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Measuring the Effects of Removing Subsidies for Private Insurance on Public Expenditure for Health Care

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Abstract

This paper investigates the effects of removing subsidies for private health insurance on public sector expenditure for hospital care. An econometric framework using simultaneous equation models is developed to analyse the interrelated decisions on the intensity and type of health care use and insurance. The results indicate that while privately insured individuals are more likely to seek hospital care as a private patient, they do not differ in their intensity of hospital care use compared with those without private insurance. The simulation results suggest that eliminating subsides could potentially yield substantial public sector savings.

JEL classification: I11, H42, C31, C15

Keywords: Demand for hospital care; private insurance; bivariate count data models; simultaneous equation models; policy simulation

1 Introduction

In many developed countries, the public sector plays an important role in the financing and provision of health care. Nearly all countries in Europe, in addition to Australia and New Zealand, have universal health care either through direct public provision of health care services or publicly sponsored health insurance. Even in the market oriented health care system of the United States, health insurance is directly subsidised for individuals and families with low incomes and the elderly, while employment-based private health insurance is indirectly subsidised through the tax system. The rationale for public involvement in health care appears to be motivated by the notion that health care is a basic and fundamental right. It is also widely recognised that promoting and protecting health is essential to human welfare and sustained economic and social development (World Health Organisation 2010).

While there are strong justifications for governments intervening in health care markets, the arguments for the provision of public subsidies for *duplicate* private health insurance in countries with universal health systems are less compelling. In these countries (e.g. Australia, Spain, United Kingdom), a private health care market coexists alongside the public sector providing health services already covered under the public system, and is financed either through direct payments or private health insurance. Indeed, public subsidies for private insurance, either in the form of tax incentives or monetary rebates on premiums, have been a source of significant policy controversy (Colombo and Tapay 2004). It is often argued that using incentives to encourage the purchase of private health insurance would stimulate the private health care market, which can relieve both capacity and cost pressures off the public system, hence resulting in faster access and higher quality care in the public sector. Questions however have been raised as to whether the private sector diverts valuable resources away from the public sector. Issues concerning the equity of access arise as privately insured individuals, who usually have higher incomes, can gain faster access to elective surgeries which in the public sector involve significant waiting times.

An important dimension in evaluating the effectiveness of subsidies for private health insurance is the question of whether subsidies could be self-financing, that is whether its introduction would lead to cost savings within the public health care system that exceed the cost of the subsidy program. The converse question, one that is pursued in this paper, is whether the public savings that are achieved by removing subsidies could more than offset the potential increase in public sector expenditure. The resultant effect on public sector cost depends on how individuals' demand for duplicate private health insurance responds to changes in the price of insurance from removing the subsidy, and consequently how decisions between public and private sector care, and the intensity of health care use, are influenced by changes in private insurance status.

This paper addresses the above questions by developing a microeconometric framework to analyse the interrelated decisions on the intensity and type of health care use and private health insurance. We estimate a series of simultaneous equation models, which accommodates the count data nature of health care utilisation measures (number of hospital admissions, length of overnight stay) and the binary nature of measures on the type (public vs. private) of hospital care and private health insurance. These models address issues of jointness in demand, selectivity and simultaneity that are pertinent in the analysis of demand for health care (Cameron et al. 1988). We apply the models to data from the Household, Income and Labour Dynamics in Australia, which is a rich source of information on the availability and types of private health insurance, expenditure on premiums, and measures of health care utilisation. An important focus of our inquiry is the price elasticity of private health insurance, which is estimated by exploiting variations in the price of private insurance that arise as a result of mandatory community rating of insurance premiums in Australia. To address the question of whether subsidies are self-financing, we use the econometric results in a simulation analysis to measure the effects of removing subsidies on premiums for private insurance on public hospital expenditure in Australia.

The paper makes two key contributions. Firstly, it contributes to the evidence-base on the effectiveness of policy instruments that are available to governments seeking to influence the public and private composition of health expenditures. This is an important policy area where the body of evidence is scarce. In Australia, private health insurance is subsidised through a 30 percent premium rebate. This subsidy program, in addition to two other initiatives, form a series of policy measures introduced by the government to encourage the purchase of private insurance from 1997 to 2001. The knowledge of the cost and benefits of subsidy programs for private insurance will be crucial for policy development as policy makers increasingly look towards sources of private finance to pay for the health care demands of their populace in the face of rapidly growing public expenditure.

Secondly, the econometric models developed in this paper contribute to the literature on multivariate 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 in 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); count models with selectivity and endogenous regressors (Terza 1998, van Ophem 2000; Greene 2005) and count data models as a system of simultaneous equations (Deb and Trivedi 2006; Atella and Deb 2008; Cheng and Vahid 2010). We emphasise that while the econometric models developed here are used in the context of analysing health care decisions, these methods can readily be extended to a variety of applications such as education (e.g. subsidy, vouchers on public or private education), and labour economics (e.g. effects of training on productivity of public and private workers).

Previewing our results, we find some evidence suggesting the presence of endogeneity between the decision to purchase private insurance and the number of overnight hospital admissions. More broadly, the results from the simultaneous equation models indicate that while privately insured individuals are more likely to seek hospital care as a private patient, they do not differ in their intensity of hospital care use, compared with those without private insurance. A key component in our analysis is the estimate on the price elasticity of demand for private hospital insurance, which we found to range from -0.17 to -0.18. These estimates are slightly lower compared to those obtained in previous studies. The results from the policy simulation suggest that the removal of subsidies for private health insurance is predicted to lead to a 10 percent increase ($1.28 billion) in public sector expenditure on hospital care, which is mainly driven by the substitution of public for private care. Given that the public expenditure on the subsidy program amounted to $3 billion in 2004-05, this implies that eliminating subsides could potentially yield substantial public sector savings.

The remainder of the paper is organised as follows. Section 2 describes a model of demand for hospital care and private health insurance in a mixed public and private system such as that in Australia. Section 3 presents the econometric models, as well as discusses the estimation and identification strategies. Section 4 describes the data used in the empirical analysis. The results from the econometric analysis are discussed in Section 5 and those of the simulation analysis are discussed in Section 6. Finally, Section 7 concludes with a discussion of the key findings in the paper.

2 Theoretical Framework

The institutional context in Australia is such that individuals can choose to obtain free hospital care as public (or Medicare) patients in public hospitals. Public hospital care is financed through Medicare, a compulsory tax-funded universal health insurance scheme which subsidies medical services and technologies according to a schedule of fees. An alternative to choosing hospital care as a publicly funded patient is private care, which can be obtained from either private or public hospitals. Individuals who choose private care are entitled to their choice of treatment doctor, better amenities such as private hospital rooms, and faster access to treatment (for elective care). Expenditure on private care is borne by private health insurance if available, by patients in the form of out-of-pocket payments, as well as through Medicare. Within this institutional setting, individuals' decision-making regarding the utilisation of hospital services involves deciding on whether to purchase private health insurance, whether to obtain public or private care, and the intensity of care. Below, a simple theoretical model elaborating on these decisions is described.

Consider an individual whose utility is directly influenced by his or her health. The individual's health is adversely affected by the illness, with illness severity denoted by the random variable S. The probability of any outcome s of S is denoted by $\pi(s)$, and while π (and other variables) is not indexed by i, it is understood that these probabilities can depend on individual characteristics such as age, gender and life habits. The utility function of the individual in each state s is assumed to take 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. In the presence of illness, the individual can mitigate the reduction in health by using hospital care services $\mathbf{m}$ of quality $\mathbf{q}$. The relationship between health h and hospital care $(\mathbf{m})$, $\mathbf{q}$ in health state s is characterised by the health production function

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

where $\mathbf{m} = (m^y, m^{ov}, st)$ is a three-dimensional vector of hospital care inputs whose elements are the number of day (m^y) and overnight (m^{ov}) hospital admissions, as well as the total number of nights in hospital (st). The total number of hospital nights st is expressed as a sum of hospital nights in each k-th overnight admission, where $st = \sum_{k=1}^{m^{ov}} st_k$. The quality indicator vector $\mathbf{q} = (q_j^y, q_k^{ov})$, where subscripts refer to the j-th day admission, and k-th overnight admission, are composite index functions that describe the quality attributes of day (q^y) and overnight (q^{ov}) hospital care such as the length of time spent on hospital waiting lists, amenities such as private hospital rooms and the choice of treatment doctor. To make the theoretical model congruent with the empirical analysis, it is assumed that $q_j^y, q_k^{ov} \in \{0, 1\}$ where the quality indicator takes a value of 0 if the individual chooses publicly (Medicare) funded hospital care, and 1 if private care is chosen.

As opposed to public hospital care which is provided free at the point of demand, private day hospital care and private hospital stay is supplied at an average price of P^y and P^{st}. We use the average price rather than a disaggregated price vector for a menu of services available to private patients since the 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 further assume that 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. Let $m_0^{y,ov}$ and $m_1^{y,ov}$ denote the number of public and private admissions respectively for both day and overnight care. Hence, the total (direct and indirect) costs of day and overnight hospital care can be expressed as $\sum_{j=1}^{m_0^y}(P^y + P_{ind})q_j^y + \sum_{j=m_0^y+1}^{m^y}(P_{ind})(1 - q_j^y)$ and $\sum_{k=1}^{m_0^{ov}}(P_{ind})(1 - q_k^{ov})st_k + \sum_{k=m_0^{ov}+1}^{m^{ov}} q_k^{ov}(P^{st} + P_{ind})st_k$ respectively.

Suppose the expenditures on consumption, health care and health insurance are afforded through income Y that is derived from both labour and non-labour sources. Prior to the realisation of the health state s, the individual can purchase private hospital insurance at a fixed nominal premium of P which reduces the average direct prices of private day hospitalisation and overnight stay to αP^y and αP^{st}, where $\alpha \in [0, 1)$ is the cost sharing parameter. Under the prevailing institutional context in Australia, individuals are incentivised to purchase private hospital insurance. The government subsidies expenditures on private health insurance through a premium rebate of r percent, hence decreasing premiums to $(1 - r)P$. A tax levy amounting to ℓ percent of income, applies to individuals whose incomes are greater than a predetermined threshold Y_T, and who do not have private health insurance. The effective outlay on insurance premium $\tilde{P}$, defined as the nominal premium net of the premium subsidy and the tax levy, when applicable, is

$$\tilde{P} = \begin{cases} (1-r)P & \text{if } Y \leq Y_T \\ (1-r)P - \ell Y & \text{if } Y > Y_T \end{cases} \tag{3}$$

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. Furthermore, define by L an indicator variable where $L = 1[Y > Y_T]$. Based on the above assumptions, the individual faces a budget constraint

$$Y = C + d(1-r)P + (1-d)L(\ell Y) + \sum_{j=1}^{m_0^y}(P^y + P_{ind})q_j^y + (1 - d(1-\alpha)) \sum_{j=m_0^y+1}^{m^y} (P_{ind})(1 - q_j^y) + \\ \sum_{k=1}^{m_0^{ov}}(P_{ind})(1 - q_k^{ov})st_k + (1 - d(1-\alpha)) \sum_{k=m_0^{ov}+1}^{m^{ov}} q_k^{ov}(P^{st} + P_{ind})st_k \tag{4}$$

which is dependent on the choice of whether or not to purchase insurance d, and the decision of whether or not 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

$$\max_{\mathbf{m},\, \mathbf{q},\, d} \sum_s \pi(s)\, U[C, h(\mathbf{m}, \mathbf{q} \,|\, s)] \tag{5}$$

given the budget constraint in (4). The solutions to the resource allocation problem are briefly discussed here. The solutions are obtained iteratively by first solving the optimal intensity of hospital care $\tilde{\mathbf{m}}_{d,\mathbf{q}} = (\tilde{m}^y_{d,\mathbf{q}}, \tilde{m}^{ov}_{d,\mathbf{q}}, \tilde{st}_{d,\mathbf{q}})$ for each patient type strategies (q^y_j, q^{ov}_k) and insurance strategy d. The solutions $\tilde{\mathbf{m}}$ for all possible values of $\mathbf{q}$ and d are used to obtain the decision rules on the choice of admission into hospital as a public or private patient by substituting $\tilde{\mathbf{m}}_{d,\mathbf{q}}$ into the health production function (2) and the utility function (1). Let $V^{q^y_j}(s)$ and $V^{q^{ov}_k}(s)$ denote the indirect utility associated with each insurance strategy d and patient type strategy (q^y_j, q^{ov}_k) for the j-th day admission and k-th overnight admission respectively. Conditional on insurance choice d and health status s, the individual will choose private care for day admission if $V^1(j,s) > V^0(j,s)$, and overnight admissions if $V^1(k,s) > V^0(k,s)$, and will choose public care otherwise. The optimal choice of admission into hospital as a public or private patient for day and overnight admissions is defined by

$$\tilde{q}^y_j(s) = \underset{q^y \in \{0,1\}}{\arg\max}\ V^{q^y}(j,s) \tag{6}$$

$$\tilde{q}^{ov}_k(s) = \underset{q^{ov} \in \{0,1\}}{\arg\max}\ V^{q^{ov}}(k,s) \tag{7}$$

The pair $\{\tilde{\mathbf{q}}(d,s), \tilde{\mathbf{m}}_{d,\tilde{\mathbf{q}}(d,s)}(s)\}$ characterises the type and intensity of care that the individual would optimally choose at each possible value of d and s, that is with or without private insurance and for every possible severity of illness. Substituting these choices into the utility function, we obtain $V^*_d(s)$ for $d = \{0,1\}$ and $s \in S$, 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. Let EV_d denote the expected utility associated with each insurance strategy d, the optimal choice regarding the purchase of insurance is therefore given by

$$\tilde{d} = \underset{d \in \{0,1\}}{\arg\max}\ EV_d. \tag{8}$$

The triplet $\{\tilde{d}, \tilde{\mathbf{q}}(\tilde{d},.), \tilde{\mathbf{m}}_{\tilde{d},\tilde{\mathbf{q}}(\tilde{d},.)}(.)\}$, in which $\tilde{d}$ is a constant but the other two elements are functions of illness severity, completely characterises the insurance choice and also the 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 analysis that any unobserved individual-specific effects that cause an individual to be on the right tail of the distribution of hospital care intensity and/or to have a preference for a particularly form of care (public or private) will affect the insurance choice decision. This simple theoretical framework presented above highlights the simultaneous nature of the three decisions – the insurance choice, care type and care intensity. In the subsequent sections, an econometric model is developed which takes into account the simultaneity of these decisions and is congruent with the count data nature of hospital length of stay and binary nature of care type and insurance choice variables. The model forms the foundation of the empirical framework designed to measure the effects of removing subsidies for private health insurance in Australia. The specification of the empirical framework is discussed next.

3 Econometric Models

This section describes the econometric models that are used to empirically investigate the determinants of the demand for day and overnight hospital care, the choice of admissions as public or private patients and the demand for private hospital insurance. The econometric model proposed below deviates from the theoretical model on three accounts. Firstly, the exact mapping between the parameters of the theoretical model, and the parameters of any particular utility function and health production function is not explored in the empirical modeling. Hence, the model is not a fully structural model in the sense of Keane (2010), although the notations in the theoretical model are maintained for consistency in exposition. Secondly, the outcome variables that are available in data used in the analysis are more limited than those described in the theoretical model. More specifically, while the data contain information on the number of day and overnight hospital admissions, information on the choice of admission as a public or private patient, as well as the length of overnight stay, are only available for the last day and overnight hospitalisation episodes. Thirdly, the joint modeling of the full set of outcome variables available in the data involves the complex task of estimating a nonlinear system of six equations. The analysis is simplified by modeling subsets of the hospital utilisation measures jointly with the decision to purchase private hospital insurance. These subsets are the frequency of day and overnight hospital admissions (Section 3.1); the patient type choice for day admission

(Section 3.2); and the patient type choice and length of hospital stay for overnight admission (Section 3.3).

3.1 Demand for day and overnight hospital admissions

The econometric model employed to examine the relationship between the demand for day and overnight admissions and the decision to purchase hospital insurance is specified as follows. Let m_i^y and m_i^{ov} be the observed frequencies for day and overnight hospital admissions for the i-th individual. The binary variable d_i denotes insurance status which assumes a value of 1 if the individual has private hospital insurance. Suppose that conditional on the exogenous covariates X_{i1} and X_{i2}, the endogenous variable d_i, and random unobserved heterogeneity terms ε_1 and ε_2, m_i^y and m_i^{ov} have independent Poisson distributions, with conditional mean parameters μ_i^y and μ_i^{ov}

$$f(m_i^y|X_{i1}, d_i, \varepsilon_{i1}) = Po[\mu_i^y] \tag{9}$$

$$f(m_i^{ov}|X_{i2}, d_i, \varepsilon_{i2}) = Po[\mu_i^{ov}] \tag{10}$$

$$\mu_i^y = \exp(X_{i1}'\beta_1 + \lambda_1 d_i + \sigma_1 \varepsilon_{i1}) \tag{11}$$

$$\mu_i^{ov} = \exp(X_{i2}'\beta_2 + \lambda_2 d_i + \sigma_2 \varepsilon_{i2}) \tag{12}$$

where ε_1 and ε_2 are standardised and assumed to be distributed standard normal, that is $\varepsilon_1, \varepsilon_2 \sim \mathrm{N}(0, 1)$. The decision rule to purchase private hospital insurance is represented by the continuous latent variable d_i^*, and the observed insurance choice d_i is in turn related to d_i^* by a dichotomous rule. These are written as

$$d_i^* = X_{i3}'\beta_3 + \varepsilon_{i3} \tag{13}$$

$$d_i = 1[d_i^* > 0] \tag{14}$$

where $\varepsilon_3 \sim$ N(0, 1). The RHS insurance variables d_i in (11) and (12) are allowed to be endogenous by assuming that ε_1 and ε_2 are correlated with ε_3. For the count data outcomes, a mixed bivariate Poisson lognormal model is adopted to gain efficiency, in which the unobserved heterogeneity terms ε_1 and ε_2 are allowed to be correlated. More specifically, it is assumed that each pair of the unobserved variables ε_1, ε_2 and ε_3 are distributed bivariate normal, that is $\varepsilon_{ij}, \varepsilon_{ik} \sim N_2[(0,0),(1,1),\rho_{\varepsilon j\varepsilon k}], \forall\, j \neq k,\ j,k = 1,2,3$. The joint conditional density for the observed data, $f(m_i^y, m_i^{ov}, d_i|\Omega_i)$ can be expressed as

$$\begin{aligned} f(m_i^y, m_i^{ov}, d_i|\Omega_i) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} & f(m_i^y|X_{i1}, d_i, \varepsilon_{i1}) \cdot f(m_i^{ov}|X_{i2}, d_i, \rho_{\varepsilon1\varepsilon2}, \varepsilon_{i1}, \zeta_i) \\ & \cdot \left[d_i\Phi\Big(\frac{X_{i3}'\beta_3 + \theta_1}{\theta_2}\Big) + (1-d_i)\Big(1 - \Phi\Big(\frac{X_{i3}'\beta_3 + \theta_1}{\theta_2}\Big)\Big)\right]\phi(\zeta_i)\phi(\varepsilon_{i1})d\zeta_i d\varepsilon_{i1} \end{aligned} \tag{15}$$

where

$$\theta_1 = \rho_{13}\varepsilon_{i1} + \Big(\frac{\rho_{\varepsilon2\varepsilon3} - \rho_{\varepsilon1\varepsilon2}\rho_{\varepsilon1\varepsilon3}}{\sqrt{1-\rho_{\varepsilon1\varepsilon2}^2}}\Big)\zeta_i$$

$$\theta_2 = \sqrt{(1-\rho_{\varepsilon1\varepsilon3}^2) - \frac{(\rho_{\varepsilon2\varepsilon3} - \rho_{\varepsilon1\varepsilon2}\rho_{\varepsilon1\varepsilon3})^2}{1-\rho_{\varepsilon1\varepsilon2}^2}}$$

and $\Omega = (X_1 \cup X_2 \cup X_3)$. ζ_i is distributed standard normal, that is $\zeta_i \sim N(0, 1)$. The joint conditional density function in (15) is used to construct the likelihood function to estimate the model.

3.2 Patient type choice for day hospital admission

The econometric model employed to examine the relationship between the decisions to obtain public or private care for day hospital care and the choice to purchase insurance is specified as follows. Suppose the decisions to seek day hospital care as a private patient and to purchase insurance are given by the continuous latent variable q^{y*} and d^* respectively where

$$q_i^{y*} = Z_{i1}'\alpha_1 + \delta d_i + v_{i1}; \quad q_i^y = 1[q_i^{y*} > 0] \tag{16}$$

$$d_i^* = Z_{i2}'\alpha_2 + v_{i2}; \quad d_i = 1[d_i^* > 0] \tag{17}$$

$$v_{i1}, v_{i2} \sim N_2[(0,0),(1,1),\rho_v] \tag{18}$$

The latent variables are related to the observed care type and insurance choices via the dichotomous rule given in (16) and (17). The RHS variable d_i in (16) is allowed to be endogenous by assuming that v_{i1} and v_{i2} are distributed bivariate normal (18). Based on the specification of the model, the joint conditional density of q_i^y, d_i, given Z_{i1}, Z_{i2}, v_{i1} and v_{i2} may be written as

$$\Phi_2\big[y_{i1}(Z_{i1}'\alpha_1 + \delta d_i), y_{i2}(Z_{i2}'\alpha_2), y_{i1}y_{i2}\rho_v\big] \tag{19}$$

where $y_{i1} = 2q_i^y - 1$ and $y_{i2} = 2d_i - 1$. The above applies only to those individuals who have been hospitalised for a day admission in the observation period. For non-hospitalised individuals, we only observe d_i. If we define the indicator value H_{di} where $H_{di} = 1$ if the i-th individual has been hospitalised for a day admission and 0 otherwise, the contribution of every observation to the likelihood function is expressed as

$$\ell_i(\Theta) = H_{di} \cdot \Phi_2\big[y_{i1}(Z_{i1}'\alpha_1 + \delta d_i), y_{i2}(Z_{i2}'\alpha_2), y_{i1}y_{i2}\rho_v\big] + (1 - H_{di}) \cdot \Phi\big[y_{2i}(Z_{i2}'\alpha_2)\big] \tag{20}$$

where Θ is the set of parameters to be estimated in equations (16), (17) and (18). Φ and Φ_2

denote the univariate and bivariate normal cumulative density function respectively.

3.3 Patient type choice and length of hospital stay for overnight admission

The econometric model used to examine the relationship between the intensity of hospital stay (st), the decision to seek public or private hospital care (q^{ov}) and the decision to purchase insurance (d) is specified as follows. Let st_i denote the duration of hospital stay and q_i^{ov} the patient type binary variable which takes the value of 1 when private care was chosen and 0 otherwise. The binary variable indicating insurance status is given by d_i as above. Suppose conditional on the exogenous covariates W_i, the endogenous patient type and insurance binary variables q_i and d_i, and the random unobserved heterogeneity term ξ_{i1}, the length of overnight stays, st_i, follows a Poisson distribution with truncation at zero, with mean parameter μ_i.

$$f(st_i|W_{i1}, d_i, q_i, \xi_{i1}) = \frac{\exp^{-\mu_i} \mu_i^{m_i}}{m_i! \ (1 - \exp^{-\mu})} \tag{21}$$

$$\mu_i = \exp(W'_{i1}\gamma_1 + \psi_1 d_i + \psi_2 q_i^{ov} + \sigma_3 \xi_{i1}) \tag{22}$$

where ξ_{i1} is $\mathrm{N}(0, 1)$. The decision rules to seek private hospital care and to purchase insurance are given by the continuous latent variables q_i^{ov*} and d_i^* and are related to the observed outcomes by the respective decision rules

$$q_i^{ov*} = W'_{i2}\gamma_2 + \psi_3 d_i + \xi_{i2}; \quad q_i^{ov} = 1[q_i^{ov*} > 0] \tag{23}$$

$$d_i^* = W'_{i3}\gamma_3 + \xi_{i3}; \quad d_i = 1[d_i^* > 0] \tag{24}$$

The RHS variables q_i^{ov} and d_i in (22) and d_i in (23) are allowed to be endogenous by assuming that each pair of ξ_{i1}, ξ_{i2} and ξ_{i3} are distributed bivariate normal

$$\xi_{ij}, \xi_{ik} \sim N_2[(0,0),(1,1),\rho_{\xi j \xi k}], \quad \forall\, j \neq k;\ j,k = 1,2,3 \tag{25}$$

The joint conditional density, $f(m_i, q_i^{ov}, d_i \,|\, \Omega_{i1})$ for the observed data can be written as

$$\int_{-\infty}^{+\infty} f(st_i \,|\, W_{i1}, q_i, d_i, \xi_{i1}) \cdot \Phi_2[y_{1i}\theta_3, y_{2i}\theta_4, \rho^*]\, \phi(\xi_{i1}) d\xi_{i1} \tag{26}$$

with

$$\theta_3 = \frac{W_{i2}\gamma_2 + \psi_3 d_i + \rho_{\xi_1\xi_2}\xi_{i1}}{(1-\rho^2_{\xi_1\xi_2})^{1/2}}$$

$$\theta_4 = \frac{W_{i3}\gamma_3 + \rho_{\xi_1\xi_3}\xi_i}{(1-\rho^2_{\xi_1\xi_3})^{1/2}}$$

$$\rho^* = y_{1i} \cdot y_{2i} \cdot \frac{(\rho_{\xi_2\xi_3} - \rho_{\xi_1\xi_2}\rho_{\xi_1\xi_3})}{\sqrt{1-\rho^2_{\xi_1\xi_2}}\sqrt{1-\rho^2_{\xi_1\xi_3}}} \tag{27}$$

where $y_{1i} = 2q_i^{ov} - 1$ and $y_{2i} = 2d_i - 1$; $\Omega_{i1} = (W_{1i} \cup W_{2i} \cup W_{3i})$. The above applies only to those individuals who have been hospitalised for an overnight admission, and for non-hospitalised individuals we observe only d_i. If we define H_{oi} as an indicator variable so that $H_{oi} = 1$ if the i-th individual has been hospitalised overnight and 0 otherwise, the contribution of the i-th observation to the likelihood function can be expressed as

$$\ell_{i1}(\Theta_1) = H_{oi} \cdot \int_{-\infty}^{+\infty} f(st_i \,|\, W_{i1}, q_i, d_i, \xi_{i1}) \cdot \Phi_2[y_{1i}\theta_3, y_{2i}\theta_4, \rho^*]\, \phi(\xi_{i1}) d\xi_{i1} + (1 - H_{oi}) \cdot \Phi[y_{2i}(W_{3i}\gamma)] \tag{28}$$

where Θ_1 is the set of all unknown parameters to be estimated.

3.4 Estimation

The likelihood functions for the econometric specifications in Sections 3.1 and 3.3 are complex and require the evaluation of integrals. Maximum simulated likelihood (MSL) techniques are used to approximate the likelihoods given that these functions do not have a closed-form expression. Quasi-Monte Carlo draws based on the Halton sequence were used in the simulations which have been shown to be more accurate and faster compared to the conventional random number generator (Bhat 2001, Train 2003). The number of simulations S has a considerable effect on the properties of the MSL estimator (Gouriéroux and Monfort 1996). We chose $S = 1500$ beyond which the estimation 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 was 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 (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 econometric model in Section 3.2 is estimated using conventional maximum likelihood techniques.

4 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 and income, and life satisfaction, health and well-being. Every member of the household 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) and information on households' expenditure on private health insurance premiums from wave 5 (2005). 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 (cf. section 4.1) were excluded from the analysis. After excluding observations with missing or ambiguous responses, 7089 observations remained in the sample.

4.1 Private hospital insurance

There are two types of private health insurance cover in Australia. The first is private hospital coverage which provides financial protection towards private hospital expenditures. The second type is ancillary or extra coverage which covers expenditures on services such as dental care, allied health (e.g. physiotherapy) and items such as eye glasses which are not covered under Medicare. In the HILDA survey, individuals were also asked to provide information on whether they have private health insurance and the type of coverage. The three coverage types are hospital, ancillary or both. We focus on whether individuals have private hospital insurance, that is they possess either hospital only or combined cover.[1] Table 1 presents the proportion of individuals with private hospital insurance by coverage and income unit types. Overall, 50.9 percent of the sample have private hospital insurance. Respondents from couple only (56.3 percent) and couple family (55.9 percent) households are more likely to be privately insured compared with lone persons (39.1 percent) or lone parent (28.1 percent) households. Combined hospital and ancillary cover is more common compared to hospital-only cover, with 79.5 percent of insured individuals having policies of this type.

In Australia, there is mandatory community rating on private health insurance premiums which stipulates that insurers must charge the same premium for a given insurance plan regardless of individuals' age, gender, health status, utilisation and claims history. Premiums however are allowed to vary by states, as well as across policies and insurers. The average annual expenditure on private hospital insurance premiums by coverage and income unit type for the HILDA data are shown in Table 1.[2] The expenditure on premiums is higher for individuals

[1] In the original data set, 6.9 percent (N=428) of the 6183 respondents who indicated that they have private health insurance have ancillary-only policies.

[2] Household expenditure data on premiums for private health insurance are obtained from Wave 5 (2005) of the HILDA survey and adjusted to account for the average growth in premiums of 7.6 percent between 2004 and 2005 (Private Health Insurance Administrative Council 2005).

with combined cover compared with hospital-only and ancillary-only cover, and are generally higher for larger households (e.g. couples versus lone person).[3] Variations in premiums would also arise from the differences in the generosity of coverage, defined by the level of deductibles, percentage of copayment, as well as comprehensiveness in terms of the menu of services covered. Unfortunately, this information is not captured in the data used in the analysis. For the purpose of benchmarking the data on premium expenditures, data from the 2003-04 Household Expenditure Survey on household expenditure on hospital, medical and dental insurance are presented at the bottom of Table 1. One would observe that the data on premiums is broadly consistent in both datasets.

4.2 Defining the price of insurance

Measuring the effects of removing subsidies for private health insurance requires estimating the price elasticity of demand for private health insurance. The two most common approaches to estimating the demand elasticity of health insurance is the use of variations in the premiums faced by individuals or firms (e.g. Marquis and Long 1995, 2001; Feldman et al. 1997) or variations in tax price of insurance (e.g. Finkelstein 2002, Gruber and Lettau 2004). In this study, we define the price of insurance as the ratio of the effective outlay on insurance premiums to expected annual benefits from private hospital insurance. The definition is interpreted as the effective price that is required for each dollar of expected benefits received.[4] Variations in the price of insurance arise because mandatory community rating requires that individuals are charged the same premium for a given insurance policy, whilst expected benefits from private insurance varies by individual characteristics such as age, gender and health status. The above definition for the insurance price also allows for one to account for variations in premiums that arise from heterogeneity in coverage types (e.g. hospital-only vs. combined cover) and household compositions (lone person vs. couple). For instance, individuals with combined hospital and ancillary cover pay a level of premium, and receive a level of expected benefit, that is higher than those with hospital-only coverage. The same reasoning applies to the level of premiums

[3]Children under the 21 years of age and full-time students below 25 years may be covered under their parents' policy without additional cost.

[4]This definition is similar to Butler (1999) who estimates elasticities of demand for private health insurance in Australia. The institutional context for the private health insurance market then is broadly similar to that in this paper, except that it pre-dates the policy measures that were introduced to encourage the purchase of private health insurance.

and expected benefits from insuring two adult members in a couple household relative to a single-person household.

The approach of defining the price of insurance requires that premiums are imputed for respondents without private hospital insurance. This is achieved by fitting an ordinary least squares (OLS) regression to data on annual premium expenditure observed from individuals with private hospital insurance. Variations in expenditure on premiums are explained by differences in coverage and policy types, and given the community rating requirements, are also likely to be influenced by risk characteristics of the population as well as factors that affect the operating cost and profitability of health insurers across states and territories within Australia. To this end, in addition to binary regressors representing coverage and policy types, a set of supply-side variables are included in the premiums equation. These include the percentage of insurance policies with an excess; the ratio of the number of health insurance contracts relative to the size of the general and health insurance workforce; the proportion of population over 65 years; the specialist-population density; and the average price of an office-based consultation with a private specialist.[5] The results from the OLS regression on log expenditure on premiums are shown in Table 3. The coefficients are mostly statistically significant and are consistent with expectations. Expenditure on premiums are higher for individuals with combined hospital and ancillary cover compared with hospital only cover, and are larger for family and couple only policies relative to single policies. Variations in the expenditure on premiums are also explained by interstate variations in supply side factors such as the number of insurance policies to workforce ratio, the supply of specialists and the price of specialists services. In the econometric analysis, we use actual reported premiums for the insured sample and predicted premiums for non-insured respondents in the calculation of the insurance price.

Several US-based studies by Feldman et al. (1997), Marquis and Long (2001) and Marquis and Louis (2002) have applied sample selection models to impute premiums which are otherwise not observed for the uninsured individuals. This approach has been justified on the grounds that selectivity correction removes the effects of omitted variables that influence both the health

[5] Data on the supply-side variables are obtained from a variety of sources: information on policies with excess and the number of health insurance contracts based on 2004–05 data published by the Private Health Insurance Administrative Council; information on the insurance industry workforce and characteristics of the Australian population is based on the 2006 Census; information on the number of specialists in Australia based on the sampling frame from wave 1 (2008) of the Medicine in Australia: Balancing Employment and Life (MABEL) longitudinal survey of doctors while the price of private specialists service is based on self-reported data also from the MABEL data.

insurance premium as well as the decision (by firms) to offer insurance. The theoretical justification is based on a behaviorial model of firms' decision to offer insurance to its employees whereby the problem of selectivity occurs when firms that do not offer insurance face higher premiums compared to those who offer insurance, for reasons such as higher perceived risk by insurers that are not observed by the researcher. In the Australian context, community rating regulations prohibit health insurers from setting premiums to discriminate based on individuals' risk and hence the selectivity problems observed by the preceding studies are likely not to be relevant.

Data on the expected benefits from private hospital insurance are calculated using statistics published by the Private Health Insurance Administrative Council (PHIAC) on the total annual benefits paid, coverage types and the number of policies sold within the 2004–05 financial year (July 2004 to June 2005). An example is illustrated in Figure 1 which shows the expected annual benefits per person for a hospital-only policy by sex, age (available in five-year bands) and states. For individuals who reported that they have private hospital insurance, we used the information on age, sex and state of residence of respondents and their family members (where applicable), as well as data on respondents' coverage types (hospital only, hospital and ancillary) and policy types (e.g. couple, family) to calculate the expected benefit accruing to each insured household.

For high income individuals, the combination of the tax and subsidy programs results in a situation where the potential tax liabilities through the Medicare Levy Surcharge exceeds the premium cost of private health insurance. When this occurs, the price of insurance is less than zero. The distributions of the insurance price for the insured and uninsured are shown in Figure 2. In the sample of 7089 observations, 528 individuals have an effective price of insurance that is less than zero, implying that they are financially better off by purchasing private insurance.[6] For this reason, these observations are excluded from the regression analyses on the decision to purchase private insurance, and decisions on the type and intensity of hospital care. They are however included in the simulation analysis. In the subsequent sections below, we describe the characteristics of the 6561 observations in the sample.

[6]Conceptually, we expect that these individuals would purchase private hospital insurance, though it is observed that a small percentage (8 percent) are not privately insured. The latter may be explained by a variety of factors, including the presence of measurement error in household income. For these uninsured individuals, the magnitude of the effective outlay on insurance premiums is small (median=-$345, mean=-$512) which suggest that the effects of measurement error, if any, is not likely to be significant.

4.3 Measures of hospital care use

In the survey, individuals were asked about the number of occasions they had been admitted to hospital as a day patient and for an overnight stay in the twelve months preceding the survey. Individuals who have been hospitalised were further queried on the duration of hospital stay and whether they were admitted as a Medicare (public) or private patient on the most recent day and overnight admission. The descriptive statistics for the hospital care utilisation measures are summarised in Table 2. The count data utilisation measures are the number of day admissions (NHPDY), overnight admissions (NHPOV) and the length of overnight hospital stay (STHPOV). The measures have mass points at 0 and 1 and exhibit overdispersion where the unconditional variance (S_y^2) is larger than its mean ($\bar{y}$). The length of overnight stay, and the binary outcome of whether individuals chose to be admitted as private patients in their last overnight hospital stay (PVHPOV), are observed only for the 876 individuals in the analysis sample who have been admitted for an overnight stay. In the latter, 46.7 percent of individuals chose private care. Of the 797 individuals who had at least one day hospitalisation episode, 58.6 percent chose to be admitted as private patients (PVHPDY) in the last day admission.

4.4 Remaining explanatory variables

The remaining 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 (drinker, smoker) and geographical information (state/territories, remoteness). The choice of variables is similar to that in Cameron et al. (1988), Cameron and Trivedi (1991), Savage and Wright (2003) and Propper (2000). In addition to variables that are available in the survey, 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.[7] The second variable is the distance to the nearest private hospital from the survey re-

[7]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 Subdivision (SSD), a spatial unit of intermediate size. In the 2001 Australian Standard Geographical Classification, there were a total

spondents' 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.[8] Distance is calculated using data on the coordinates (longitude and latitude) of centroids via the haversine formula.

The descriptive statistics for the explanatory variables are presented in Table 4. The average age of the sample is 49.9 years, with a range of 25 to 99 years. Females make up roughly 54 percent of the sample. The average annual household income is $59,620. Approximately 47 percent of individuals have no postschool qualification (Year 12 and below). By occupations, 40 percent of individuals are not in the labour force, while the two largest groups are Professionals (24 percent) and Clerical and Services Workers (16 percent). Measures of individuals' health status include indicators of self-assessed health status collected in wave 3 and a set of binary variables that indicate the presence of chronic conditions that affect physical and social functioning. For the self-assessed health status, 45 percent of individuals reported to be in excellent or very good health in the wave 3 survey, with 36 percent indicating that their health is good and 19 percent fair and poor. On the presence of chronic conditions, 39 percent of individuals reported having chronic conditions that limit the type and amount of work they can do; 4.2 percent indicated that they have difficulty with self care activities; 8.6 percent have limitations in mobility activities and 0.8 percent have difficulty communicating in their own language. Indicators of health risk factors include whether individuals consume alcohol daily (9.7 percent) and are regular smokers (18 percent). Geographical information include state/territory indicators as well as remoteness categories. Approximately 60 percent of individuals reside in major cities in Australia. The average size of the general and health insurance workforce within a statistical subdivision is 800 and the mean distance to the nearest private hospital is 30.27 km.

In the regression analysis, the entire set of covariates described above is included in the intensity of hospital use, and the choice of patient types and insurance equations except for the age, gender and income unit types (presence of dependent children, couple vs. single) variables which are excluded from the insurance equation. The effects of these covariates on the propensity to insure have been factored into the insurance price variable, through the calculation of

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.

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

the expected benefits from insurance. The implicit assumption here is that age, gender and household composition are not expected to have an independent effect on the propensity to insure after controlling for the price of insurance. We emphasise that these exclusions are justified on theoretical grounds, and are not required for identification of the econometric models. We discuss the identification strategy next.

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. The model is Section 3.1 constitutes a mixed bivariate Poisson lognormal model with a single common endogenous binary insurance variable while that in Section 3.2 is a probit model for the patient type (day hospitalisation) equation with one endogenous binary variable. The model in Section 3.3 consist of a Poisson lognormal model with endogenous insurance and patient type binary variables, as well as a probit model for the patient type (overnight hospitalisation) equation with one endogenous insurance variable. Identification for the model in Section 3.1 requires that there is at least one variable in X_3 that is excluded from X_1 and X_2, and for the model in Section 3.2 one variable in Z_2 that is excluded from Z_1. Furthermore, identification for the model in Section 3.3 requires that there is one variable in W_3 that is excluded from W_1 and W_2 , and one variable that is in W_2 that is excluded in W_1.

To satisfy the above exclusion restrictions, we include the size of the general and health insurance workforce in the insurance equation (X_3, Z_2, W_3) but not in the patient type choice (Z_1, W_2), frequency of admissions (X_1, X_2) and length of stay equations (W_1). We argue that this variable performs the role as a proxy for the accessibility to insurance services which influences the ease with 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 private hospital care and the intensity of hospital care use. In addition, we include the distance to the nearest private hospital in the patient type for overnight hospitalisation 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.

5 Results

We estimate the simultaneous equation models as well as their corresponding single equation variants to assess the relative merits of the different models. For the single equation models, the number of hospital admissions and length of stay are estimated using a Poisson lognormal model, while the patient type and insurance equations are estimated using simple probit regressions. An underlying assumption of these single equation models is that the insurance and patient type regressors, d and q, may be treated as exogenous. For the bivariate Poisson lognormal model in Section 3.1, the likelihood ratio test overwhelmingly rejects the single equation model in favour of the simultaneous model. The likelihood ratio test statistic is 1462.93, which rejects the null hypothesis that the correlation parameters $\rho_{\epsilon_j \epsilon_k}$ are jointly equal to zero. For the models in Sections 3.2 and 3.3, the likelihood tests cannot reject the null hypothesis that the correlation parameters are zero.

We note that the correlation parameters are individually statistically significant in some cases (see end of Table 6 and 7). For the model on the number of hospital admissions, there is significant positive correlation ($\rho_{\epsilon_1 \epsilon_2}$) between the unobserved determinants of day and overnight hospital admissions. This result is expected as individuals' treatment regimen may involve overnight hospitalisations for more intensive investigations and interventions and further day admissions for follow-up procedures. The estimate of the correlation ($\rho_{\epsilon_2 \epsilon_3}$) between the unobservables in the conditional mean equation for overnight hospital admissions and the insurance equation is statistically significant from zero which suggests that there is evidence of endogeneity in the decision to purchase private insurance on the number of overnight hospital admissions. The positive sign of the correlation parameter indicates that the unobserved factors that positively influence the propensity to purchase private insurance have a positive effect on the intensity of day admission.

Below, we discuss the results on the determinants of the intensity of hospital care use and the choice to receive public or private care. We first discuss the estimates of the marginal effects of private insurance, and thereafter elaborate on the coefficient estimates for the remaining explanatory variables. The discussions are based on the results from the simultaneous equation models. For the discussion on the marginal effects, the results obtained under the single equation models are included for comparison.

Before proceeding, a note on interpreting the marginal effects and coefficients. For the count data outcome measures, the marginal effects for binary variables (e.g. insurance) is expressed as a proportional change in the expected outcome $E(m|X)$ from changing x_j from 0 to 1, which is calculated as $E(m \,|\, x_j = 1, \bar{X})/E(m \,|\, x_j = 0, \bar{X}) = e^{\beta_j + \sum_{i \neq j} \beta_i x_i}/e^{\sum_{i \neq j} \beta_i x_i} = e^{\beta_j}$. For the binary outcomes measures, the marginal effects are calculated in the usual way with the remaining covariates at their mean values. All standard errors for the marginal effects are calculated via the delta method. To interpret the coefficient estimates on binary variables for the count data measures, $e^{\beta_j} \approx 1 + \beta_j$ when β_j is small so the coefficient approximates the proportional increase in $E(m|X)$ as x_j changes from 0 to 1. For a continuous explanatory variable x_k, the coefficient β_k is a semi-elasticity. Hence an increase in x_k by 0.01 changes the expected length of stay $E(m|X)$ by β_k percent.

5.1 Marginal effects of insurance

Table 5 presents the marginal effects of private health insurance on the intensity and type of hospital care use. From the results of the simultaneous equation models presented in Column 2, the estimates of the marginal effect of insurance on the number of day and overnight hospitalisations indicate that the expected intensity of day and overnight hospitalisations are respectively 0.76 and 0.68 times that of individuals without private insurance. These estimates however are not statistically significant from unity. This suggests that after accounting for the potential endogeneity of insurance, private health insurance does not have a significant impact on the intensity of day and overnight hospital use. In contrast, the estimates obtained from the single equation models in Column 3 are larger than 1, which indicates that privately insured individuals utilise both day and overnight hospital care at a higher intensity. Moving on to the length of stay, the estimate of the marginal effect of insurance on the duration of overnight private stay, derived from interacting the insurance and patient type binary variables in length of stay equation, is 1.99 and is not statistically significantly larger than 1. This result suggests that privately insured individuals do not have longer duration of private hospital stays compared to those without private insurance. As with the intensity of hospitalisations, the estimate from the single equation model suggests that privately insured individuals have a significantly higher duration of hospital stay. On the choice of private and public care, the estimates suggest that individuals with private insurance are 69 percent and 55 percent more likely to seek private care for day and overnight admissions respectively. These estimates are slightly smaller in magnitude compared to those obtained from the single equation models.

5.2 Coefficient estimates

The coefficient estimates from the simultaneous equation models are presented in Table 6 and 7. The estimates in columns 2–4 of Table 6 correspond to the model of hospital admissions and insurance (c.f Section 3.1), and those presented in columns 5–6 refer to the model on the choice of private care for day hospital admission (c.f Section 3.2). The estimates in Table 7 refer to the model on private care and length of stay for overnight admission (c.f Section 3.3).

The intensity of hospital care use and patient type choices are significantly influenced by demographic and socioeconomic characteristics such as age, sex, household income and employment status. Both the number of overnight hospital admissions and the length of stay have an inverse U-shape relationship with age. Household income has a positive effect on the propensity to seek private care for overnight but not for day admissions. This is suggestive of the role of household income towards affording the potentially large out-of-pocket expenditures associated with private overnight admissions. The differences in the intensity of hospital care use by occupation are indicative of the opportunity cost of time associated with taking time off work to seek hospital care.

Health status plays an important role in influencing the intensity of hospital care use. Individuals who report being in fair or poor health in the previous year have a higher number of hospital admissions compared with those in excellent health. Individuals suffering from chronic conditions that limit their capacity to work as well as affect their ability to care for themselves also have a higher expected number of admissions. Geographical indicators, namely state and remoteness indicators, may represent variations in clinical norms and practices surrounding hospital treatment or reflect the extent of accessibility to public and private hospitals. The coefficient on the distance variable indicates that individuals who live further away from private hospitals are less likely to seek private hospital care although the estimates are not statistically significant. Finally, the positive and statistically significant estimates on the standard deviations of the heterogeneity terms strongly suggest the presence of overdispersion in the data, which justifies the use of the Poisson lognormal model.[9]

The estimates from the models of demand for private hospital insurance are presented in columns 4 and 6 of Table 6, and column 3 in Table 7. The coefficients on the insurance price variable are negative as expected and are statistically significant from zero. The price elasticity of demand for hospital insurance implied from these coefficient estimates ranges from -0.165 to -0.176.[10] Household income is positively associated with the propensity to purchase private insurance. This is conditional on individuals' tax liabilities under the Medicare Levy Surcharge, which has been factored in the calculation of the the insurance price. Individuals with higher educational attainment, and in 'white collar' occupations are more likely to be privately insured. Healthier individuals, as measured by self-assessed health status, are more likely to be privately insured. Finally, the coefficients on the headcount variable which serves as the exclusion restriction, have an expected sign and are statistically different from zero. Individuals living in areas with greater accessibility to insurance services are more likely to purchase private hospital insurance.

6 Policy simulations

We use the econometric estimates to simulate the removal of subsidies for private health insurance and evaluate the effects on the utilisation of public and private hospital care. A representative sample was first constructed by taking 10,000 random draws from the analysis sample,

[9]For Poisson lognormal model, the conditional variance $V[m_i \,|\, X_i]$ is given by $E[m_i \,|\, X_i, \xi_i]\{1+\tau E[m_i \,|\, X_i, \xi_i]\}$ where $\tau = [\exp(\sigma^2) - 1]$ (See equations 2.2-23 and 2.2-26 in Greene (2005)). Overdispersion is present in the data if $V[m_i \,|\, X_i] > E[m_i \,|\, X_i, \xi_i]$ which occurs if $\sigma > 0$.

[10]The price elasticity is defined as a percentage change in the expected probability of choosing private hospital insurance given a one-percent increase in the price of insurance. This is calculated as a weighted sum of the price elasticities across all individuals, which is given by $\frac{1}{N}\sum_{i=1}^{N} \frac{\partial \hat{P}_i}{\hat{P}_i} / \frac{\partial X_j}{X_j}$, where $\hat{P}_i = \Phi(X\hat{\beta})$.

using information on the age-sex distribution of the Australian population in 2005. Model calibration is performed for binary outcomes by taking random draws of error terms in accordance with the relevant estimates of the correlation matrices using Cholesky transformation. A total of 500 sets of draws are taken, and the simulated outcomes obtained across all draws are used in the construction of confidence intervals. For the count data measures, the conditional mean $E[m_i|X_i]$ is calculated as $\hat{\mu}_i \exp(\hat{\sigma^2}/2)$.

Under the scenarios considered for the simulations, private hospital insurance premiums are increased stepwise by 10 percent from 0 (baseline) to a maximum of 42.85 percent, the latter of which corresponds to the full removal of the 30 percent government rebate on private health insurance premiums. We consider its impact on (i) the expected number of day and overnight hospital admissions; (ii) expected probability of choosing private care for day hospitalisation; and (iii) the expected probability of choosing private care, and length of stay for overnight hospitalisation. We begin by computing in each simulation scenario the predicted private health insurance choice for every observation in the simulation sample. We use the predicted insurance choices to compute the predicted patient types choices and the expected intensity of day and overnight hospital use based on the (recursive) structure and specification of the econometric models in Section 3.

The expected impact on public and private hospital use, based on the estimates obtained from the simultaneous equation models, is presented in Table 8. In the simulation sample of 10000 observations, the number of observations for individuals who have been hospitalised for day and overnight care is 1256 and 1389 respectively. The simulation results indicate that the removal of subsidies for premiums on private health insurance is expected to reduce the proportion of the privately insured population by 5.23–6.01 percentage points, from 49.85 percent in the baseline scenario to roughly 44 percent. These changes correspond to a decrease in the privately insured population by 0.12-0.14 percent points for a 1 percent increase in premiums. The reduction in the proportion of those privately insured is expected to lead to a small increase in the number of day and overnight admissions, by 1.42 percent and 1.75 percent respectively. The direction and magnitude of the effects on the frequency of hospital admissions follows the negative (and statistically insignificant) coefficients on the insurance binary variable shown in Table 6 above. On the choice of public or private care, the expected change in the fraction of individuals with private insurance is predicted to reduce the proportion seeking private day and overnight hospital care by 7.79 percent and 9.52 percent respectively. The model also predicts small changes to expected length of overnight stay, but these estimates are generally not statistically significant.

The simulation results described above differ slightly from those based on the single equation models, which are shown in Table 9. While the magnitude of the decrease in the privately insured population is similar across both models, the simulations based on the single equation models predict a decrease in expected number of the day and overnight admissions. This is consistent with estimates of the insurance effects from the single equation models in Table 5 which indicate that insured individuals have a higher number of hospital admissions. The magnitude of the decrease in the proportion seeking private care is higher for day admissions (8.69 vs 7.79 percent) and smaller for overnight admissions (7.79 and 9.52 percent) in the single equation compared to those from the simultaneous equation models. As with the simultaneous models, the effects on length of stay are small and not statistically significant

We combine the estimates obtained from the simulation analysis with published statistics on hospital activity and expenditure to assess the effects of removing subsidies for private health insurance on public expenditure for hospital care. From the estimates in Tables 8 and 9, we consider how changes in the proportion with private insurance influence the number and type of day and overnight hospital admissions, and exclude changes to length of stay given that the estimates are not statistically significant. We first calculate the expected change in the number of day and overnight public hospital separations for each of the simulation scenarios by applying the simulation estimates to published statistics on separations from public hospital in 2004–05 (Australian Institute of Health and Welfare 2006). These are then multiplied by the expenditure per unit separation from public hospitals to calculate the changes to the total expenditure on public hospitals. To calculate the former, we use published data on the total recurrent expenditure on public hospitals ($21,758 million in 2004–05). Both the data on activity and expenditure are adjusted using the public patient day proportion, and where applicable, the admitted patient cost proportion.[11] For the activity data, we also apply published statistics on the average public cost weights for day and overnight separations to adjust for the relative

[11]The admitted patient cost proportion and the public patient day proportion are 0.70 and 0.84 respectively. See Table 4.1 in Australian Institute of Health and Welfare (2006)

differences in the resource use across the two types of hospital care.

Table 10 summarises the expected impact on public sector expenditures. The estimates from the simultaneous equation models (top panel in Table 10) predict that removing the 30 percent rebate on private health insurance is expected to increase the total public expenditure on inpatient hospital care from \$12.8 billion to \$14.2 billion, an increase of \$1.38 billion or 10.8 percent. This increase is driven to a large extent by the substitution of public for private care (9.0 percent), and to a smaller degree by the increase in the expected number of hospital admissions (1.8 percent). The single equation models (bottom panel in Table 10) however predict a smaller increase in public expenditure of 7.6 percent from the baseline, or a increase of \$976 million. The difference in the expected impact on public expenditure between the two sets of econometric models, measured in monetary terms, is \$404 million dollars.

7 Conclusions

Our simulation results indicate that removing subsidies on private health insurance would be expected to increase public expenditure on hospital care by \$1.38 billion, as individuals substitute away from obtaining private hospital care and utilised the public sector at a higher intensity. These results suggest that eliminating subsidies could potentially yield substantial public sector savings, given that the cost of the subsidy program, which amounted to \$3 billion in 2004–05, is considerably higher than the cost of the expected increase in public hospital use. This result is consistent with a number of international studies, which similarly conclude that subsidies on private health insurance are not self-financing. For instance, through an ex-ante policy simulation analysis, López Nicolás and Vera-Hernández (2008) estimate that removing tax subsidies on private insurance in Spain is not expected to lead to significant increase in public sector cost, whilst the tax forgone amounts associated with the subsidy amounts to €92.5 million. Emmerson et al. (2001) analysed the abolishment of tax relief on private medical insurance in the United Kingdom and obtained an estimate of the price elasticity of insurance that is substantially smaller than is required for subsidies on private insurance to be self-financing.

A critical component in our analysis is the estimate on the price elasticity of demand for private hospital insurance. Our estimates range from -0.17 to -0.18, which are slightly lower compared to those obtained in previous studies. For Australia, Butler (1999) reports estimates ranging from -0.35 and -0.44, while the estimate in Frech III et al. (2003) is -0.37. In other countries with duplicate private insurance similar to that in Australia, King and Mossialos (2005) and López Nicolás and Vera-Hernández (2008) both report an estimate of -0.5 for the United Kingdom and Spain respectively. In the case of supplementary health insurance in Canada, Stabile (2001) reports an estimate of -0.4 while Finkelstein (2002) estimates elasticities of -0.46 to -0.49. The comparability of our estimates with those from the studies cited above is somewhat limited due to differences in study designs (e.g. how the price of insurance is defined, sources of variations in price) and the institutional environment.[12]

While the simulation analysis suggests substantial benefits from eliminating subsidies, the effects in reality would depend on the price-setting behaviour by private health insurers. If insurers responded by decreasing premiums charged on insurance policies, this would limit the number of individuals dropping private health insurance cover, which would dampen the magnitude of the increase, if any, in public expenditure on hospital care and potentially resulting in larger public sector savings. Moreover, it is important to qualify that we focused our inquiry on the effects on the cost to the public sector in terms of public expenditure on hospital care. It is plausible that changes to the level of subsidies may have spillover effects on both private health care providers and insurers, which may influence the profitability and viability of the private health care sector.

An important question is how subsidising private health insurance compares with other policy tools. For the case of Australia, what would be the cost, and impact, of varying the parameters of the tax levy and subsidies on private insurance? A broader question that is pertinent to countries with mixed systems is how applying a tax exemption on premiums compares with a premium rebate in terms of its net effect on public sector expenditure. These are important policy questions that are crucial for evidence-based policy making and are deferred for further research in the future.

[12] The definition of the insurance price adopted in this paper is similar to that in Butler (1999), who uses data which predates the series of policy measures introduced in 1997 to 2001. We experiment with excluding the Medicare Levy Surcharge from the calculation of the insurance price, but instead account for the tax levy through the use of a binary variable in the insurance equation, and obtained elasticity estimates that are similar in magnitude as those in Butler (1999).

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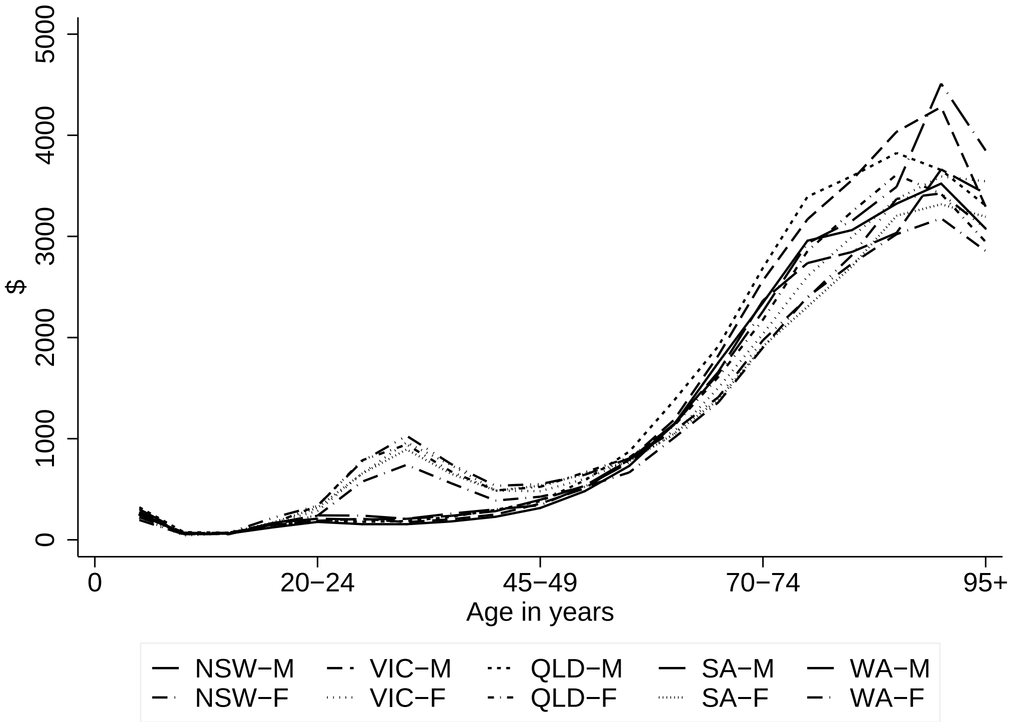

Figure 1: Expected annual hospital benefits by age, sex & states

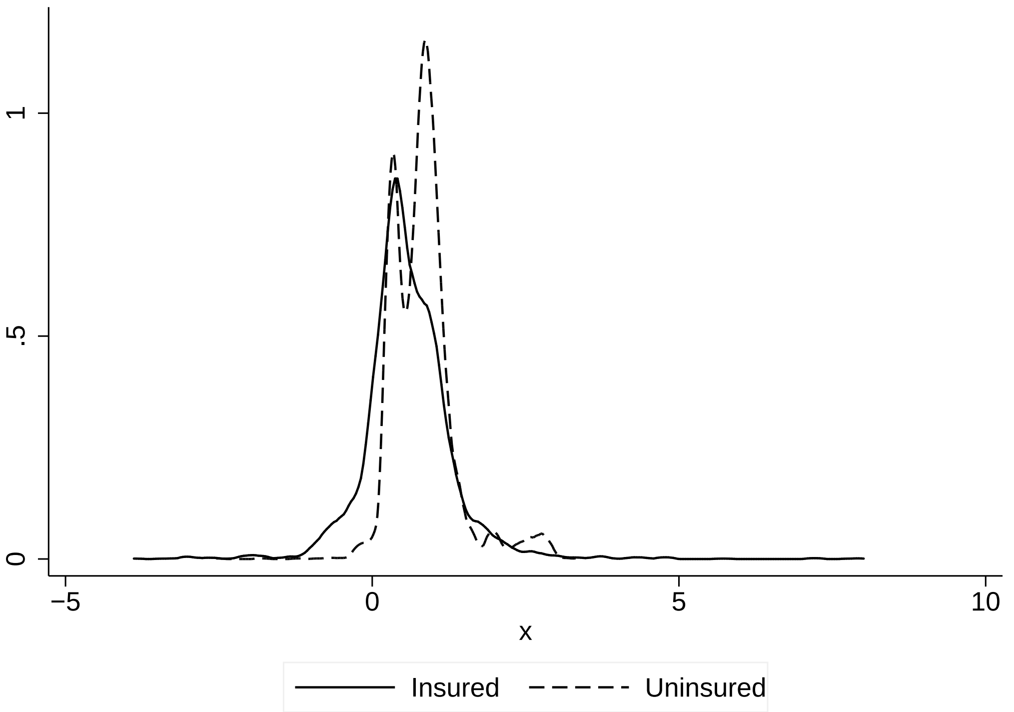

Figure 2: Kernel density: Price of insurance by insurance status

Table 1: Private hospital insurance status and premiums by coverage and income unit types

	Lone person	Lone parent	Couple only	Couple family	Total
Insurance status					
No hospital cover	789 (60.9%)	264 (71.9%)	1086 (43.7%)	1085 (44.9%)	3224 (49.1%)
With hospital cover	507 (39.1%)	103 (28.1%)	1397 (56.3%)	1330 (55.9%)	3337 (50.9%)
% Hospital only	22.7	17.5	23.2	17.1	20.5
% Hospital & Ancillary	77.3	82.5	76.8	82.9	79.5
Premiums ($)					
Ancillary only[a]	410.45	670.76	712.03	683.75	
Hospital only	751.95	894.39	1,261.79	1,345.17	
Hospital & Ancillary	1,095.72	1,549.65	1,766.07	1,939.09	
Total	957.20	1,326.58	1,602.96	1,761.21	
HES (2003-04)[b]	982.90	1,367.55	1,694.08	1,740.29	

[a] Individuals with ancillary only policies are not included in the analysis but shown here for comparison.

[b] Source: Confidentialised Unit Record Files (CURF) from the Household Expenditure Survey (HES) 2003-04. Derived from weekly household expenditure on 'hospital, medical and dental insurance'.

Table 2: Summary statistics: hospital care utilisation measures

Frequency	NHPDY	NHPOV	STHPOV	PVHPDY	PVHPOV
$\Pr(y=0)$	0.874	0.868		0.414	0.533
$\Pr(y=1)$	0.099	0.097	0.309	0.586	0.467
$\Pr(y=2)$	0.018	0.022	0.131		
$\Pr(y=3)$	0.005	0.006	0.123		
$\Pr(y=4)$	0.001	0.004	0.081		
$\Pr(y=5)$[a]	0.001	0.002	0.104		
Range	0-12	0-12	1-135	0-1	0-1
Mean ($\bar{y}$)	0.175	0.194	5.073		
Variance (S_y^2)	0.386	0.372	66.253		
$S_y^2/\bar{y}$	2.202	1.920	13.060		
N	6561	6561	876	797	876

LEGEND: NHPDY/NHPOV: Number of day/overnight hospital admissions; STHPOV: Length of stay in the last overnight admission; PVHPDY/PVHPOV: Admitted as private patient in the last day/overnight hospital admission.

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

Table 3: OLS regression of log annual expenditure on premiums

Variables	Coeff	Std Err.
Hospital & ancillary cover	0.310***	0.025
Family policy	0.575***	0.023
Couple-only policy	0.543***	0.030
Sole parent policy	0.198	0.184
% over 65 years	9.127***	1.990
% of policy with excess	4.778***	1.822
Policy to workforce ratio	-0.035***	0.013
Avg specialist fees ('00)	0.0045***	0.00086
Specialist density	-0.923***	0.253
(Specialist density)^2	0.0045**	0.0012
Constant	51.186***	12.367
Number of obs.	3533	
R-squared	0.204	

Table 4: Descriptive statistics: explanatory variables (N=6561)

Variable	**Description**	**Mean**	**Std dev**
Insurance price	Log of insurance price	-0.50	0.82
Age	Age	49.92	15.46
Female	Female (0/1)	0.54	0.50
Couple	Couple income unit (1/0)	0.75	0.44
Depchild	Have dependent children (1/0)	0.42	0.49
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	0.32
Other	Person is born in other countries (0/1)	0.12	0.31
Education Qualification (qual.):			
School (*Ref*)	Person's highest qual. is Year 12 or below (0/1)	0.47	0.50
Certificate	Person's highest qual. is a Certificate (0/1)	0.23	0.42
Dipl/Adv Dipl	Person's highest qual. is a (Advanced) Diploma (0/1)	0.097	0.30
Bach. and postgrad	Person's highest qual. is a degree or above(0/1)	0.21	0.41
HH Income	Annual household income ($ '000)	59.62	40.05
Occupation category:			
Unemploy (Ref)	Not in employment (0/1)	0.40	0.49
Manager/Admin	Managers and Administrators (0/1)	0.062	0.24
Professional	Professionals (0/1)	0.24	0.42
Clerical/Service	Clerical and Service workers (0/1)	0.16	0.36
Trades/Transport	Trades, Production, Transport, Labourers (0/1)	0.15	0.36
Self assessed health (SAH):			
Very Good/Excellent (*Ref*)	Person's SAH in t-1 is excellent or very good (0/1)	0.45	0.50
Good	Person's SAH in t-1 is good (0/1)	0.36	0.48
Fair/Poor	Person's SAH in t-1 is fair or poor (0/1)	0.19	0.39
Chronic health conditions (conds.):			
Work Limiting	Conds. limit amount and type of work (0/1)	0.39	0.67
Self Care	Conds. causes difficulties with self care (0/1)	0.042	0.20
Mobility	Conds. causes difficulties with mobility activities (0/1)	0.086	0.28
Communication	Conds. causes difficulties with communication (0/1)	0.0079	0.089
Alcohol daily	Person drinks alcohol daily (0/1)	0.097	0.30
Regular smoker	Person is a regular smoker (0/1)	0.18	0.39
State:			
NSW (*Ref*)	Person lives in New South Wales (0/1)	0.29	0.45
VIC	Person lives in Victoria (0/1)	0.25	0.43
QLD	Person lives in Queensland (0/1)	0.21	0.41
SA	Person lives in South Australia (0/1)	0.091	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)	0.039	0.19
ACT	Person lives in the Australian Capital Territory (0/1)	0.017	0.13
Remoteness:			
Major cities (*Ref*)	Person resides in major cities (0/1)	0.58	0.49
Inner region	Person resides in inner regional areas (0/1)	0.28	0.45
Other	Person resides in outer regional and (very) remote (0/1)	0.15	0.35
Headcount	Number ('000) of persons working in the health and general insurance industry (respondents' residential local area)	0.80	1.88
Distance	Euclidian distance (in km) to the nearest private hospital	30.27	89.71

Table 5: Marginal effect of private insurance on utilisation and public/private choice.

Outcome variables	Simultaneous Equation	Single Equation
NHPDY	0.763	1.264**
	(0.332)	(0.109)
NHPOV	0.679	1.225**
	(0.223)	(0.109)
STHPOV|PVHPOV=1	1.989	2.389***
	(0.792)	(0.543)
PVHPDY	0.691***	0.740***
	(0.249)	(0.031)
PVHPOV	0.554*	0.749***
	(0.304)	(0.027)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in parenthesis.

Note: For count outcomes, test for statistical significance from the null hypothesis that the marginal effect, which is interpreted as a proportional change in the expected outcome, is equal to 1. For binary outcomes, marginal effect is the change in the expected probability of the event occurring.

LEGEND: **NHPDY/NHPOV**: Number of day/overnight hospital admissions.
STHPOV|PVHPOV=1: Length of overnight stay for private patients.
PVHPDY/PVHPOV: Private patient in the last day/overnight hospital admission.

Table 6: Model estimates: demand for hospital admissions and choice of private care for day admissions

	Hospital admissions			*Private day admission*	
Variable	**NHPDY**	**NHPOV**	**PHI**	**PVHPDY**	**PHI**
Insurance Price			-0.202***		-0.213***
			(0.030)		(0.030)
Insurance	-0.270	-0.387		2.055*	
	(0.435)	(0.328)		(1.052)	
Age	0.0015	-0.111***		-0.026	
	(0.017)	(0.015)		(0.025)	
$(\text{Age})^2$	2.92e-05	0.00101***		0.00031	
	(0.00015)	(0.000136)		(0.00023)	
Female	0.273***	0.208**		-0.207	
	(0.083)	(0.083)		(0.139)	
Couple	0.109	0.071		-0.081	
	(0.101)	(0.098)		(0.153)	
Depchild	-0.183*	0.013		-0.164	
	(0.102)	0.100)		(0.160)	
Country of birth:					
Main English	0.075	0.103	-0.261***	-0.263	-0.279***
	(0.118)	(0.114)	(0.056)	(0.197)	(0.059)
Other	-0.178	-0.098	-0.229***	-0.211	-0.240***
	(0.135)	(0.125)	(0.061)	(0.204)	(0.063)
Education:					
Certificate	0.069	0.037	0.037	0.065	0.045
	(0.102)	(0.104)	(0.040)	(0.183)	(0.042)
Dipl/Adv Dipl.	0.176	-0.019	0.223***	0.612***	0.239***
	(0.132)	(0.138)	(0.058)	(0.219)	(0.060)
Bach. and postgrad.	0.168	0.126	0.266***	-0.0079	0.279***
	(0.118)	(0.114)	(0.053)	(0.198)	(0.055)
HH Income	0.0075*	0.0011	0.011***	0.0097	0.012***
	(0.0040)	(0.0031)	(0.0014)	(0.0068)	(0.0014)
$(\text{HH Income})^2$	-1.83e-05	1.07e-05	-2.08e-05***	-3.46e-05	-2.17e-05***
	(1.49e-05)	(1.22e-05)	(7.08e-06)	(2.54e-05)	(7.48e-06)
Occupation:					
Manager/Admin	-0.259	-0.594***	0.463***	0.065	0.477***
	(0.196)	(0.205)	(0.086)	(0.353)	(0.088)
Professional	-0.470***	-0.526***	0.185***	0.287	0.192***
	(0.138)	(0.136)	(0.055)	(0.205)	(0.0564)
Clerical/Service	-0.263**	-0.668***	0.054	-0.042	0.058
	(0.127)	(0.136)	(0.056)	(0.204)	(0.058)
Trades/Transport	-0.575***	-0.808***	-0.263***	0.0444	-0.276***
	(0.155)	(0.160)	(0.055)	(0.265)	(0.057)
Self assessed health:					
Good	0.236**	0.290***	0.047	-0.173	0.050
	(0.093)	(0.092)	(0.038)	(0.141)	(0.040)
Fair/Poor	0.616***	0.750***	-0.134***	-0.302*	-0.139**
	(0.111)	(0.110)	(0.052)	(0.167)	(0.054)
Health conditions:					

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Table 6– continued from previous page

Variable	NHPDY	NHPOV	PHI	PVHPDY	PHI
Work Limiting	0.308***	0.378***	0.0284	0.134	0.030
	(0.0544)	(0.0538)	(0.0269)	(0.092)	(0.028)
Self Care	0.412**	0.365**	-0.095	-0.167	-0.103
	(0.174)	(0.150)	(0.092)	(0.250)	(0.097)
Mobility Activities	-0.025	0.254**	-0.089	0.046	-0.084
	(0.143)	(0.127)	(0.067)	(0.216)	(0.071)
Communication Diff.	-0.152	0.062	-0.149	-1.319**	-0.171
	(0.416)	(0.299)	(0.175)	(0.593)	(0.186)
Alcohol daily	0.207	-0.026	0.186***	0.495**	0.199***
	(0.126)	(0.129)	(0.059)	(0.208)	(0.062)
Regular smoker	-0.239*	-0.142	-0.508***	0.039	-0.532***
	(0.132)	(0.120)	(0.049)	(0.249)	(0.049)
State:					
VIC	0.399***	0.184*	0.114**	-0.096	0.117**
	(0.112)	(0.104)	(0.055)	(0.165)	(0.057)
QLD	0.202*	0.104	-0.085	0.317*	-0.084
	(0.110)	(0.108)	(0.060)	(0.182)	(0.063)
SA	0.344**	0.344**	0.209***	0.218	0.233***
	(0.142)	(0.139)	(0.076)	(0.237)	(0.079)
WA	0.124	0.225*	0.214***	0.282	0.226***
	(0.145)	(0.134)	(0.073)	(0.260)	(0.076)
TAS/NT	0.482**	-0.373	-0.037	0.560**	-0.028
	(0.194)	(0.242)	(0.109)	(0.264)	(0.115)
ACT	0.394	0.449	0.091	-0.425	0.096
	(0.287)	(0.284)	(0.175)	(0.399)	(0.183)
Remoteness:					
Inner regional	-0.054	0.273***	-0.058	-0.360**	-0.060
	(0.096)	(0.094)	(0.054)	(0.156)	(0.056)
Other					
	0.0833	0.203*	-0.028	-0.324	-0.034
	(0.113)	(0.117)	(0.09)	(0.245)	(0.095)
Headcount			0.121***		0.130***
			(0.036)		(0.037)
$(\text{Headcount})^2$			-0.014***		-0.015***
			(0.0035)		(0.0037)
Distance			-0.149*	-0.132	-0.156*
			(0.081)	(0.234)	(0.084)
$(\text{Distance})^2$			0.015	0.019	0.016
			(0.010)	(0.028)	(0.011)
Constant	-3.592***	-0.265	-0.662***	-0.570	-0.694***
	(0.499)	(0.459)	(0.080)	(0.770)	(0.079)
σ	1.311***	1.265***			
	(0.057)	(0.053)			
Correlation					
$\rho_{\varepsilon_1\varepsilon_2}$		0.500***			
		(0.086)			
$\rho_{\varepsilon_1\varepsilon_3}$		0.236			
		(0.190)			

Continued on next page

Table 6– continued from previous page

Variable	**NHPDY**	**NHPOV**	**PHI**	**PVHPDY**	**PHI**
$\rho_{\varepsilon_2 \varepsilon_3}$		0.281*			
		(0.153)			
ρ_v					0.127
					(0.582)
Loglikelihood		-9059.02			-4101.26
Number of observations		6561			6561

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parenthesis, clustered at household level.

LEGEND: **NHPDY/NHPOV**: Number of day/overnight hospital admissions;
PVHPDY: Private patient in the last day hospital admission.
PHI: Have private hospital insurance.

Table 7: Model estimates: demand for hospital stay, choice of private patient and private insurance

	Overnight hospital stay		
Variable	**STHPOV**	**PVHPOV**	**PHI**
Insurance Price			-0.215***
			(0.030)
Insurance	-0.250	1.542	
	(0.367)	(1.046)	
Private Pat.	-0.622*		
	(0.374)		
Insurance X Private Pat.	0.937***		
	(0.285)		
Age	-0.036**	-0.0077	
	(0.018)	(0.025)	
$(\text{Age})^2$	0.00043***	0.00019	
	(0.00016)	(0.00022)	
Female	0.052	-0.023	
	(0.101)	(0.119)	
Couple	-0.015	-0.162	
	(0.111)	(0.132)	
Depchild	0.428***	-0.270	
	(0.141)	(0.176)	
Country of birth:			
Main English	0.108	-0.263	-0.277***
	(0.141)	(0.177)	(0.059)
Other	0.225*	-0.517***	-0.241***
	(0.132)	(0.181)	(0.063)
Education:			
Certificate	0.115	-0.023	0.040
	(0.109)	(0.153)	(0.042)
Dipl/Adv Dipl.	0.132	0.157	0.238***
	(0.160)	(0.215)	(0.060)
Bach. and postgrad.	0.072	-0.058	0.278***
	(0.140)	(0.201)	(0.055)
HH Income	-0.0043	0.012**	0.012***
	(0.0036)	(0.0057)	(0.0014)
$(\text{HH Income})^2$	2.53e-05*	-1.99e-05	-2.14e-05***
	(1.36e-05)	(2.29e-05)	(7.54e-06)
Occupation:			
Manager/Admin	-0.468**	0.0912	0.484***
	(0.236)	(0.308)	(0.088)
Professional	-0.357***	0.571***	0.195***
	(0.137)	(0.175)	(0.056)
Clerical/Service	-0.211	0.056	0.059
	(0.153)	(0.205)	(0.058)
Trades/Transport	0.050	0.0013	-0.271***
	(0.188)	(0.323)	(0.057)
Self assessed health:			
Good	-0.035	0.016	0.049

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Table 7– continued from previous page

Variable	**STHPOV**	**PVHPOV**	**PHI**
	(0.109)	(0.145)	(0.040)
Fair/Poor	0.212	-0.165	-0.141***
	(0.130)	(0.169)	(0.054)
Health conditions:			
Work Limiting	0.091	0.159*	0.031
	(0.064)	(0.089)	(0.028)
Self Care	0.123	-0.015	-0.103
	(0.172)	(0.221)	(0.097)
Mobility Activities	0.092	0.082	-0.093
	(0.130)	(0.177)	(0.070)
Communication Diff.	0.244	-0.523	-0.177
	(0.244)	(0.518)	(0.188)
Alcohol daily	0.149	0.0377	0.193***
	(0.139)	(0.202)	(0.062)
Regular smoker	-0.101	-0.473**	-0.530***
	(0.145)	(0.187)	(0.049))
State:			
VIC	-0.068	-0.085	0.116**
	(0.112)	(0.166)	(0.057)
QLD	-0.164	0.039	-0.092
	(0.124)	(0.161)	(0.063)
SA	-0.172	0.190	0.220***
	(0.133)	(0.188)	(0.079)
WA	-0.106	0.201	0.224***
	(0.157)	(0.217)	(0.076)
TAS/NT	0.242	-0.089	-0.040
	(0.204)	(0.299)	(0.114)
ACT	-1.055***	-0.240	0.099
	(0.383)	(0.333)	(0.183)
Remoteness:			
Inner regional	0.104	-0.268*	-0.057
	(0.099)	(0.143)	(0.056)
Other	0.091	-0.650**	-0.031
	(0.125)	(0.262)	(0.095)
Headcount			0.129***
			(0.037)
$(\text{Headcount})^2$			-0.0144***
			(0.0037)
Distance		0.538**	-0.157*
		(0.261)	(0.084)
$(\text{Distance})^2$		-0.076**	0.017
		(0.032)	(0.011)
Constant	1.386***	-1.437*	-0.694***
	(0.536)	(0.844)	(0.079)
σ	0.971***		
	(0.038)		
$\rho_{\xi_1\xi_2}$	0.0027		
	(0.161)		

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Table 7– continued from previous page

Variable	**STHPOV**	**PVHPOV**	**PHI**
$\rho_{\xi_1\xi_3}$	0.095		
	(0.182)		
$\rho_{\xi_2\xi_3}$	0.435		
	(0.549)		
Loglikelihood		-6206.81	
Number of observations		6561	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parenthesis, clustered at household level.

LEGEND: **STHPOV**: Length of overnight hospital stay in last admission;
PVHPOV: Admitted as private patient in last overnight hospital admission;
PHI: Have private hospital insurance.

Table 8: Simulating changes in insurance premiums (Simultaneous Equation)

$N = 10000$						
	% $\triangle$ in Premium					
	Baseline	+10%	+20%	+30%	+40%	+42.85%
–Number of day and overnight admissions–						
% PHI=1	49.85	48.37	47.07	45.90	44.82	44.53
% $\triangle$ PHI=1		-2.97%	-5.57 %	-7.93%	-10.08%	-10.67%
		[-3.84,-2.27]	[-6.67,-4.54]	[-9.11,-6.69]	[-11.37,-8.74]	[-12.04,-9.35]
%$\triangle E$(NHPDY)	0.18	0.39%	0.74%	1.06%	1.35%	1.42%
		[0.29,0.52]	[0.58,0.91]	[0.87,1.27]	[1.13,1.56]	[1.19,1.64]
%$\triangle E$(NHPOV)	0.23	0.48%	0.91%	1.30%	1.65%	1.75%
		[0.32,0.76]	[0.69,1.27]	[1.00,1.71]	[1.31,2.02]	[1.39,2.15]
–Public-private choice: day admission– ($^a N_{HOSPDY} = 1256$)						
% PHI=1	49.85	48.30	46.95	45.72	44.62	44.32
% $\triangle$ PHI=1		-3.10%	-5.82 %	-8.28%	-10.50%	-11.10%
		[-3.84,-2.30]	[-6.92,-4.74]	[-9.59,-7.02]	[-11.78,-9.23]	[-12.40,-9.83]
% PVHPDY=1	57.32	55.67	54.72	53.85	53.06	52.86
% $\triangle$ PVHPDY=1		-2.89%	-4.55%	-6.05%	-7.44%	-7.79%
		[-4.35,-1.78]	[-6.26,-2.98]	[-8.26,-4.17]	[-9.72,-5.43]	[-10.17,-5.73]
–Public-private choice & length of stay: Overnight admission– ($^a N_{HOSPOV} = 1389$)						
% PHI=1	49.85	47.96	46.41	45.33	44.09	43.84
% $\triangle$ PHI=1		-3.79%	-6.90 %	-9.06%	-11.56%	-12.05%
		[-3.89,-3.75]	[-7.02,-6.82]	[-9.21,-8.94]	[-11.72,-11.43]	[-12.22,-11.94]
% PVHPOV=1	46.15	45.28	43.70	42.84	42.19	41.76
% $\triangle$ PVHPOV=1		-1.87%	-5.30%	-7.18%	-8.58%	-9.52%
		[-1.87,-1.87]	[-5.30,-5.30]	[-7.18,-7.18]	[-8.58,-8.58]	[-9.52,-9.52]
% $\triangle E$(STHPOV|PUB)	4.95	-0.45%	-0.43%	-0.80%	-1.01%	-1.12%
		[-0.50,-0.31]	[-0.53,-0.23]	[-0.95,-0.56]	[-1.17,-0.71]	[-1.29,-0.83]
% $\triangle E$(STHPOV|PVT)	4.45	0.17%	-0.33%	0.0014%	0.086%	0.12%
		[0.24,0.24]	[-0.33,-0.33]	[0.0014,0.0014]	[0.086,0.086]	[0.12,0.12]

Note: 95% confidence intervals in parenthesis based on 2.5 and 97.5 percentiles of the distribution.

[a] N_{HOSPDY}/N_{HOSPOV}: Number of observations hospitalised for day/overnight admissions.

LEGEND: **NHPDY/NHPOV**: Number of day/overnight hospital admissions; **STHPOV**: Length of stay in the last overnight admission; **PVHPDY/PVHPOV**: Admitted as private patient in the last day/overnight hospital admission; **PHI**: Private hospital insurance.

Table 9: Simulating changes in insurance premiums (Single Equation)

$N = 10000$						
	% △ in Premium					
	Baseline	+10%	+20%	+30%	+40%	+42.85%
–Number of day and overnight admissions–						
% PHI=1	48.96	47.45	46.11	44.92	43.82	43.52
% △ PHI=1		-3.09%	-5.81 %	-8.26%	-10.50%	-11.17%
		[-3.92,-2.37]	[-6.92,-4.73]	[-9.54,-7.02]	[-11.89,-9.18]	[-12.48,-9.72]
%△E(NHPDY)	0.17	-0.36%	-0.67%	-0.96%	-1.22%	-1.28%
		[-0.46,-0.26]	[-0.82,-0.54]	[-1.13,-0.79]	[-1.41,-1.04]	[-1.49,-1.10]
%△E(NHPOV)	0.21	-0.28%	-0.53%	-0.75%	-0.95%	-1.01%
		[-0.40,-0.18]	[-0.68,-0.40]	[-0.92,-0.60]	[-1.13,-0.78]	[-1.21,-0.83]
–Public-private choice: day admission– ($^a N_{HOSPDY} = 1182$)						
% PHI=1	48.96	47.45	46.11	44.92	43.82	43.52
% △ PHI=1		-3.09%	-5.81 %	-8.26%	-10.50%	-11.17%
		[-3.92,-2.37]	[-6.92,-4.73]	[-9.54,-7.02]	[-11.89,-9.18]	[-12.48,-9.72]
% PVHPDY=1	59.31	57.35	56.28	55.29	54.39	54.15
% △ PVHPDY=1		-3.30%	-5.11%	-6.77%	-8.29%	-8.69%
		[-4.85,-2.15]	[-7.26,-3.27]	[-9.23,-4.75]	[-10.78,-5.90]	[-11.43,-6.32]
–Public-private choice & length of stay: Overnight admission– ($^a N_{HOSPOV} = 1339$)						
% PHI=1	48.96	47.45	46.11	44.92	43.82	43.52
% △ PHI=1		-3.09%	-5.81 %	-8.26%	-10.50%	-11.17%
		[-3.92,-2.37]	[-6.92,-4.73]	[-9.54,-7.02]	[-11.89,-9.18]	[-12.48,-9.72]
% PVHPOV=1	43.76	42.67	41.73	40.88	40.10	39.88
% △ PVHPOV=1		-2.50%	-4.65%	-6.59%	-8.38%	-8.88%
		[-4.86,-0.85]	[-7.59,-2.31]	[-9.89,-3.92]	[-12.03,-5.29]	[-12.46,-5.80]
% △E(STHPOV|PUB)	4.74	-0.17%	-0.29%	-0.39%	-0.49%	-0.52%
		[-0.88,0.61]	[-1.16,0.78]	[-1.43,0.82]	[-1.76,0.86]	[-1.72,0.93]
% △E(STHPOV|PVT)	4.80	-0.51%	-1.01%	-1.48%	-1.92%	-2.05%
		[-2.12,0.55]	[-3.18,0.59]	[-3.97,0.59]	[-4.87,0.40]	[-5.02,0.30]

Note: 95% confidence intervals in parenthesis based on 2.5 and 97.5 percentiles of the distribution.

[a] N_{HOSPDY}/N_{HOSPOV}: Number of observations hospitalised for day/overnight admissions.

LEGEND: **NHPDY/NHPOV**: Number of day/overnight hospital admissions; **STHPOV**: Length of stay in the last overnight admission; **PVHPDY/PVHPOV**: Admitted as private patient in the last day/overnight hospital admission; **PHI**: Private hospital insurance.

Table 10: Expected public sector expenditure on hospital care ($ in millions)

Change in premiums	Baseline	+10%	+20%	+30%	+40%	+42.85%
		– Simultaneous Equation –				
Total expenditure on public hospitals	12,794[a]	13,132	13,557	13,834	14,061	14,172
Difference in expenditure		339	763	1,041	1,268	1,379
Percentage change in expenditure		2.65%	5.97%	8.14%	9.91%	10.78%
		– Single Equation –				
Total expenditure on public hospitals	12,794[a]	13,105	13,330	13,533	13,719	13,770
Difference in expenditure		312	536	739	952	976
Percentage change in expenditure		2.44%	4.19%	5.78%	7.23%	7.63%

[a] The baseline estimate of the total recurrent expenditure on public inpatient care is calculated by multiplying the total recurrent expenditure on public hospitals by the admitted patient cost and public patient day proportions ($21,758 mil X 0.7 X 0.84 = $12,794 mil).