THE UNIVERSITY OF MELBOURNE

FACULTY OF BUSINESS & ECONOMICS

Melbourne Institute Working Paper Series

Working Paper No. 22/11

Demand for Hospital Care and Private Health Insurance in a Mixed Public–Private System: Empirical Evidence Using a Simultaneous Equation Modeling Approach

Terence Chai Cheng and Farshid Vahid

MELBOURNE INSTITUTE®
of Applied Economic and Social Research

Demand for Hospital Care and Private Health Insurance in a Mixed Public–Private System: Empirical Evidence Using a Simultaneous Equation Modeling Approach*

Terence Chai Cheng† and Farshid Vahid‡

† Melbourne Institute of Applied Economic and Social Research, The University of Melbourne

‡ Department of Econometrics and Business Statistics, Monash University

Melbourne Institute Working Paper No. 22/11

ISSN 1328-4991 (Print)

ISSN 1447-5863 (Online)

ISBN 978-0-7340-4255-2

September 2011

* We wish to thank Hans Van Ophem, Hugh Gravelle, Pravin Trivedi and Peter Sivey for their helpful comments and suggestions, as well as participants at presentations at the 10th World Congress of the Econometric Society 2010, the IRDES Workshop on Applied Health Economics and Policy Evaluation, Australian Health Economics Society Conference, and seminars at the Health, Econometrics and Data Group at the University of York, the Melbourne Institute of Applied Economic and Social Research and University of Adelaide. T. Cheng acknowledges the financial support provided through a PhD scholarship from the Australian Centre for Economic Research on Health. This paper uses unit record data from the in-confidence version of the Household, Income and Labour Dynamics in Australia (HILDA) survey. The HILDA project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). I would like to especially thank Michelle Summerfield and the HILDA team at the Melbourne Institute for facilitating my access to the data. The findings and views reported in this paper are mine and should not be attributed to either FaHCSIA or the Melbourne Institute. Corresponding author: Dr T. Cheng, Email: techeng@unimelb.edu.au.

Melbourne Institute of Applied Economic and Social Research

The University of Melbourne

Victoria 3010 Australia

***Telephone* (03) 8344 2100**

***Fax* (03) 8344 2111**

***Email* melb-inst@unimelb.edu.au**

***WWW Address* http://www.melbourneinstitute.com**

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 indicate that there is no evidence of endogeneity between the decision to purchase insurance on the type and intensity of hospital care use. We find some evidence of 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.

JEL classification: I11, H42, C31, C15

Keywords: Simultaneous equation models, count data, demand for hospital care, moral hazard, public–private mix

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.

Understanding the determinants of individuals' decisions to purchase private health insurance, and how these decisions influence the choice to seek public or private health care, and the intensity of care, will be crucial in assessing the effects of private health insurance on the performance of health systems with mixed financing. Within the available literature, studies have examined each of these decisions either separately or in combination with one other theme. In 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). The empirical evidence in this literature generally finds that the demand for public medical care is negatively influenced by waiting times associated with obtaining medical care from the public sector (McAvinchey and Yannopoulos 1993; Martin and Smith 1999), and that the demand for private sector care is positively associated with the availability of private health insurance (Gertler and Strum 1997; Srivastava and Zhao 2008). Individuals' choices between public and private care have also been observed to be persistent over time (Propper 2000) .

The relationship between health care use and private health insurance, in health systems where the public sector plays a dominant role, has been examined by a number of studies. The empirical evidence from Australia and Ireland have found that individuals with private insurance have higher usage health care services (Cameron et al. 1988; Harmon and Nolan 2001), and have a higher duration of private hospital stays (Savage and Wright 2003). In Germany, it is shown that the availability of add-on insurance does not lead to a higher number of hospital and doctor visits (Riphahn et al. 2003). A key methodological issue that these studies have to address is that individuals' insurance status is potentially endogenous to health care use. This problem arises because of simultaneity in these decisions – that the demand for health care is influenced by the availability of insurance, and the decision to purchase health insurance in turn depends on the expected utilisation of health services in the future (Cameron et al. 1988).

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 argue that these decisions are simultaneously determined and propose an 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. Models such as the Poisson and Negative Binomial models have been the traditional workhorse models employed to analyse non-negative and integer-valued (count) outcomes and have been widely applied to many fields within economics. These models have been extended into more advanced models with a variety of applications such as the multivariate count data models (e.g. Munkin and Trivedi 1999; Riphahn et al. 2003; Fabbri and Monfardini 2009; Hellström 2006) and count models with selectivity and endogenous regressors (Terza 1998, van Ophem 2000; Greene 2005). There has been to date only a handful of studies that attempt to extend count data 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, and Deb and Trivedi (2006) who 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, the data used in the empirical analysis and discusses the identification strategy. 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

[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.

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 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

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

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-bones 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

The model for counts that is adopted in this paper is the Poisson lognormal model which is derived by introducing a heterogeneity term, as a normally distributed variable, into the conditional mean equation in the conventional Poisson regression model.[2] This model serves as a convenient platform to accommodate the presence of endogenous binary regressors. The specification of the econometric model is as follows. 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

[2] The Poisson lognormal mixture has been presented in the literature in a variety of ways (Greene 2005). A specific representation of the model, with an exponential of a normally distributed heterogeneity term, dates back to Greene (1995) and Million (1998).

the endogenous variables q_i and d_i, m_i follows a Poisson distribution with truncation at zero. The probability density function is

$$f(m_i \,|\, X_i, q_i, d_i, \xi_i) = \frac{\exp^{-\mu_i} \mu_i^{m_i}}{m_i! \, (1 - \exp^{-\mu})} \tag{14}$$

with the conditional mean parameter μ_i

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

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

$$q_i^* = Z_i\alpha + \beta_1 d_i + v_i \tag{16}$$

$$d_i^* = W_i\gamma + \eta_i \tag{17}$$

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

$$\begin{aligned} q_i &= 1\,[q_i^* > 0] \\ d_i &= 1\,[d_i^* > 0] \end{aligned} \tag{18}$$

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

$$
\begin{aligned}
\xi_i, v_i &\sim N_2[(0,0),(1,1),\rho_{\xi v}] \\
\xi_i, \eta_i &\sim N_2[(0,0),(1,1),\rho_{\xi \eta}] \qquad (19) \\
v_i, \eta_i &\sim N_2[(0,0),(1,1),\rho_{v \eta}]
\end{aligned}
$$

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

$$
\begin{pmatrix} v_i \,|\, \xi_i \\ \eta_i \,|\, \xi_i \end{pmatrix} \sim N_2 \left[\begin{pmatrix} \rho_{\xi v}\xi_i \\ \rho_{\xi\eta}\xi_i \end{pmatrix}, \begin{pmatrix} 1-\rho_{\xi v} & \rho_{v\eta}-\rho_{\xi v}\rho_{\xi\eta} \\ \rho_{v\eta}-\rho_{\xi v}\rho_{\xi\eta} & 1-\rho_{\xi\eta} \end{pmatrix} \right] \qquad (20)
$$

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

$$
\begin{aligned}
\int_{-\infty}^{\infty} \Big[&(1-q_i)(1-d_i) f(m_i \mid X_i, q_i = 0, d_i = 0, \xi_i)\; P(q_i = 0, d_i = 0 \mid \Omega_i, \xi_i) + \\
&(q_i)(1-d_i) f(m_i \mid X_i, q_i = 1, d_i = 0, \xi_i) P(q_i = 1, d_i = 0 \mid \Omega_i, \xi_i) + \\
&(1-q_i)(d_i) f(m_i \mid X_i, q_i = 0, d_i = 1, \xi_i) P(q_i = 0, d_i = 1 \mid \Omega_i, \xi_i) + \\
&(q_i)(d_i) f(m_i \mid X_i, q_i = 1, d_i = 1, \xi_i)\; P(q_i = 1, d_i = 1 \mid \Omega_i, \xi_i) \Big]\, d\xi_i \qquad (21)
\end{aligned}
$$

where $\Omega_i = (X_i \cup Z_i \cup W_i)$. From (15), (16), (17), (20) and (21), 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

$$
g(q_i, d_i \,|\, Z_i, W_i, \xi_i) = \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*] \qquad (22)
$$

where

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

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

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

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 (21) may be expressed as

$$f(m_i, q_i, d_i \,|\, \Omega_i, \xi_i) = f(m_i \,|\, X_i, q_i, d_i, \xi_i) \cdot g(q_i, d_i \,|\, Z_i, W_i, \xi_i) \tag{23}$$

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), (18) and (19). 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

$$\ell_i(\Theta) = H_i \cdot \int_{-\infty}^{+\infty} f(m_i \,|\, \Omega_i, q_i, d_i, \xi_i) \cdot \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*]\, \phi(\xi_i) d\xi_i + (1-H_i) \cdot \Phi[y_{2i}(W_i\gamma)] \tag{24}$$

where Θ is the set of all unknown parameters in equations (15), (16), (17) and (19). Equation (24) 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 (24) 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

$$\widehat{\ell}_i(\Theta) = H_i \cdot \frac{1}{S}\sum_{1}^{S} f(m_i \,|\, \Omega_i, q_i, d_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*] + (1 - H_i) \cdot \Phi[y_{2i}(W_i\gamma)] \tag{25}$$

Correspondingly, the simulated log-likelihood function is

$$\ln\widehat{\mathrm{L}}(\Theta) = \sum_{i=1}^{N} \ln\left\{ H_i \cdot \frac{1}{S}\sum_{1}^{S} f(m_i \,|\, \Omega_i, q_i, d_i, \xi_i^s) \cdot \Phi_2[y_{1i}\Theta_1(\xi_i^s), y_{2i}\Theta_2(\xi_i^s), \rho^*] + (1-H_i) \cdot \Phi[y_{2i}(W_i\gamma)] \right\} \tag{26}$$

The maximum simulated likelihood estimator (MSL) maximises the simulated log-likelihood in (26). 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 "cluster-robust" formula (Deb and Trivedi 2002, p.608). The robust sandwich formula is more appropriate compared with the information matrix and outer product formula as the former takes into account the influence of simulation noise (Mcfadden and Train 2000). Moreover, given that the sample includes multiple observations from each household in the data (e.g. couples in a family income unit), the "cluster-robust" formula accounts for this sampling scheme instead of treating each observation as independent.

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. Therefore, an increase in x_j by 0.01 changes the expected length of stay $E(m \,|\, X)$ 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

$$\frac{E(m \mid x_j = 1, X)}{E(m \mid x_j = 0, X)} = \frac{e^{\beta_j + \sum_{i \neq j} \beta_i x_i}}{e^{\sum_{i \neq j} \beta_i x_i}} = e^{\beta_j} \tag{27}$$

For binary outcome variables, the marginal effect of a change in the continuous variable X_k is given as $\phi(X\hat{\beta}) \cdot \partial(X\hat{\beta})/\partial X_k$ where $\hat{\beta}$ are the estimates of the coefficients. For discrete explanatory variables, the marginal effect when X_k changes from 0 to 1 is given as $\Phi(X\hat{\beta} \mid X_k = 1) - \Phi(X\hat{\beta} \mid X_k = 0)$. The standard errors of all marginal effects are calculated using the delta method.

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 (e.g. 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).

The government responded by introducing a series of policy changes with the aim of encouraging the uptake of private health insurance. The first of three policies was the Private Health Insurance Incentive Scheme (PHIIS) introduced in July 1997, which involved using tax subsidies to encourage the purchase of private health insurance amongst lower income individuals and tax penalties for individuals without insurance. For the tax penalty component of PHIIS, singles and families (inclusive of couples) with an annual household income greater than $50,000 and $100,000 respectively, are liable for a tax levy (referred to as Medicare Levy Surcharge) amounting to one percent of their taxable income if they do not have private health insurance. In early 1998, the subsidy component of the PHIIS was replaced 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 a full description of the three policies. 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.

4.2 Data

The empirical analysis uses data from the In-Confidence version of the Household, Income and Labour Dynamics in Australia (HILDA) survey. HILDA is a nationally representative longitudinal survey which collects extensive information on household and family formation, labour force participation, income and life satisfaction, health and well-being. Every member aged 15 and over are surveyed via a face-to-face interview and are requested to complete a self-completion questionnaire. We focus on data from wave 4 (2004) of the HILDA survey where approximately 12408 individuals from 6987 households were surveyed. A health module, in addition to the core survey questions, was included in wave 4 in which information on hospital care use and private health insurance status was collected. We combined the wave 4 data with responses on self assessed health status from wave 3 (2003). In the analysis sample, observations where the respondents age is below 25 years and those from multiple family households were excluded. Given the emphasis on the relationship between hospital care use and private health insurance, individuals with private health insurance policies that cover only ancillary services were excluded from the analysis. After excluding observations with missing or ambiguous responses, 7395 observations remained in the sample of which 962 individuals indicated that they have had at least one overnight hospitalisation 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 7395 observations, 3828 (51.8%) individual have private hospital insurance. The survey also contains information on the whether individuals chose to be hospitalised as a public or private patient, and the number of nights in hospital at the most recent hospitalisation episode. Table 1 shows the frequency of hospital nights by insurance status and patient type for the 962 individuals who have been hospitalised. Amongst the hospitalised individuals, 489 (50.8%) 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 489 insured individuals, 84.5% (N=413) chose to be hospitalised as private patients while 15.5% (N=76) were public patients. Conversely, only 9.7% (N=46) of 427 uninsured individuals chose private care, with 90.3% (N=427) opting to be public patients. Secondly, uninsured individuals who chose public hospital care stayed the highest number of nights – an average of 5.24 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 (5.00 vs. 3.22 nights). Thirdly, the variance and range of the observed length of hospital stay is highest for uninsured public patients followed by insured private patients.

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, levy status), health status measures (presence of chronic conditions), health risk factors (drinker, 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). In addition, we include two variables that are obtained through external data sources. The first is the size of the "general and health insurance" industry workforce within the intermediate local area of the survey respondents' residential location. This variable is derived using information on industry and location of employment based on data from the 2001 Australian Census of Population and Housing.[3] The second variable is the distance to the nearest private hos-

[3]The industry category is Industry Code 742 (Other Insurance), which includes 7421 (Health Insurance) and 7422 (General Insurance) based on the Australian and New Zealand Standard Industrial Classification (ANZSIC) in 1993. The unit of reference for defining the location of employment is the Statistical

pital from the survey respondents' location of residence. This is defined as the euclidian distance between the centroids of the postal area of survey respondents' and the postal area of the nearest private hospital.[4] Distance is calculated using data on the coordinates (longitude and latitude) of centroids via the haversine formula.

[Insert Table 2 about here]

The variables names, description and summary statistics of these explanatory variables are presented in Table 2. Females make up 54% of the sample. The average age of individuals in the sample is 49.36 years, with a range 25 and 99 years. 76% of individuals are from couple income units and 43% have dependent children. In terms of education attainment, 45% do not have any post-school educational qualifications (Year 12 and below) while 23% have a bachelor degree or higher. The mean annual household income is $68,297. 23% of the sample have a level of household income that is above the income threshold and are required to pay the Medicare Levy Surcharge if they do not have private health insurance. On the distribution of the sample by occupational types, 37% are either not in the labour force or are unemployed and the two largest groups are "Professionals" (26%) and "Clerical and Service workers" (16%).

Measures of individuals' health status include indicators of self assessed health status (SAH) collected in wave 3, and a set of binary variables that indicate the presence of chronic conditions that affect physical and social functioning. We employ the SAH measures from the wave 3 survey to avoid issues of reverse causation as the outcome of interest is health care use that occur in the 12 months preceding the survey. In terms of SAH, 47% of individuals reported to be in excellent or very good health, with 35% indicating that their health is good and 18% fair and poor. 38% of individuals reported having chronic conditions that limit the type and amount of work they can do; 4.0% indicated that they have difficulty with self care activities; 8.2% have limitations in mobility activities and 0.8% have difficulty communicating in their own language. Indicators of health risk factors include whether individuals consume alcohol daily (9.6%) and are regular smokers

Subdivision (SSD), a spatial unit of intermediate size. In the 2001 Australian Standard Geographical Classification, there were a total 207 SSDs, with each SSD containing an average of 22 postal areas. The postal codes of respondents in the HILDA survey are linked to the SSD using the 2001 Australian Bureau of Statistics (ABS) "Statistical Subdivision and Postal Area Concordance" data that is available by request from the ABS.

[4]Data on the centroids of postal areas are obtained from Australian Bureau of Statistics (2006).

(18%). Geographical information include state/territory indicators as well as remoteness categories. Approximately 59% of individuals reside in major cities in Australia. The average size of the general and health insurance workforce within a statistical subdivision is 866 and the mean distance to the nearest private hospital is 30 km.

4.5 Identification and exclusion restrictions

Formally, the econometric model described in Section 3 is identified by the nonlinearity of the functional form and error distributions. However, the reliance on such an identification scheme is unappealing. In the econometric model, equations (14) and (15) constitute a Poisson lognormal regression with endogenous insurance and patient type binary variables, and equation (16) is a probit model with an endogenous insurance variable. Identification requires that there is at least one variable in W that is excluded from Z and X , and one variable that is in Z that is excluded in X.

To satisfy the first set of exclusion restrictions, we include the size of the general and health insurance workforce in the insurance equation but not in the patient type choice and length of stay equations. We argue that this variable performs the role as a proxy for the accessibility to insurance services which influences the ease to which individuals can acquire information on health insurance products. This variable is likely to influence whether individuals choose to purchase private hospital insurance but not the choice between public and patient hospital care and the intensity of hospital stay.

For the second exclusion restriction, we include the distance to the nearest private hospital in the patient type equation but exclude the variable from the length of stay equation. Data on distance to hospitals have frequently been employed as instruments to address selection bias in studies on treatment outcomes and hospital quality (e.g. McClellan et al. 1994; Gowrisankaran and Town 1999). For our purpose, individuals' choice to seek private or public hospital care is based on a variety of factors which include the types and severity of illness, the availability of private hospital insurance, as well as the proximity of private hospitals. The distance to private hospitals is very likely to be uncorrelated with the unobserved type and severity of individuals' medical conditions and for this reason would justify as an excluded variable in the length of stay equation.

We impose an additional restriction that the levy variable is included only in the insurance equation. This variable accounts for whether individuals are liable to pay the Medicare Levy Surcharge if they do not purchase private health insurance and is expected to influence only the decision to insure. All other exogenous covariates, apart from the exclusions discussed above, are included all three equations.

5 Results

We estimated a variety of models with different combinations of the correlation parameters $\rho_{\xi\upsilon}, \rho_{\xi\eta}$ and $\rho_{\upsilon\eta}$ 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 Poisson lognormal model and the patient type and insurance equations are estimated using separate probit regressions. An implicit assumption underlying this specification is that the patient type and insurance binary regressors are exogenous.

The estimates and standard errors of the correlation parameters are presented at the bottom of Table 3. The log-likelihood for the simultaneous equation model (-6681.22) is larger compared to the separate regression models (-6681.21), the latter calculated as the sum of the log-likelihood values from the three separate regressions. These results show that the estimates of all three correlation parameters are both individually and jointly not statistically significant from zero, and indicates that the insurance and patient type binary variables are not endogenous. For the discussion of the estimates on the insurance and patient type effects in Section 3, the results from the simultaneous equation will be compared with that obtained under the single equation models. The discussion in the remaining sections of this paper will be based on former model.

5.1 Marginal effects of insurance and patient type

[Insert Table 3 about here]

Table 3 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. The estimates from the simultaneous equation model described in Section 3 is presented in the column 2. For comparison, the results from the single equation Poisson lognormal and probit regressions for the length of stay and public/private patient choice respectively are presented in column 3. In the public/private choice equation, the estimate of the marginal effect of the insurance binary variable is 0.700 and statistically significant. All else being equal, individuals with private hospital insurance are 70% 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 hence insured individuals are more likely to seek private relative to public hospital care. The estimate obtained from the probit regression, under the exogeneity assumption, is 0.738 and is very similar in magnitude.

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*[5] 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. From column 2, the estimate of the insurance effect among privately admitted patients is 2.457 which is indicative that private patients with insurance have proportionally higher expected length of stay compared with those without insurance. This estimate is however not statistically significantly larger than 1. The estimate from the Poisson lognormal model is very similar in magnitude compared to that for the simultaneous equation model and is statistically significantly larger than 1. This result suggest that the expected length of private hospital stay by privately insured individuals is 2.537 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*.[6] Insofar as the insurance variable reflect the incentive effects of insurance, we would expect a priori that private hospital insurance would have no impact on the intensity of public hospital care use. This is observed in the empirical results, given that the estimate of the public patient effect

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

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

is not significantly smaller than 1. 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 3 as the *patient type effect*. The result indicates that the length of hospital stay by private patients is on average 0.414 times that of publicly admitted patients. The estimate from the single equation model is also similar in terms of magnitude.

5.2 Other findings

[Insert Table 4 about here]

Columns 2 and 3 in Table 4 presents the marginal effects and standard errors of the other explanatory variables on the length of hospital stay. The expected length of hospital stay is significantly higher for individuals with dependent children, and for those who were not born in Australia. The estimates on the other demographic variables suggest that length of hospital stay is higher for females in the childbearing years, although this estimate, together with those of age and gender, are generally not statistically significant. The coefficients on the age and squared age variables (not reported in Table 4) indicate an inverse U-shape relationship between age and the intensity of hospital stay.

Compared with those who are not in employment, the expected length of stay is shorter for individuals in 'white collar' occupations such as managers, professionals and clerical workers. Individuals in 'blue collar' occupations such as tradespersons and labourers on the other hand have relatively higher duration of hospital stay. A possible explanation for the shorter length of stay as suggested by the theoretical model is that individuals in "white collar" occupations face a higher opportunity cost of time involved in seeking hospital care which can otherwise be devoted to work or leisure. In addition, it is plausible that occupation performs the role as a proxy for illness severity insofar that individuals involved in manual work are likely to have more severe health conditions.

The estimates of the coefficients on education suggest that the intensity of hospital use is higher for individuals with more years of education. This result is consistent with the theoretical predictions of Grossman's human capital model in that more educated individuals will choose a higher optimal stock of health and consequently undertake more investments in health (Grossman 2000). Individuals' health status play the role of proxies for illness severity and we observed that expected length of stay is increasing with poorer health as measured by the self assessed health status as well as the presence of chronic medical conditions though the latter estimates are not generally not statistically significant. We expect that individuals undertaking risky behaviours such as regular alcohol consumption and smoking may have more severe health conditions and require a higher intensity of hospital care but the empirical results appear mixed.

Columns 4 and 5 in Table 4 presents the results on the factors that influence the choice of hospital admission as a public or private patient. Household income has a positive effect on the propensity to seek private hospital care. This is expected given that private health care is by nature a normal good and that the utilisation of private hospital services may involve out-of-pocket payments even when private health insurance is available. We observe that professionals are considerably more likely to obtain private care. A possible channel by which income and employment characteristics can affect the propensity for private hospital care is through their relationship with the monetary valuation of the time spent on hospital waiting lists (Propper 1990, 1995). For instance, 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. Individuals in relatively poorer health, measured in terms of self assessed health status appears to be more likely to seek public care. To the extent that these health status indicators proxy for the severity of individuals' illness conditions, this result is consistent with the notion that individuals are more likely to seek private care for medical conditions that are less severe (e.g. elective treatments). We expect that individuals living further away from private hospitals may be less likely to obtain private care due to the higher indirect cost (e.g. travel cost, time) involved. Our findings suggest that this is the case only for individuals who reside a considerable distance away from private hospitals.[7] On the whole, the distance to the nearest private hospital is positively associated with the

[7] The coefficients on distance and squared distance (not reported in Table 4) are 0.465 and -0.0717 respectively, and are both highly statistically significant. The distance, beyond which the propensity for private care becomes negatively related with distance, is 324 km (approximately three standard deviations from the mean). An examination of the sample, for observations where distance to nearest private hospital is greater than 324 km, revealed that individuals are all residing in outer regional and remote areas within Australia.

likelihood of obtaining private care.

Columns 6 and 7 of Table 4 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 lower for those with dependent children. Individuals whose household income are above the Medicare Levy Surcharge threshold, and are liable for the additional tax levy if they do not have private health insurance, are more likely to purchase private health insurance. Socioeconomic factors such as income and post school education qualfications are positively associated with the purchase of insurance. Individuals in 'white collar' occupations are more likely to be privately insured compared to 'blue collar' workers and those not in employment. Privately insured individuals are more likely to be in better self assessed health and are more likely to be without chronic conditions. Health risk factors such as regular smoking decreases the propensity to purchase private hospital insurance. On geographical factors, individuals living in Victoria and Western Australia have a higher probability of purchasing private hospital insurance relative to those living in New South Wales. Finally, individuals residing in geographical areas with a larger health insurance workforce, and hence potentially have more access to insurance services and information, are more likely to be privately insured.

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.

Our 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.

We find some evidence of moral hazard effect of private hospital insurance amongst patients who sought hospital care as a private patient. This result is consistent 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. Savage and Wright (2003) 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.[8] 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.

It is important to emphasise that within the context of a parallel public and private hospital care system such as Australia's, the 'incentive' or 'moral hazard' effect of private health insurance refers to the incremental use of private health care resulting from a decrease in the effective price of obtaining private care due to the presence of private

[8]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.

insurance. This phenomenon is unique to countries with parallel systems of finance and is to be distinguished from how moral hazard is traditionally interpreted in countries where health care is afforded predominantly through a single source of finance. For this reason, the empirical strategy adopted in this paper implicitly assumes that the probability of hospitalisation is exogenous. Strictly speaking, the effect of private insurance on whether or not an individual is hospitalised cannot be interpreted as indicative of moral hazard because the outcome variable represents both public and/or private hospital care use. In addition, our empirical strategy is congruent to modeling length of hospital stay and the public/private patient choice using only observations from the sub-sample of hospitalised individuals, which is the approach is adopted by Savage and Wright (2003). An alternative approach is to explicitly model the probability of hospitalisation by extending the econometric model to a four-equation model which would involve a separate set of exclusion restrictions in addition to those that have been proposed in this paper. This extension however is not attempted in this paper and left as a potential area of future work.

References

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

Australian Bureau of Statistics (2006). Census of Population and Housing: Census geographic areas digital boundaries 2006. Cat no. 292.0.30.001 Australian Bureau of Statistics.

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), 33–41.

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 (2002). The structure of demand for health care: latent class versus two-part models. *Journal of Health Economics 21*, 601–625.

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.

Fabbri, D. and C. Monfardini (2009). Rationing the public provision of healthcare in the presence of private supplements: evidence from the Italian NHS. *Journal of Health Economics 28*, 290–304.

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.

Gowrisankaran, G. and R. J. Town (1999). Estimating the quality of care in hospitals using instrumental varibles. *Journal of Health Economics 18*, 747–767.

Greene, W. (1995). Sample selection in the Poisson regression model. Working Paper EC-95-06, Department of Economics, Stern School of Business, New York University.

Greene, W. (2005). Functional form and heterogeneity in models for count data. *Foundation and Trends in Econometrics 1*(2), 113–218.

Grossman, M. (2000). The human capital model. In A. Culyer and N. J.P. (Eds.), *Handbook of Health Economics*, Chapter 7. Elsevier Science B.V.

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

Hellström, J. (2006). A bivariate count data model for household tourism demand. *Journal of Applied Econometrics 21*, 213–226.

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.

McClellan, M., B. J. McNeil, and J. P. Newhouse (1994). Does more intensive treatment of Acute Myocardial Infraction in the elderly reduce mortality? analysis using instrumental variables. *Journal of the American Medical Association 272*, 859–866.

Million, A. (1998). Models for correlated count data. Unpublished dissertation, University of Munich.

Munkin, M. and P. Trivedi (1999). Simulated maximum likelihood estimation of multivariate mixed-Poisson regression models, with application. *Econometrics Journal 2*, 29–48.

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 Resources 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). Incentive effects in the demand for health care: a bivariate panel count data model. *Journal of Applied Econometrics 18*(4), 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*, University of York.

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.

van Ophem, H. (2000). Modeling selectivity in count data models. *Journal of Business and Economic Statistics 4*, 503–511.

Table 1: Summary statistics of key outcomes for hospitalised individuals

	Without Insurance (N=473)		With Insurance (N=489)		
Hospital Nights	Public Patient (N=427)	Private Patient (N=46)	Public Patient (N=76)	Private Patient (N=413)	Total (N=962)
Pr(m=1)	110 (25.8%)	24 (52.2%)	32 (42.1%)	127 (30.8%)	293 (30.5%)
Pr(m=2)	65 (41.0%)	6 (65.2%)	6 (50.0%)	53 (43.6%)	130 (44.0%)
Pr(m=3)	64 (56.0%)	3 (71.7%)	10 (63.2%)	38 (52.8%)	115 (55.9%)
Pr(m=4)	38 (64.9%)	2 (76.1%)	5 (69.7%)	38 (62.0%)	83 (64.6%)
Pr(m=5)[a]	36 (73.3%)	2 (80.4%)	5 (76.3%)	54 (75.1%)	97 (74.6%)
Range	1-135	1-21	1-21	1-80	1-135
Mean	5.24	3.22	4.66	5.00	5.04
Variance	82.32	14.44	35.16	51.88	62.37

[a] For brevity, only frequencies up to Pr(m=5) are presented for the count utilisation measure. See 'Range' for information on all realisations.

Note: Percentages in the parenthesis are cumulative frequencies.

Table 2: Descriptive statistics: explanatory variables (N=7395)

Variable	Description	Mean	Std dev
Female	Female (0/1)	0.54	0.50
Age	Age	49.36	15.16
Age2	Squared age	2665.76	1623.87
Couple	Couple income unit (1/0)	0.76	0.43
Depchild	Have dependent children (1/0)	0.43	0.50
Childbear	Female age between 25 to 39 years (1/0)	0.17	0.38
Income	Annual household income ($ '000)	68.30	59.54
Income2	Squared annual household income	8209.07	31380.99
Levy	Household income above Medicare Levy Surcharge threshold (0/1)	0.23	0.42
Country of birth:			
Australia (*Ref*)	Person is born in Australia (0/1)	0.77	0.42
Main English	Person is born in main english speaking countries (0/1)	0.12	0.33
Other	Person is born in other countries (0/1)	0.11	0.32
Education qualification (qual.):			
School (*Ref*)	Highest qual. is Year 12 or below (0/1)	0.45	0.50
Certificate	Highest qual. is a Certificate (0/1)	0.22	0.42
Diploma	Highest qual. is a (Advanced) Diploma (0/1)	0.10	0.30
Degree	Highest qual. is a degree or above(0/1)	0.23	0.42
Occupation category:			
Unemploy (Ref)	Not in employment (0/1)	0.37	0.48
Manager/Admin	Managers and Administrators (0/1)	0.070	0.25
Professional	Professionals (0/1)	0.26	0.44
Clerical/Service	Clerical and Service workers (0/1)	0.16	0.36
Trades/Transport	Trades, Production, Transport, Labourers (0/1)	0.15	0.35
Self assessed health (SAH):			
SAH_VG (*Ref*)	SAH in t-1 is excellent or very good (0/1)	0.47	0.50
SAH_GD	SAH in t-1 is good (0/1)	0.35	0.48
SAH_FP	SAH in t-1 is fair or poor (0/1)	0.18	0.39
Chronic health conditions (conds.):			
Work Limiting	Conds. limit amount and type of work (0/1)	0.38	0.67
Self Care	Conds. causes difficulties with self care (0/1)	0.040	0.20
Mobility	Conds. causes difficulties with mobility activities (0/1)	0.082	0.28
Communication	Conds. causes difficulties with communication (0/1)	0.0080	0.089
Alcohol Daily	Person drinks alcohol daily (0/1)	0.096	0.30
Regular Smoker	Person is a regular smoker (0/1)	0.18	0.38
State:			
NSW (*Ref*)	Person lives in New South Wales (0/1)	0.30	0.46
VIC	Person lives in Victoria (0/1)	0.25	0.43
QLD	Person lives in Queensland (0/1)	0.20	0.40
SA	Person lives in South Australia (0/1)	0.094	0.29
WA	Person lives in Western Australia (0/1)	0.10	0.30
TAS/NT	Person lives in Tasmania or Northern Territory (0/1)	0.038	0.19
ACT	Person lives in the Australian Capital Territory (0/1)	0.019	0.14
Remoteness:			
Major cities (*Ref*)	Person resides in major cities (0/1)	0.59	0.49
Inner region	Person resides in inner regional areas (0/1)	0.27	0.44
Other	Person resides in outer regional and (very) remote (0/1)	0.14	0.35
Headcount	Number ('000) of the persons working in the health and general insurance industry (respondents' residential local area)	0.866	1.998
Headcount2	Squared headcount	4.74	19.59
Distance	Euclidian distance (in km) to the nearest private hospital	0.29	0.92
Distance2	Squared distance	0.93	6.78

Table 3: Marginal effects of the patient type and insurance variables

	Simultaneous Equation Model		Poisson Lognormal/Probit	
	dF/dX	Std. err.	dF/dX	Std. err.
	- Public/Private Patient -			
Insurance effect	0.700***	0.184	0.738***	0.026
	- Hospital Length of Stay [a] *-*			
Moral hazard effect	2.457	1.094	2.537**	0.626
Insurance on public patient effect	0.858	0.319	0.891	0.156
Patient type effect	0.414***	0.165	0.444***	0.108
	- Correlation Parameters -			
$\rho_{\xi v}$	0.051	0.153		
$\rho_{\xi \eta}$	0.067	0.157		
$\rho_{v \eta}$	0.108	0.449		
Log-likelihood value	-6681.22		-6681.21	

***, **, * 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.

[b]Robust standard errors clustered at level of the household.

Table 4: Marginal effects of the remaining explanatory variables

	Length of Stay		Public/Private		Insurance	
	dF/dX	Std. err.	dF/dX	Std. err.	dF/dX	Std. err.
Female	0.990	0.099	0.0096	0.051	0.039***	0.013
Age	0.978	0.022	-0.0059	0.0015	0.031***	0.0036
Childbear	1.127	0.186	-0.066	0.094	-0.0023	0.022
Depchild	1.418**	0.177	-0.052	0.072	-0.053***	0.020
Couple	0.930	0.100	-0.042	0.058	0.092***	0.020
Country of Birth:						
Main English	1.088	0.139	-0.068	0.071	-0.142***	0.022
Others	1.263*	0.161	-0.193***	0.066	-0.119***	0.024
Income	1.000	0.0019	0.0031**	0.0015	0.0039***	0.00046
Levy					0.101***	0.030
Education:						
Certificate	1.110	0.116	0.0026	0.062	0.030*	0.017
Diploma	1.141	0.164	0.030	0.089	0.107***	0.022
Degree	1.108	0.151	-0.056	0.082	0.134***	0.020
Occupation:						
Manager/Admin	0.829	0.174	0.0056	0.119	0.231***	0.028
Professional	0.773	0.097	0.194***	0.071	0.136***	0.021
Clerical/Service	0.829	0.122	0.053	0.092	0.096***	0.022
Trades/Transport	1.089	0.189	0.039	0.108	-0.017	0.025
Self Assessed Health:						
SAH_GD	1.028	0.109	-0.043	0.056	-0.012	0.015
SAH_FP	1.300*	0.159	-0.065	0.069	-0.091***	0.021
Work Limiting	1.107	0.069	0.064**	0.032	-0.010	0.011
Self Care	1.119	0.180	0.0015	0.087	-0.027	0.038
Mobility	1.100	0.140	0.036	0.069	-0.039	0.028
Communication	1.110	0.262	-0.194	0.173	-0.122	0.077
Alcohol Daily	1.167	0.150	-0.016	0.080	0.035	0.024
Regular Smoker	0.883	0.109	-0.141**	0.067	-0.150***	0.019
State:						
VIC	0.941	0.100	-0.033	0.062	0.032*	0.021
QLD	0.886	0.105	0.042	0.064	-0.033	0.024
SA	0.845	0.104	0.061	0.072	0.036	0.030
WA	0.959	0.152	0.090	0.083	0.080***	0.028
TAS/NT	1.386	0.285	-0.047	0.114	-0.0047	0.045
ACT	0.326***	0.125	-0.069	0.124	0.072	0.067
Remoteness:						
Inner region	1.046	0.098	-0.077	0.058	-0.048**	0.022
Other	1.039	0.121	-0.199**	0.091	-0.053	0.037
Headcount					0.041***	0.011
Distance			0.127*	0.077	-0.041*	0.025
Heterogeneity σ	0.963***	0.038				

***, **, * 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.