound values are very similar to those using the lower bound. For example, the estimate of the moral hazard effects using the upper bound values is 1.021 and is not significantly different from 1. Both the estimates of the insurance on public patient and patient type effects are also very similar with those reported above.

[Insert Table 5 about here]

5.2 Determinants of length of inpatient stay

Columns 2 and 3 in Table 5 presents the marginal effects and standard errors of the remaining explanatory variables on the expected length of hospital stay. For the demographic variables, holding all else constant, age has a 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 the expected length of stay is higher for females in the childbearing years. Of the socioeconomic variables, length of hospital stay is shorter for individuals engaged in full-time and part-time employment relative to those who are unemployed. A possible explanation suggested by the theoretical model is 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.

Two sets of health indicators are 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. Individuals with mental health and congenital conditions have comparatively longer length of stay. On the other hand, muscular conditions are associated with a lower intensity of hospital nights. The second is a count measure of the number of chronic and long-term conditions individuals suffer from. This is not presented in Table 5. A priori, one would expect that individuals with poorer health should on average require a greater intensity of care when hospitalised. The marginal effect estimate on the count measure of medical conditions however is not statistically 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.

On the geographical effects, individuals from Western Australia and Tasmania have on longer expected length of stay as compared to those from New South Wales. To the extent that individuals' health status is adequately controlled for, the geographical variations in the length of stay may be indicative of differences in medical norms and practices surrounding the treatment of hospital patients. Finally, 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[13] in the data, which justifies the use of the lognormal random effects

[12] This is not reported in Table 4. When upper bound values are used, the distribution of hospital nights is recorded as 0, 2 nights, 4, 7 and 8 nights.

[13] 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

Poisson.

5.3 Determinants of patient type choice

Columns 4 and 5 in Table 5 presents the results on the determinants that influence the choice of hospital admission as a public or private patient. Holding all else equal, females are more likely than their male counterparts to seek private hospital care. 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. Individuals whose origin of birth is neither Australia nor the main English speaking countries are 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 between single and couple income unit types. In terms of the socioeconomic factors, the propensity to seek private hospital care is positively associated with household income and employment in the private sector.

A 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 are not available. Instead, the ICD10 categories of medical conditions are used as proxies for health status. Having diseases of the neoplasm, endocrine or nervous system decreases the propensity of seeking private hospital care. On the other hand, individuals suffering from diseases of the eye and 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 residing in remote areas are also less likely to obtain public or private care when compared to their metropolitan counterparts.

5.4 Demand for private hospital insurance

Columns 6 and 7 of Table 5 presents the results on the decision to purchase private hospital insurance. Females and individuals who are older are more likely to have private hospital insurance. The propensity to insure is also higher for couple households and those with dependent children. Income is positively associated with the purchase of insurance which is likely to be driven by pure income effects as well as the incentivisation through the tax levy that applies to high income individuals without private health insurance. Individuals with post school education qualifications such as diplomas, bachelor degrees and or higher are more likely to have private insurance. A significant factor that influence insurance status is the availability of government health concession cards. In terms of occupational types, managers and administrators are more likely have private health insurance compared with those who are not in employment whereas those in production/transport or are labourers are less likely to have insurance.

We experimented with several types of explanatory variables that describe respondents' health status. The first is the sixteen indicators of ICD10-AM disease categories of which a number are significantly associated with insurance purchase. For instance, individuals with conditions relating to the eye (e.g. cataract, glaucoma), endocrine and the genitourinary system have a higher propensity to be privately insured. The second measure of health status is the number of long-term chronic medical conditions which reflects the extent of good health

if $V[m_i \,|\, X_i] > E[m_i \,|\, X_i, \xi_i]$ which occurs if $\sigma > 0$.

(not reported in Table 5). The results indicate that the propensity to purchase insurance is increasing in the number of long-term medical conditions. 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. These variables behave as proxies for individuals' health status, risk aversion and attitudes towards good health. Finally, in terms of geographical factors 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. Individuals residing in inner and outer regional areas of Australia are less likely than those in major cities to purchase private hospital insurance. This may be because private hospital facilities are less available in non-metropolitan areas.

6 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 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.

We do not find evidence of moral hazard effect amongst patients who sought hospital care as a private patient. This result is in contrast with the findings of 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.[14] 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 this 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 this 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

[14]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.

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 this study to 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 of work in the future.

The findings indicate that the length of hospital stay by privately admitted patients is on average significantly shorter than that of public (Medicare) patients. 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.

The results also 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 consistent with Gertler and Strum (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 this 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 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, employment in the private sector, age and the presence of dependent children are factors that increases the probability of obtaining private hospital care.

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References

ABS (2006a). National health survey - Confidentialised Unit Record Files. Cat. no. 4324.0. Australian Bureau of Statistics.

ABS (2006b). National health survey: User's guide - electronic publication 2004-05. Cat no. 4363.0.55.001. Australian Bureau of Statistics.

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.

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

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

Cameron, A. C., 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.

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.

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

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

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

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.

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

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

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

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.

Keane, M. P. (2010). Structural vs. atheoretic approaches to econometrics. *Journal of Econometrics 156*, 3–20.

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

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 estimtaes 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.

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

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

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.

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

Srivastava, P. and X. Zhao (2008). Impact of private hospital insurance on the choice of public versus private care. *HEDG Working Paper 08/17.*

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.

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

Table 1: Summary statistics of key outcomes for hospitalised individuals

	No Insurance (N=1,289)		With Insurance (N=1,117)		
Hospital Nights	Public Patient (N=1,192)	Private Patient (N=97)	Public Patient (N=198)	Private Patient (N=919)	Total (N=2,406)
0	398 (33.4%)	38 (39.2%)	88 (44.4%)	368 (40.0%)	825 (37.5%)
1	350 (29.4%)	38 (39.2%)	42 (21.2%)	233 (25.4%)	597 (27.2%)
3	169 (14.2%)	7 (7.2%)	27 (13.6%)	124 (13.5%)	291 (13.2%)
5	145 (12.2%)	9 (9.3%)	22 (11.1%)	125 (13.6%)	267 (12.2%)
8	130 (10.9%)	5 (5.2%)	19 (9.6%)	69 (7.5%)	218 (9.9%)
Mean	2.20	1.48	1.94	1.94	2.07
Variance	6.76	4.50	6.61	5.92	6.57

Note: Percentages in parenthesis sums vertically but may not sum up to 100% due to rounding.

Table 2: Variable names and description

Variable	Description
Female	= 1 if the respondent is female
Married	= 1 if the respondent is married in a registered or defacto marriage
Dependent	= 1 if the respondent has at least one dependent child
Couple	= 1 if the income unit is Couple with or without dependent children
Age	= The middle value in each age interval decile
Childbearing	= 1 if the respondent is female and age between 25 to 39 years
Country of Birth (COB)	
Australia (Reference)	= 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 (Edu)	
School (Reference)	= 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 (Reference)	= 1 if the respondent is not employed
Manager/Admin	= 1 occupational category "Managers and Administrators"
Professional	= 1 occupational category "Professionals"
Asc Professional	= 1 occupational category "Associate Professionals"
Tradesperson	= 1 occupational category "Tradesperson/Related Workers"
Adv Clerical/Service	= 1 occupational category "Advanced Clerical/Service Workers"
Int Clerical/Service	= 1 occupational category "Intermediate Clerical/Service Workers"
Production/Transport	= 1 occupational category "Intermediate Production/Transport Workers"
Ele Clerical/Service	= 1 occupational category "Elementary Clerical/Sales/Service Workers"
Labourer	= 1 occupational category "Labourers and Related Workers"
Employment (Employ)	
Full-time (FT)	= 1 if the respondent is engaging in full-time employment
Part-time (PT)	= 1 if the respondent is engaging in part-time employment
Sector of employment	
Public Sector (Reference)	= 1 if the sector of employment is the public sector
Private Sector	= 1 if the sector of employment is the private sector
Alcohol 3-day	= 1 if the respondent's alcohol 3-day risk level is high
Smoker Regular	= 1 if the respondent currently smokes daily
NSW (Reference)	= 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 (Reference)	= 1 if the ASGC remoteness is "Major Cities"
ASGC_Inner	= 1 if the ASGC remoteness is "Inner Regional Australia"
ASGC_Others	= 1 if the ASGC remoteness is "Others"

Table 3: Descriptive statistics of explanatory variables by hospitalisation status

	Hospitalised (N=2,406)	Non-hospitalised (N=11,643)	Full sample (N=14,049)
Female	0.600	0.470	0.542
Dependent	0.312	0.341	0.335
Couple	0.588	0.608	0.603
Single	0.412	0.392	0.397
Age[1]	53.41 (17.49)	50.17 (15.71)	50.81 (16.12)
Childbear	0.203	0.156	0.163
COB-Aust	0.751	0.728	0.733
COB-Main_Eng	0.126	0.130	0.128
COB-Others	0.123	0.143	0.139
Edu-School	0.496	0.471	0.476
Edu-Voc	0.237	0.229	0.230
Edu-Dip	0.104	0.112	0.111
Edu-Degree	0.163	0.189	0.184
Household Inc[1]	543.19 (373.77)	624.75 (383.43)	610.18 (382.84))
Hconcard	0.554	0.414	0.440
Occup-N_Emloy	0.553	0.383	0.414
Occup-Mgmr/Adm	0.051	0.068	0.065
Occup-Prof.	0.096	0.135	0.128
Occup-A/Prof.	0.067	0.083	0.080
Occup-TradesP	0.042	0.070	0.065
Occup-Adv Clr/Svc	0.015	0.023	0.021
Occup-Int Clr/Svc	0.075	0.100	0.095
Occup-Prod/Trans	0.033	0.051	0.048
Occup-Ele Clr/Svc	0.033	0.039	0.038
Occup-Labour	0.036	0.049	0.047
Employ-FT	0.281	0.445	0.416
Employ-PT	0.165	0.172	0.170
Employ-Not	0.017	0.021	0.021
Employ-NILF	0.536	0.362	0.394
Public Sector	0.105	0.139	0.133
Private Sector	0.342	0.476	0.453
ICD10-Infectious/Parasitic	0.017	0.011	0.012
ICD10-Neoplasm	0.069	0.024	0.032
ICD10-Blood	0.033	0.175	0.020
ICD10-Endocrine	0.256	0.175	0.190
ICD10-Mental/Behavioural	0.160	0.128	0.134
ICD10-Nervous	0.123	0.100	0.104
ICD10-Eye	0.759	0.703	0.714
ICD10-Ear	0.237	0.179	0.191
ICD10-Circulatory	0.406	0.272	0.297
ICD10-Respiratory	0.350	0.332	0.335
ICD10-Digestive	0.176	0.086	0.102
ICD10-Skin	0.050	0.044	0.045
ICD10-Muscular	0.547	0.449	0.466
ICD10-Genitourinary	0.087	0.040	0.048
ICD10-Congenital	0.013	0.009	0.010
ICD10-Others	0.182	0.119	0.133
Alcohol 3-day	0.128	0.148	0.145
Smoker Reg	0.193	0.213	0.209
Walk	0.498	0.522	0.518
Overweigh	0.235	0.195	0.201

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Table 3: Descriptive statistics of explanatory variables (Continued)

	Hospitalised (N=2,406)	Non-hospitalised (N=11,643)	Combined (N=14,049)
NSW	0.210	0.202	0.204
VIC	0.163	0.164	0.164
QLD	0.156	0.160	0.159
SA	0.171	0.179	0.178
WA	0.126	0.105	0.109
TAS	0.108	0.109	0.109
NT	0.003	0.005	0.005
ACT	0.063	0.075	0.072
ASGC-Major Cities	0.595	0.613	0.610
ASGC-Inner Region	0.247	0.229	0.232
ASGC-Others	0.158	0.159	0.158

[1] For continuous variables, standard deviations are presented in the parenthesis.

Table 4: Marginal effects under endogenous and exogenous assumptions

	Endogenous		Exogenous	
	dF/dX	S.E	dF/dX	S.E
	- Public/Private Patient -			
Insurance effect	0.723***	0.033	0.717***	0.017
	- Hospital Length of Stay [a] *-*			
Moral hazard effect	1.116	0.288	1.624***	0.259
Insurance on public patient effect	0.668***	0.164	0.983	0.109
Patient type effect	0.570***	0.095	0.610***	0.097
	- Correlation Parameters -			
$\rho_{\xi\eta}$	0.258*	0.146		
$\rho_{v\eta}$	-0.270	0.191		

***, **, * denote significance at 1%, 5% and 10% respectively. For marginal effects on the binary variables in the length of stay equation, the null hypothesis is $H_0 : e^{\beta_j} = 1$.

[a] Marginal effects are interpreted as proportional change in expected length of stay.

Table 5: Marginal effects of the remaining explanatory variables

	Length of Stay		Public/Private		Insurance	
	dF/dX	S.E	dF/dX	S.E	dF/dX	S.E
Female	0.970	(0.069)	0.058**	0.029	0.042***	0.011
Dependent	1.170	(0.106)	0.070*	0.040	0.054***	0.013
Couple	1.077	(0.075)	0.046	0.030	0.104***	0.010
Country of Birth:						
Main English			-0.056	0.037	-0.116***	0.014
Others			-0.089**	0.039	-0.126***	0.014
Age[a]	2.190***	(0.440)	0.006***	0.001	0.010***	0.000
Childbear	1.836***	(0.234)				
Household income[a]	0.0087	(0.024)	0.026***	0.006	0.048***	0.002
Health Card					-0.182***	0.014
Education:						
Vocational					0.026***	0.012
Diploma					0.051***	0.016
Degree					0.113***	0.016
Employment Status:						
Employ-FT	0.767***	(0.077)				
Employ-PT	0.891	(0.081)				
Employment Sector:						
Private			0.086*	0.044		
Unemployed+NILF			0.028	0.051		
Occupation:						
Manager/Admin					0.144***	0.024
Professional					0.030	0.022
Asc Professional					0.053**	0.022
Tradesperson					-0.043*	0.023
Adv Clerical/Service					0.120***	0.034
Int Clerical/Service					0.001	0.020
Production/Transport					-0.079***	0.025
Ele Clerical/Service					-0.007**	0.003
Labourer					-0.129***	0.024
ICD10 Disease Categories:						
Infectious/Parasitic	0.880	0.214	0.101	0.103	-0.052	0.046
Neoplasm	0.976	0.111	-0.078*	0.045	0.035	0.026
Blood	1.030	0.174	-0.002	0.082	-0.028	0.033
Endocrine	1.000	0.069	-0.061**	0.030	0.027**	0.013
Mental/Behavioural	1.210***	0.098	-0.023	0.038	-0.352**	0.014
Nervous	0.970	0.088	-0.089**	0.037	0.012	0.016
Eye	1.060	0.086	0.060*	0.036	0.050***	0.013
Ear	0.942	0.069	-0.036	0.031	-0.020	0.013
Circulatory	1.027	0.069	-0.041	0.029	-0.012	0.012
Respiratory	0.965	0.058	0.023	0.028	0.003	0.010
Digestive	1.036	0.081	-0.040	0.034	0.012	0.016
Skin	0.954	0.124	-0.067	0.055	0.030	0.023
Muscular	0.851***	0.054	0.061**	0.028	-0.001	0.010
Genitourinary	0.998	0.100	-0.023	0.044	0.038*	0.022
Congenital	1.691***	0.365	0.049	0.117	0.073	0.051
Others	1.114	0.085	-0.018	0.035	0.013	0.014

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Table 5: Marginal effects of the remaining explanatory variables (Continued)

	Length of Stay		Public/Private		Insurance	
	dF/dX	S.E	dF/dX	S.E	dF/dX	S.E
Alcohol 3-day Risk			0.002	0.043	-0.034**	0.014
Smoker Regular			-0.060	0.036	-0.175***	0.012
VIC	1.125	(0.107)	0.006	0.045	0.032**	0.016
QLD	1.112	(0.110)	0.153***	0.046	0.012	0.016
SA	1.144	(0.108)	0.013	0.043	0.061***	0.015
WA	1.419***	(0.146)	-0.003	0.046	0.072***	0.018
TAS	1.391***	(0.156)	0.176***	0.055	0.086***	0.019
NT	1.246	(0.650)	0.077	0.153	0.190***	0.068
ACT	0.864	(0.130)	0.073	0.066	-0.046**	0.020
ASGC-Inner Region	1.072	(0.081)	-0.051	0.036	-0.046***	0.013
ASGC-Others	1.077	(0.092)	-0.070*	0.039	-0.100***	0.014
Heterogeneity σ	1.052***	(0.315)				

***, **, * denote significance at 1%, 5% and 10% respectively. For marginal effects on the binary variables in the length of stay equation, the null hypothesis is $H_0 : e^{\beta_j} = 1$.

[a]The marginal effects of age and household income are interpreted as a percentage change resulting from a unit increment in the explanatory variables.

Estimates of the ICD-10 disease category binary variables are not presented above.