Demand for hospital care and private health insurance in a mixed public-private system: empirical evidence using a simultaneous equation modeling approach.

Terence Cheng¹ Farshid Vahid²

IRDES, 25 June 2010

The 2010 IRDES WORKSHOP on Applied Health Economics and Policy Evaluation

24-25 June 2010 - Paris - France

www.irdes.fr/Workshop2010

¹MIAESR, University of Melbourne

²Department of Econometrics and Business Statistics, Monash University = $-\infty$

Outline

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへぐ

1 Motivation

- **2** Economic Model
- **3** Econometric Model
- 4 Financing hospital care in Australia
- 5 Data

6 Results





Background

With rapidly growing public expenditure on health and long term care, policy makers have sought to identify alternative ways to finance health care:

- Expansion of private health care markets through greater reliance on private health insurance have generated considerable interest
- Extensive debate on the effects of private markets on the public health care system

Aims and objectives

This paper empirically examines the relationship between (1) the intensity of health care use, (2) the choice to seek public or private health care and (3) the decision to purchase private health insurance

- Examine the effect of the availability of private health insurance on choice to receive public or private hospital care and on intensity of care.
- Examine how public and private patients differ in the intensity of hospital care use.

Previous studies in the literature have examined these themes either separately or in combination with one other theme.

1 Demand for public and private health care

- Cost of waiting on waiting lists and price of private care (Lindsay and Feigenbaum 1984, Cullis and Jones 1986)
- Effects of waiting times (Mcavinchey and Yannopoulos 1993, Martin and Smith 1999)
- Availability of private health insurance (Gertler and Strum 1997, Srivastas and Zhao 2008)
- Difference in the casemix of patients that seek public care compared with private care (Hopkins and Frech 2001, Sundararajan et al 2004)

Previous studies in the literature have examined these themes either separately or in combination with one other theme.

1 Demand for public and private health care

- Cost of waiting on waiting lists and price of private care (Lindsay and Feigenbaum 1984, Cullis and Jones 1986)
- Effects of waiting times (Mcavinchey and Yannopoulos 1993, Martin and Smith 1999)
- Availability of private health insurance (Gertler and Strum 1997, Srivastas and Zhao 2008)
- Difference in the casemix of patients that seek public care compared with private care (Hopkins and Frech 2001, Sundararajan et al 2004)
- 2 Demand for public and private health care
 - Demand for health care and health insurance are inter-related (Cameron et al., 1988).
 - Mixed public and private system (Savage and Wright 2003)

Contribute to the literature on simultaneous equation count data models:

• Count data models with endogenous regressors have been developed (e.g. Terza 1998, Greene 2007), little attempts to extend these models to a system of simultaneous equations. Examples are Atella and Deb (2008) and Deb and Trivedi (2006).

Consumer's Problem

We assume that the individual is an expected utility maximiser who solves the following resource allocation problem

$$\max_{m, q, d} \sum_{s} \pi(s) U[C, h(m, q \mid s)]$$
(1)

subjected to

$$Y = C + dP + [1 - d(1 - \alpha)]q(p^{m} + p^{q})m + p_{ind}m \qquad (2)$$

- m: intensity of health care
- q: quality (private) health care, m = [0, 1]
- d: insurance, d = [0, 1]
- P: insurance premium
- α : degree of cost sharing, $\alpha \in \{0, 1\}$
- $P_{ind}^{m,q}$: unit prices of m and q, indirect price

Optimal m*

Let $m_{d,q}^*$ be the optimal intensity of hospital care for each insurance d and patient type strategy q, conditional on health state s.

The optimal intensity of hospital care if the individual chooses to obtain public (q = 0) is

$$m_{d,0}^* = m[P_{ind}, Y - dP, s]$$
 (3)

and private care (q=1) is

$$m_{d,1}^* = m[(1 - d(1 - \alpha))(P^m + P^q), P_{ind}, Y - dP, s]$$
 (4)

Patient type choice

Let $V_{d,q}(s)$ denote the individual's indirect utility associated with insurance strategy d and patient type strategy q. The individual will choose private care if and only if

$$V_{d,1}^*(s) > V_{d,0}^*(s)$$
 (5)

where

$$V_{d,0}^{*}(s) = V[P_{ind}, Y - dP, s] V_{d,1}^{*}(s) = V[(1 - d(1 - \alpha))(P^{m} + P^{q}), P_{ind}, Y - dP, s]$$
(6)

More generally,

$$V_{d,q^*}^*(s) = \max \left[V_{d,0}(s), V_{d,1}(s) \right]$$
(7)

Insurance choice

Given that the individual is an expected utility maximiser, the expected utility EV_d associated with the purchase of insurance is given as

$$EV_d = \sum_{s} \pi(s) [V_{d,q^*}(s)]$$
(8)

The individual will choose to purchase private hospital insurance if and only if

$$EV_1 > EV_0 \tag{9}$$

The three optimal solutions form the basis of the empirical model.

Designing the Econometric Model

1 Features of dependent variables in the data

• Hospital LOS: Non-negative, integer value. Overdispersion.

- Public/Private and Insurance Choices: Binary responses
- 2 The structure of economic decision making as suggested by results from the theoretical model, viz-a-viz simultaneity in quality and insurance decisions.

Econometric Model

Let m_i be the observed duration of hospital stay for the *i*th individual. Suppose conditional on exogenous covariates X_i , public/private choice q_i , insurance choice d_i and ξ_i , $m_i \sim Poisson$

$$f(m_i | X_i, q_i, d_i, \xi_i) = \frac{\exp^{-\mu_i} \mu_i^{m_i}}{m_i!}$$
(10)

where

$$\mu_i = \exp(X_i\theta + \lambda_1 d_i + \lambda_2 q_i + \sigma\xi_i)$$
(11)

and ξ_i is a standardised heterogeneity term which is distributed standard normal, that is $\xi_i \sim N[0, 1]$.

The decision rules to obtain hospital care as a public patient and to purchase private health insurance are given by q_i^* and d_i^* respectively where

$$q_i^* = Z_i \alpha + \beta_1 d_i + v_i$$

$$d_i^* = W_i \gamma + \eta_i$$
(12)

where v_i , $\eta_i \sim N[0,1]$. The observation rules of q_i and d_i are

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

(日) (日) (日) (日) (日) (日) (日) (日)

The RHS variables q_i and d_i in equation (11) and d_i in (12) are allowed to be endogenous by assuming that ξ_i , v_i and η_i are correlated. More specifically, it is assumed that each pair of ξ_i , v_i and η_i are distributed bivariate normal where

 $\xi_i, v_i \sim N_2[(0,0), (1,1), \rho_{\xi v}]$

$$\xi_i, \eta_i \sim N_2[(0,0), (1,1), \rho_{\xi\eta}]$$
 (14)

 $v_i, \eta_i ~\sim N_2[(0,0), (1,1), \rho_{v\eta}]$

 $N_2[(\mu_1, \mu_2), (\sigma_1^2, \sigma_2^2), \rho]$, μ denotes the mean, σ^2 the variance and ρ the correlation parameter.

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

$$\begin{split} &\int_{-\infty}^{\infty} \left[(1-q_i)(1-d_i)f(m_i \mid X_i, q_i = 0, d_i = 0, \xi_i) \; P(q_i = 0, d_i = 0 \mid \Omega_i, \xi_i) + \right. \\ & (q_i)(1-d_i)f(m_i \mid X_i, q_i = 1, d_i = 0, \xi_i)P(q_i = 1, d_i = 0 \mid \Omega_i, \xi_i) + \\ & (1-q_i)(d_i)f(m_i \mid X_i, q_i = 0, d_i = 1, \xi_i)P(q_i = 0, d_i = 1 \mid \Omega_i, \xi_i) + \\ & (q_i)(d_i)f(m_i \mid X_i, q_i = 1, d_i = 1, \xi_i) \; P(q_i = 1, d_i = 1 \mid \Omega_i, \xi_i) \right] d\xi_i \end{split}$$

(15)

where $\Omega_i = (X_i \cup Z_i \cup W_i)$.

The joint probability of the four possible outcomes of the pair (q_i, d_i) conditional on Z_i , W_i and ξ_i may be succinctly written as

$$g(q_i, d_i | Z_i, W_i, \xi_i) = \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*]$$
(16)

where

$$\Theta_1 = -rac{Z_i lpha + eta_1 d_i +
ho_{\xi
u} \xi_i}{(1 -
ho_{\xi
u}^2)^{1/2}}$$

$$\Theta_2=-rac{W_i\gamma+
ho_{\xi\eta}\xi_i}{(1-
ho_{\xi\eta}^2)^{1/2}}$$

$$\rho^* = y_{1i} \cdot y_{2i} \cdot \frac{(\rho_{v\eta} - \rho_{\xi v} \rho_{\xi \eta})}{\sqrt{1 - \rho_{\xi v}^2} \sqrt{1 - \rho_{\xi \eta}^2}}$$

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

Let the joint conditional density for the observed data $f(m_i, q_i, d_i | \Omega_i)$ be expressed as

1 . . .

$$f(m_i, q_i, d_i | \Omega_i) = \int_{-\infty}^{+\infty} f(m_i, q_i, d_i | \Omega_i, \xi_i) \phi(\xi_i) d\xi_i \qquad (17)$$

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへで

where $\phi(\xi_i)$ is the standard normal density.

Let the joint conditional density for the observed data $f(m_i, q_i, d_i | \Omega_i)$ be expressed as

$$f(m_i, q_i, d_i | \Omega_i) = \int_{-\infty}^{+\infty} f(m_i, q_i, d_i | \Omega_i, \xi_i) \phi(\xi_i) d\xi_i \qquad (17)$$

where $\phi(\xi_i)$ is the standard normal density. Given the previous assumption that m_i , q_i and d_i are related only through the correlations between ξ_i , v_i and η_i , conditioned on ξ_i , m_i is independent of q_i and d_i . Hence, $f(m_i, q_i, d_i | \Omega_i, \xi_i)$ in (17) may be expressed as

$$f(m_i, q_i, d_i | \Omega_i, \xi_i) = f(m_i | X_i, q_i, d_i, \xi_i) \cdot g(q_i, d_i | Z_i, W_i, \xi_i)$$
(18)

Substituting (16) into (18), we obtain

$$f(m_i, q_i, d_i | \Omega_i) = \int_{-\infty}^{+\infty} f(m_i | \Omega_i, q_i, d_i, \xi_i) \cdot \Phi_2[y_{1i}\Theta_1, y_{2i}\Theta_2, \rho^*] \phi(\xi_i) d\xi_i$$
(19)
Equation (19) will be used to construct the log-likelihood function.

Estimation

Estimation using maximum simulated likelihood.

Pseudo-random numbers drawn from Halton sequence.

Number of simulations S has considerable effects on the properties of the MSL estimator. MSL asymptotically equivalent to ML if $\sqrt{N}/S \rightarrow 0$ when $N, S \rightarrow \infty$.

 Choice of number of simulations S: increased stepwise by factor of 2 from 50 (min) to 3000 (max). Use S = 2000.

Implemented in Stata using numerical derivatives.

Financing hospital care in Australia

Medicare, Australia's universal health insurance scheme subsidises medical care and technologies according to a schedule of fees.

Hospital care is free as a public patient in public hospitals. Patients pay for private care in public or public hospitals afforded as direct payments or by private health insurance (PHI).

Significant policy changes were introduced from 1997 to 2000 to encourage the purchase of PHI. The percentage of the population with PHI increased from 30.1% in Dec 1999 to 45.7% in Sep 2000. Currently, about 44% of population have PHI.

Data & Dependent Variables

Data

This study uses microdata from the National Health Survey (NHS) 2004/05.

Sample Size

Sample of **2,406** observations for which respondents had indicated they have been hospitalised at least once in last twelve months.

3 key dependent variables

- 1 Do individuals have private health (hospital) insurance?
- 2 Did individuals chose to be admitted as a Medicare (public) or private patient at the *last* hospitalisation?
- **3** Length of hospital stay (LOS) at the last hospitalisation.

Dependent Variables

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへで

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

Table 1: Descriptive statistics: insurance status, patient type and length of stay

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

Explanatory variables

The explanatory variables can be classified into the following categories. These variables are similar to that in Cameron et al. (1998), Cameron and Trivedi (1991), Savage and Wright (2003) and Propper (2000).

- Demographic & socioeconomic characteristics (age, gender, household income)
- Health status measures (ICD10-AM categories for chronic conditions)
- **3** Health risk factors (alcohol risk, smoker)
- **4** Geography (State/Territories, remoteness)

Exclusion restrictions are introduced to strengthen the identification of the model.

Model selection

	Correlation			Selection Criterion		
Model	ρ_{12}	ρ_{13}	ρ_{23}	Loglikelihood ^c	AIC	BIC
(1) FSEM	0.154	0.208	-0.362^{**}	-6592.40	13450.81	14220.31
(2) $\rho_{\xi v} = 0$		0.242*	-0.364 **	-6592.58	13449.16	14212.88
(3) $\rho_{\xi\eta} = 0$	0.300		-0.361*	-6593.49	13450.98	14214.69
(4) $\rho_{\xi_v} = \rho_{\xi_n} = 0$			-0.310*	-6594.26	13450.52	14208.45
(5) Single Eq $(\rho_{ij} = 0)$				-6595.74	13451.47	14203.62
				Best Model		
Model	Null I	lo	LR Stat ^b	LR Test	AIC	BIC
(1) vs. (2)	$\rho_{\xi v} =$	0	0.36	(2)	(2)	(2)
(1) vs. (3)	$\rho_{\xi\eta} =$	0	2.17	(3)	(1)	(3)
(1) vs. (4)	$\rho_{\xi v} =$	$\rho_{\xi\eta} = 0$	3.71	(4)	(4)	(4)
(2) vs. (3)		Non-nes	sted	-	(2)	(2)
(2) vs. (4)	$\rho_{\xi\eta} =$	0	3.36^{*}	(2)	(2)	(4)
(2) vs. (5)	$\rho_{\xi\eta} =$	$\rho_{v\eta} = 0$	6.31**	(2)	(2)	(5)

Table 4: Estimates of correlation parameters & model selection

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

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

b. Critical values for LR test: $\chi^2_{1,\alpha=0.05} = 3.84$, $\chi^2_{2,\alpha=0.05} = 5.991$, $\chi^2_{1,\alpha=0.1} = 2.706$, $\chi^2_{2,\alpha=0.1} = 4.605$

c. The log likelihood value for Model (5) is the sum of log likelihood values from the three single equation models.

Insurance & Patient Type Effects

Table: Marginal effects under endogenous and exogenous assumptions

	Endogenous		Exogen	Exogenous			
	dF/dX	S.E	dF/dX	S.E			
	Public/Private Patient						
Insurance	0.810*** ^a	0.033	0.717***	0.017			
	Hospital Length of Stay						
Patient-Type	-0.641***	0.182	-0.556***	0.175			
Moral Hazard Effect ^b	0.139	0.209	0.451***	0.124			
Insurance on Pub_Pat ^c	-0.428	0.272	-0.195	0.130			
Correlation Parameters							
ρ_{En}	0.237*	0.076					
Ρνη	-0.349**	0.155					
Log likelihood	-6592.5	580	-6595.7	737			

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

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

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 のへぐ

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

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

Other explanatory variables

The decision to admit as a public or private patient is influenced by

- Marital status (+), Age (+), Household income (+)
- Country of birth: Others (-)

The length of hospital stay is influenced by

- Age (+), Employment (-)
- Chronic conditions (n.s)

Decision to purchase insurance

• Female (+), Age (+), Couple IU (+), Household income (+)

◆□▶ ◆□▶ ◆臣▶ ◆臣▶ □臣 = のへで

• Education attainment (+), Smoker (-), Remote (-).

Discussion of key results

 Average LOS by private patients is 0.64 nights shorter than for public patients.

- Consistent with existing evidence that the public hospital system is utilised by patients with more complex health needs (Sundarajan et al 2004, Hopkins and Frech, 2001).

- Effects of private health insurance is limited to reducing public hospital waiting lists and waiting times for elective the public sector.

Discussion of key results

 Average LOS by private patients is 0.64 nights shorter than for public patients.

- Consistent with existing evidence that the public hospital system is utilised by patients with more complex health needs (Sundarajan et al 2004, Hopkins and Frech, 2001).

- Effects of private health insurance is limited to reducing public hospital waiting lists and waiting times for elective the public sector.
- 2 Not significant moral hazard effect for privately admitted patients.

- Contrast with Australian based studies (Savage and Wright 2003, Cameron et al. 1988). For example, the former finds that duration of private hospital stay is 1.5 to 3.2 times longer among those privately insured.

References

- Cameron, CA, Trivedi PK, Milne F and Piggot J (1998). A microeconometric model of the demand for health care and health insurance in Australia. *Review of Economic Studies*. 55(1), 85-106.
- 2 Greene, W. (2007). Functional form and heterogeneity in models for count data. Working Paper 07-10, Department of Economics, Stern School of Business, New York University.
- 3 Hopkins S, Frech HE (2001). The rise of private health insurance in Australia: early effects on insurance and hospital markets. *Economic and Labour Relations Review*. 12: 225-238.
- Savage E, Wright DJ (2003). Moral hazard and adverse selection in Australian private hospitals: 1989-1990. *Journal of Health Economics*. 22(3): 331-359.
- 5 Terza, J. V. (1998). Estimating count data models with endogenous switching: sample selection and endogenous treatment effects. *Journal of Econometrics*, 84:129-154.

Appendix

◆□▶ ◆□▶ ◆臣▶ ◆臣▶ 臣 の�?

By the assumption of joint normality, $(v_i | \xi_i)$ and $(\eta_i | \xi_i)$ are distributed bivariate normal

$$\begin{pmatrix} \mathsf{v}_i \mid \xi_i \\ \eta_i \mid \xi_i \end{pmatrix} \sim \mathsf{N}_2 \begin{bmatrix} \begin{pmatrix} \rho_{12}\xi_i \\ \rho_{13}\xi_i \end{pmatrix}, \begin{pmatrix} 1 - \rho_{12} & \rho_{23} - \rho_{12}\rho_{13} \\ \rho_{23} - \rho_{12}\rho_{13} & 1 - \rho_{13} \end{pmatrix} \end{bmatrix}$$
(20)

and

$$v_i | \xi_i = \rho_{12} \xi_i + \epsilon_{1i} (1 - \rho_{12}^2)^{1/2}, \quad \epsilon_{1i} \sim N[0, 1]$$
 (21)

$$\eta_i | \xi_i = \rho_{13} \xi_i + \epsilon_{2i} (1 - \rho_{13}^2)^{1/2}, \quad \epsilon_{2i} \sim \mathcal{N}[0, 1]$$
(22)

By substituting $v_i | \xi_i$ into q_i^* and using the decision rule for q_i , the probability of observing $q_i = 1$ is expressed as

$$P(q_{i} = 1) = P\left(\epsilon_{1i} > -\frac{Z_{i}\alpha + \beta_{1}d_{i} + \rho_{12}\xi_{i}}{(1 - \rho_{12}^{2})^{1/2}}\right)$$

$$= P\left(\epsilon_{1i} < \frac{Z_{i}\alpha + \beta_{1}d_{i} + \rho_{12}\xi_{i}}{(1 - \rho_{12}^{2})^{1/2}}\right)$$
(23)

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

$$P(q_i = 0) = P\left(\epsilon_{1i} > \frac{Z_i \alpha + \beta_1 d_i + \rho_{12} \xi_i}{(1 - \rho_{12}^2)^{1/2}}\right)$$
(24)