E Multivariate analysis in detail

The purpose of this appendix is to detail the data and statistical techniques the Commission has used its multivariate analysis of the performance of public and private hospitals. A summary of previous selected studies is presented in section E.1. A description of the methods applied is given in section E.2. Data sources and the Commission's approach to assembling the dataset are outlined in section E.3. The variables used in the analysis are described in section E.4. Results of the analysis and post-estimation statistics are presented in section E.5. The Commission's proposed future analysis is discussed in section E.6.

E.1 Previous studies

There are a large number of multivariate studies of hospital performance that have been undertaken worldwide. Despite this large number, only a few have used Australian data. O'Neill et al. (2008), for example, in a detailed study of 79 data envelopment analysis (DEA) studies did not include any Australian studies in their review. A similar pattern can be gleaned from literature reviews by Butler (1995), Peacock et al. (2001), Hollingsworth (2008) and Hollingsworth and Peacock (2008).

This is not to say that there have not been any Australian studies. The Commission reviewed thirteen of the more commonly cited Australian studies published since the mid-1990s. These include Butler (1995), SCRCSSP (1997), Webster, Kennedy and Johnson (1998), Yong and Harris (1999), Wang and Mahmood (2000a, 2000b), Paul (2002), Queensland Department of Health (2004), Mangano (2006), Jensen, Webster and Witt (2007), Gabbitas and Jeffs (2008), and Chua, Palangkaraya and Yong (2008, 2009).

A summary of the methods and data used in the overseas and Australian studies is given in table E.1. The table is organised according to the type of function (cost or production) and modelling techniques used (DEA, stochastic frontier analysis (SFA), stochastic distance function (SDF) or other). Studies that employed more than one modelling technique (such as Webster, Kennedy and Johnson 1998) are therefore reported more than once.

Table E.1 **Selected literature review**

Author(s) and year published	*No. of hospitals and year(s)*	*Dependent variable*	*Independent variables*	*External factors*	*Quality or patient safety*
Cost function – Stochastic frontier analysis					
Herr (2008)	1594 German public, non-profit private, and for-profit private hospitals, 2001-2003.	Total (adjusted) costs.	No. of cases, no. of weighted cases, unit prices for doctors, nurses, other staff, no. of beds, surgery ratio, total adjusted costs per bed, total adjusted costs per weighted case.	No subsidies dummy, East dummy, female ratio, 75+ ratio.	Occupancy rate, nurse-bed ratio, average length of stay (ALOS), mortality rate.
Yaisarwang and Burgess (2006)	131 US Vets Affairs hospitals, 2000.	Total (adjusted) costs.	Medical, nursing and other salaries, no. of operating beds, outpatient services, inpatient services, access indicators (occupancy rate, waiting days, market penetration).	Intensive care unit intensity index, urban, teaching and psychiatric hospital status.	In-hospital mortality rate, readmission rate, length of stay for readmissions, average days to readmit.
Jacobs (2001)	232 National Health Service hospitals, 1995-96.	Cost Index (actual cost divided by expected cost).	Emergency room (ER) visits, casemix weight, index of unexpected ER visits, occasions of outpatient services.	Transfers to and from a hospital, patients under 15, patients over 60, female patients, teaching, market forces factor.	None.
Wang and Mahmood (2000a)	113 NSW public hospitals (in two peer groups – large and small) 1997-98.	Total variable cost.	Inpatient casemix index, occasions of service, ER visits, input price of medical staff, average non-medical costs, average available beds, percentage sameday separations.	Dor and Farley index, inpatient casemix index.	ALOS of acute separations.
Yong and Harris (1999)	35 large Victorian acute public hospitals for 1994-95.	Total operating expend., admitted patient cost.	Weighted-inlier equivalent separations (WIES), occasions of service, emergency services, average medical wage, nursing wage, other staff wage, hotelling wage, medical support staff wage, size (number of beds).	Metropolitan hospital, teaching status.	Occupancy rate, staff per WIES.
Rosko and Chilingerian (1999)	195 Pennsylvania acute care hospitals, 1989.	Total costs.	Inpatient separations, outpatient visits, wage rate, average price of capital, casemix index.	Severity of illness index, teaching variables, Herfindahl index.	None.
Linna (1998)	Finnish hospitals from 1988 to 1994.	Net operating cost.	Inpatient admissions, accident and emergency visits, hourly wage index, index on local government expenditure, time dummy.	Research and development variable, teaching dummy.	Readmission rate.
Webster, Kennedy, Johnson (1998)	280 Australian private hospitals in 1994-95.	Total operating expenditure.	Bed unit costs, materials unit costs, staff unit costs, revenue (output), occupied bed days, squared and cross terms.	None.	None.

(Continued next page)

Table E.1 (continued)

Author(s) and year published	*No. of hospitals and year(s)*	*Dependent variable*	*Independent variables*	*External factors*	*Quality or patient safety*
Zuckerman, Hadley and Iezzoni (1994)	1600 US hospitals in 1984 and 1985.	Total operating cost.	Medicare admissions, Medicare post admission days, non-Medicare admissions and non-Medicare post-admission days, outpatient visits, average salary per FTE (full-time equivalent), average capital cost per bed.	Percent male patients, percent older patients, scores for disease status, plus a large number of factors descr bing characteristics of hospitals.	Transfers from another hospital, mortality rates of certain patients.
Vitiliano and Toren (1994)	443 US nursing homes for 1987 and 1990.	Total costs.	Patient days, admissions and transfers, per cent low care patients, wages of medical aids, registered nurse wages, property expenses (per square feet).	Voluntary, public, corporate, proprietorship, partnership.	None.
Cost function – Ordinary least squares					
Dor and Farley (1996)	500 US acute non-federal general hospitals.	Total variable (operating) cost.	Inpatient discharges, casemix index, outpatient services, surgery share, ER visits, average salary, average capital price.	Severity of illness index, source of hospital funding.	None.
Butler (1995)	121 Queensland public hospitals and 35 private hospitals.	Average cost per casemix-adjusted separation.	ALOS, occupancy rate, case flow rate, no. of beds.	None.	None.
Scott and Parkin (1995)	76 Scottish acute hospitals for 1992-93.	Total variable cost.	No. of acute discharges, no. of other discharges, acute length of stay (LOS), other LOS, outpatient and ER visits, beds.	None.	None.
Granneman, Brown and Pauly (1986)	867 US hospitals in 1982.	Total annual cost.	No. of acute inpatient, sub-acute, and intensive care days and discharges, and accident and emergency visits, outpatient and other visits, wage rates for four categories.	Revenue sources, location dummies, per capita income of region, teaching status and presence of particular facilities.	None.
Single output production function – Stochastic frontier analysis					
Herr (2008)	1594 German public, non-profit private, and for-profit private hospitals, 2001–2003.	No. of cases, no. of weighted cases.	No. of doctors, no. of nurses, no. of other staff, no. of beds, total adjusted costs per bed, total adjusted costs per weighted case.	No subsidies dummy, East dummy, female ratio, 75+ ratio, surgery ratio.	Occupancy rate, nurse-bed ratio, ALOS, morality rate.

(Continued next page)

Table E.1 (continued)

Author(s) and year published	*No. of hospitals and year(s)*	*Dependent variable*	*Independent variables*	*External factors*	*Quality or patient safety*
Mangano (2006)	116 Victorian public hospitals, 1992-93 to 1995-96.	Total WIE separations, total inpatients treated.	No. of FTE nurses, no. of FTE medical support staff, no. of admin and clerical staff and no. of FTE hotelling staff, average no. of available beds.	Teaching and metropolitan location status.	None.
Brown (2003)	20 per cent sample of hospitals in 17 US states, 1992 to 1996.	Inpatient separations.	No. of FTE employees, no. of beds, capital expenses, casemix index.	Share of admissions enrolled in health management organisations, share enrolled in preferred provider organisations, teaching dummy, public & for-profit status.	None.
Webster, Kennedy, Johnson (1998)	300 private hospitals for 1994-95.	Revenue, composite of occupied bed days.	No. of FTE staff, no. of beds, cost of materials, (plus squared and cross terms).	Hi tech dummies.	None.
Multi-output production function – Data envelopment analysis					
Chua, Palangkaraya and Yong (2009)	123 Victorian public hospitals between 2003-04 and 2004-05.	Total WIES	No. of FTE doctors, no. of FTE registered and other nurses, no. of FTE admin, domestic and other staff, no. of beds, expenditures on drug, medical and surgical supplies.	Second-stage Tobit regression testing for the effects of hospital competition.	Risk-adjusted unplanned readmissions (output).
Vitikainen, Street and Linna (2009)	40 Finnish public acute hospitals in 2005.	Casemix-adjusted inpatient admissions (episodes, days and cases), outpatient visits and ER visits	Hospital operating costs.	None.	None.
Nayar and Ozcan (2008)	53 non-federal hospitals in Virginia in 2003.	Casemix-adjust. separations, outpatient visits (including accident and emergency).	No. of total staff, no. of beds, costs (excluding payroll and costs), total assets.	Teaching FTEs (as an output).	Percent of patients receiving: antibiotics; oxygenation; and aged 65+ given pneumoccal vaccination.
Mangano (2006)	100 Victorian public hospitals, 1992-93 to 1995-96.	WIES, total inpatients treated.	No. of FTE non-medical staff, average no. of available beds.	None.	None.

(Continued next page)

Table E.1 (continued)

Author(s) and year published	*No. of hospitals and year(s)*	*Dependent variable*	*Independent variables*	*External factors*	*Quality or patient safety*
Harrison and Sexton (2006)	Between 471 and 480 private, public, not-for-profit for 1998 and for 2001.	Admissions, outpatient visits.	No. of FTE staff, no. of beds, operating expenses, no. of services.	None.	None.
Queensland Department of Health (2004)	Queensland public hospitals for 2000-01 to 2002-03.	Weighted separations, outpatient occasions of service, other admitted care .	No. of FTE staff, non-labour costs and gross asset values	None.	None.
Biørn et al (2003)	Unspecified no. of Norwegian hospitals between 1992 and 2000.	Casemix-adjusted separations, fee-weighted outpatient visits .	No. of FTE physicians, no. of other FTE staff, medical costs, total expenses.	Dummies for funding source and university affiliation and location.	None.
Hofmarcher, Paterson, and Riedel (2002)	93 Austrian hospitals between 1994 and 1996.	Patient days, no. of discharges, LDF points.	No. of medical staff, no. of para-medical staff, no. of admin. staff, no. of beds, no. of wards, Index of casemix complexity.	None.	None.
Al Shammari (1999)	15 Jordanian hospitals, 1991–1993.	Patient days, minor operations, major operations.	No. of physicians, no. of health personnel, no. of bed days.	None.	None.
Wang and Mahmood (2000b)	113 NSW public hospitals for 1997.	Inpatient casemix index, inpatient admissions, outpatient visits, ER visits.	No. of doctors, no. of nurses, no. of non-medical staff, no. of beds, other expenses.	None.	ALOS of acute separations.
Webster, Kennedy, Johnson (1998)	301 private hospitals for 1994-95.	Inpatient days, surg. days, non-patient services, nursing home days, surg. proc., inpatient separations, ER visits, comp. output.	No. of FTE medical staff, contract value of visiting medical officers, no. of FTE nurses, no. of FTE other staff, no. of beds, cost of materials.	None.	None.
Burgess and Wilson (1998)	2420 US hospitals with 100+ beds, 1985 to 1988.	Acute inpatient days, casemix-adjusted discharges, long-term care days, no. of outpatient visits, ambulatory surgeries, inpatient surgeries.	No. of registered nurses, no. of practice nurses, no. of other clinical staff, no. of non-clinical staff, no. of acute beds, no. of long-term beds, casemix index.	None.	None.
O’Neill (1998)	40 Philadelphia and Pittsburgh hospitals (27 urban and 13 teaching) with 300+ beds in 1992.	Casemix-adjust. inpatient medical separations, casemix-adjust. inpatient surgical separations, casemix-adjust. outpatients, no. of trained residents.	No. of FTE staff, no. of beds, operational expenditure (excluding payroll and capital).	Capital intensity index for specialist units.	None.
SCRCSSP (1997)	109 Victorian public hospitals for 1994-95.	Three categories of WIES outputs.	No. of FTE non-medical staff, no. of FTE medical staff, all FTE staff, non-salary costs, medical salaries, total salaries.	None.	Unplanned readmission rates.

(Continued next page)

Table E.1 (continued)

Author(s) and year published	*No. of hospitals and year(s)*	*Dependent variable*	*Independent variables*	*External factors*	*Quality or patient safety*
Ferrier and Valdmanis (1996)	360 US rural hospitals for 1989.	No. of acute days, subacute days, no. of intensive days, no. of surgeries, discharges, outpatients	No. of FTE staff, no. of beds, size, regional location, ownership.	None.	Occupancy rate.
Bedard and Wen (1990)	58 New York and West Pennsylvania hospitals 1974 to 1979.	No. of inpatient separations, no. of surgical operations, no. of outpatient visits.	No. of FTE staff, no. of beds; cost of labour, non-payroll expenditure.	None.	None.
Morey and Dittman (1996)	105 North Carolina hospitals in 1978.	No. of patient days for persons aged under 14, patient days for persons aged 14 to 65, patient days for persons aged over 65.	Cost of nursing services, cost of ancillary services (for example, radiology), cost of administration and general services.	No. of intensive-care beds, acute beds and other beds, percent each of intensive-care patient days, intensive or acute-care patient days, capital value of hospital.	None.
Borden (1988)	52 New Jersey hospitals 1979 to 1984.	No. of cases treated for high most common diagnosis-related groups (DRGs), all other DRG separations combined.	No. of total FTE staff, no. of FTE nurses, no. of beds, other non-payroll expenses.	None.	None.
Multi-output production function with some outputs defined as undesirable – Data envelopment analysis					
Clement et al. (2008)	667 hospitals from 10 US states for 2000.	No. of births, outpatient surgeries, ER visits, outpatient visits, casemix-adjusted admissions.	No. of FTE registered nurses, no. of FTE practice nurses, no. of other FTE staff, no. of beds, and capital.	None.	Risk-adjusted acute myocardial infraction, congestive heart failure, stroke, gastrointestinal haemorrhage, pneumonia.
Multi-output production function – Stochastic distance function					
Ferrari (2006)	52 Scottish public hospitals for 1991-92 to 1996-97.	Inpatients index, outpatients et al. services index.	No. of medical staff, no. of nursing staff, no. of other staff, no. of beds, capital.	None.	None.

(Continued next page)

Table E.1 (continued)

Author(s) and year published	*No. of hospitals and year(s)*	*Dependent variable*	*Independent variables*	*External factors*	*Quality or patient safety*
Siciliani (2006)	17 Italian hospitals between 1996 and 1999.	No. of discharges, surgical discharges, medical discharges.	No. of physicians and nurses, no. of other personnel, no. of beds.	None.	None.
Paul (2002)	223 NSW public hospitals in 1995-96.	No. acute inpatient seps, non- and sub-acute bed-days, OOS, Inpatient seps separated into public and private, and were unweighted.	No. of FTE staff, no. of beds, capital, cost of materials, no. of services, no. of diagnoses.	Research, rurality, index of education and occupation, teaching.	Standardised mortality ratio.
Löthgren (2000)	26 Swedish county hospitals 1989–1994.	No. of operations, no. of physician visits, no. of inpatient admissions.	Cost expenditure, no. of beds.	None.	None
Gerdtham, Löthgren, Tambour and Rehnberg (1999)	26 Swedish county hospitals 1989–1995.	No. of operations, no. of physician visits, no. of inpatient admissions.	Cost expenditure, no. of beds.	Reimbursement mechanism, university hospital status, patient age.	None
Grosskopf, Margaritis and Valdmanis (1995)	108 Not-for-profit and public hospitals in California and New York in 1982.	No. of acute patient days, no. of intensive care inpatient days, no. of inpatient and outpatient surgeries, no. of ER visits.	No. of physicians, no. of FTE non-medical staff, net plant assets.	None	None
Malmquist productivity change (including when some outputs are undesirable)					
Weng et al. (2009)	65 Iowa hospitals between 2001 and 2005.	Average speeds of: treatment per case, swing bed service, no. of admitted patients, no. of swing bed patients.	No. of staff members, no. of available beds.	None.	None.
Arocena and Garcia-Prado (2007)	20 Costa Rican public hospitals between 1997–2001.	No. of casemix-adjusted discharges, no. of casemix-adjust. outpatient services.	No. of FTE physicians, no. of FTE nurses, no. of beds, expenditure on goods and services.	None.	No. of casemix-adjusted hospital readmissions.
Chen (2006)	40 Taiwanese public and private hospitals.	No. of seps, no. of surgeries, no. of intensive cares, no. outpatient visits.	No. of doctors, no. of nurses, no. of beds, cost of other medical supplies, no. of doctors and nurses per department.	Second stage regression of public status, severity of illness, Herfindahl index.	ALOS and occupancy rate in a second-stage regression
Sola and Prior (2001); Prior (2006)	8 private and 12 public hospitals for 1990–1993.	No. of acute days, no. of long stay days, intensive days, no. of visits.	No. of FTE health staff, no. of FTE other staff, no. of beds, cost of materials.	None	No. of infections.
Maniadakis and Thanassoulis (2000)	75 Scottish hospitals for 1991-92 to 1995-96.	No. of ER patients, no. of inpatients, no. of day cases, no. of outpatients.	No. of doctors, no. of nurses, no. of other staff, no. of beds, cubic metre floor space.	None	None

(Continued next page)

Table E.1 (continued)

Author(s) and year published	*No. of hospitals and year(s)*	*Dependent variable*	*Independent variables*	*External factors*	*Quality or patient safety*
Webster, Kennedy, Johnson (1998)	280 private hospitals for 1991-92 to 1994-95.	No. of occupied bed days.	No. of FTE staff, no. of beds, cost of materials.	None	None
Linna (1998)	Finnish hospitals from 1988 to 1994.	No. of inpatient admissions, no. of AandE visits.	Hourly wage index, index on local government expenditure, time.	RandD variable, teaching dummy.	Readmission rate
Färe, Grosskopf, Lindgren and Poullier (1997)	19 OECD countries from 1974 to 1989.	No. of bed days, no. of discharges.	No. of physicians, no. of beds; No. of physicians per person, beds per person.	None.	Life expectancy for women over 40, reciprocal of infantry mortality rate.
Burgess and Wilson (1995)	1545 profit, non-profit, Vets Aff., and Local Govt hospitals for 1985–1988.	No. of inpatient days, no. of casemix separations, no. of long stay days, no. of outpatients, no. of ER surgeries, no. of inpatient surgeries.	No. of registered and practice nurses, no. of other clinical staff, no. of non-clinical staff No. of acute and long-term beds, value of capital, casemix severity.	None.	None.
Färe, Grosskopf and Valdmanis (1989)	39 Michigan hospitals with 200+ beds in 1982.	No. of acute care patients, no. of ICU patients, no. of emerg. patients, and no. of surgeries.	No. of doctors, no. of FTE non-doctor staff, no. of admissions, no. of beds.	None.	None.

	No. of hospitals and year(s)	*Dependent variables*	*Independent variables*
Patient-level modelling			
Chua, Palangkaraya and Yong (2008)	130 Victorian public hospital admitted patients with heart disease, 2000-01 to 2004-05.	Aggregate index of standardised hospital mortality rate	No. of episodes of care, proportion with: heart disease, admissions via emerg. department, old, with high Charlson score, and with private health insurance. Dummies for hospital location and status
Jensen, Webster and Witt (2007)	130 Victorian public hospitals admitted patients with heart disease, 1996 to 2005.	Readmission for AMI within 6 months, or death within 30 days of admission, mortality within 30 days of an unplanned 6-month readmission.	Charlson comorbidity index, gender, country of birth, Indigenous status, marriage status, SEIFA index, hospital status (private, public teaching, public non-teaching).
Dormont and Milcent (2004)	36 French public hospitals 1994–1997.	Average cost per stay, for acute myocardial infarction	Gender, age profile, length of stay, hospital admission, home admission, methods of treatment.

Some lessons from Australian and overseas studies

An examination of the Australian studies provides the following indicative conclusions:

- private hospitals are less costly than public hospitals (when medical costs are excluded)
- private hospitals give rise to better health outcomes than public hospitals
- for-profit private hospitals are more technically efficient than not-for-profit private hospitals
- metropolitan public acute hospitals are more technically and cost efficient than smaller rural hospitals.

A review of the overseas literature, however, generates some different impressions with respect to the comparison between public and private hospitals:

- public hospitals are generally more technically efficient than not-for-profit hospitals, which in turn are more efficient than for-profit hospitals (for example, Hollingsworth 2008)
- teaching hospitals are generally less efficient than non-teaching hospitals, possibly due to their more complex workloads (for example, Hollingsworth 2008)
- larger hospitals tend to be more efficient than smaller hospitals, possibly due to greater opportunities for scale economies (for example, Prior 2006; Vitikainen et al. 2009)
- urban hospitals tend to be more efficient than non-urban hospitals (for example, Färe, Grosskopf and Valdmanis 1989).

These, sometimes contradictory, impressions should not be generalised for public and private hospitals in Australia, and possibly overseas because of the:

- limited scope of the studies
- inadequate representation of hospital services
- inadequate representation of health outcomes, quality and patient safety
- method by which factors outside the control of hospitals are controlled
- country-specific dimensions that affect the way in which public and private hospitals are managed and the services they provide.

Even though the Commission is unable to draw firm conclusions about the studies' findings, lessons can be drawn about the methods employed in each of these studies.

Scope of studies

To date, no known Australian study has examined the comparative performance of public and private hospitals nationally. Of the studies reviewed by the Commission, most Australian studies examined the performance of public hospitals of one jurisdiction (commonly New South Wales or Victoria) (Chua, Palangkaraya and Yong 2008, 2009; Jensen, Webster and Witt 2007; Mangano 2006; Paul 2002; SCRCSSP 1997; Wang and Mahmood 2000a, 2000b; Yong and Harris 1999). Only three studies in the Commission's literature review examined the performance of both public and private hospitals, and these were limited to one jurisdiction (Butler 1995; Chua, Palangkaraya and Yong 2008, 2009). Only one study was conducted on a national scale, but was limited to private hospitals (Webster, Kennedy and Johnson 1998).

Inadequate representation of hospital services

A hospital's performance should, ideally, be judged in terms of the cost of providing incremental improvements to its patients' health outcomes (Melbourne Institute of Applied Economic and Social Research, sub. 16). However, this is a problem for hospital-level studies because health-outcome measures cannot be readily constructed.[1] Instead, hospital performance is typically modelled by separately accounting for the intermediate outputs of hospitals (such as inpatient services, emergency department visits, and outpatient services) and the measurable aspects of quality and patient safety.

While the majority of Australian studies have sought to adjust for the casemix differences of inpatient services, not all have included emergency department visits and outpatient services as intermediate outputs (for example, Chua, Palangkaraya and Yong 2009; Mangano 2006; SCRCSSP 1997; Webster, Kennedy and Johnson 1998). This is particularly important when comparing public and private hospitals, given that relatively more public hospitals operate emergency departments than private hospitals.

Health outcomes, quality and patient safety

While some studies have directly measured patient health outcomes (for example, Chua, Palangkaraya and Yong 2008; Jensen, Webster and Witt 2007), the majority of Australian studies either ignored or only gave a cursory treatment to patient

[1] This tends not to be an issue for patient-level studies (which make use of the incidence of mortality) and country-level studies (which make use of life expectancies and disability-adjusted life expectancies).

health outcomes, quality and patient safety. The same can be said for most of the overseas studies.

There appear to be two broad approaches to measuring quality and patient safety:

- Indirect (or proxy) variables are used to describe the level of patient care in a hospital. These include the average length of stay, the occupancy rate, and the ratio of clinical workforce per bed or patient (for example, Chen 2006; Ferrier and Valdmanis 1996; Herr 2008).
- Direct variables of quality and patient safety. The most commonly used measures are readmission rates and mortality rates (for example, Linna 1998; Nayar and Ozcan 2008; Yaisarwang and Burgess 2006).

Factors outside the control of hospitals

Finally, most Australian studies did not adequately account for factors outside the control of hospitals (for example, Queensland Department of Health 2004; Webster, Kennedy and Johnson 1998). Again, the same can be said for many overseas studies (for example, Färe, Grosskopf and Valdmanis 1995; Maniadakis and Thanassoulis 2000).

Where external factors have been taken into account, they have tended to include:

- patient characteristics, such as:
  – patient comorbidities (for example, Zuckerman, Hadley and Iezzoni 1994)
  – gender and age profile of patients (for example, Zuckerman, Hadley and Iezzoni 1994)
  – patient socioeconomic characteristics (for example, Jensen, Webster and Witt 2007; Paul 2002)
- financial incentives of hospitals, such as:
  – source of patient revenues — the extent to which a hospital is funded using a prospective payment system or operates under capped budgets (for example, Brown 2003; Dor and Farley 1996)
  – market power of the hospital (for example, Chua, Palangkaraya and Yong 2009; Rosko and Chilingerian 1999)
- geographic characteristics, such as:
  – hospital location (for example, Granneman, Brown and Pauly 1986; Herr 2008)

- hospital roles, functions and specialisation, such as:
  - whether it is a teaching or university hospital, the extent of research and development (for example, Linna 1998; Yong and Harris 1999)
  - the presence of specialist facilities or technologies (for example, O'Neill 1998; Yaisarwang and Burgess 2006)
  - the extent to which the hospital participates in inter-hospital transfers (for example, Jacobs 2001).

There is a risk that hospital efficiency estimates would be biased if any of these 'external' factors are ignored. Worthington (2004), for example, argued that ignoring patient characteristics could result in estimates of hospital efficiency representing differences in patient characteristics rather than the hospital's performance.

Ownership or financial incentives?

One striking difference between the Australian and overseas studies is the comparative efficiency of public and private hospitals. While it is conceivable that private hospitals are more (cost) efficient in Australia and less technically efficient overseas, it is possible that these findings reflect other confounding factors (Hollingsworth 2008). One such factor is the way in which public and private hospitals are funded.

There are three mechanisms by which publicly- and privately-owned hospitals are funded:

- prospective payment systems (PPS) — in which hospitals are paid a fixed price for each unit of output they provide
- per diem funding — where hospitals are paid for each patient in accordance with the number of days spent in hospital
- global budget caps — where hospital budgets are capped.

Publicly-owned hospitals have traditionally been funded under capped global budgets and privately-owned hospitals have been funded by private insurers on a per diem basis. PPS funding (or casemix funding as it is known in Australia) is increasingly being adopted to fund both public and private hospitals in Australia and overseas.

When hospitals are compared in terms of their funding mechanisms, a tentative conclusion is that PPS funding is at least as efficient as funding under capped budgets, and that both are more efficient than per diem funding. For example:

- US hospitals funded under the Medicare PPS were observed to have lower costs than those that did not (Rosko and Chilingerian 1999; Zuckerman et al. 1994)
- Norwegian hospitals that were funded by PPS were found to be more efficient than those that were funded by global budgets (Biørn et al. 2003)
- even though public hospitals in Germany were found to be more cost and technically efficient than private hospitals (Herr 2008), the author noted that this might be because public hospitals were funded under global budget caps and private hospitals were paid on a per diem basis
- there is some evidence that US hospitals that receive prospective payment funding are more technically efficient than those that are funded on a per diem basis (Bedard and Wen 1990; Morey and Dittman 1996), though Borden (1988) came to the opposite conclusion
- the introduction of PPS funding arrangements in Taiwan has led to improvements in productivity and quality, and improvements were strongest among public hospitals. PPS was observed to lead to excessive medical services among private hospitals (Chen 2006)
- Löthgren (2000) and Gerdtham et al. (1999) each found that Swedish hospitals funded with capped budgets were more efficient than those that were funded on an output basis, but the authors acknowledged that they did not distinguish between PPS and per diem funding arrangements.

A related confounding factor is that the generosity of the payer may also make a difference to the reported efficiency. For example, Dor and Farley (1994) found that US Medicare and private health insurance (PHI) pay relatively more than Medicaid (and residual purchasers) and as a consequence, experienced higher hospital costs. A third confounding factor is the role played by health management organisations, which Brown (2003) found to make private hospitals more efficient than not-for-profit private hospitals.

A key lesson for this study is to distinguish between ownership and funding models, to the extent that such data are available.

E.2 Commission’s approach to modelling hospital performance

Hospitals are complex in the services they provide. There is also considerable diversity between them in terms of the services they provide and their patients. Hospitals can be compared in terms of technical and cost efficiency.

The Commission’s analysis in this report focuses on understanding the factors that drive technical efficiency in the hospital sector. To achieve this, the first stage of analysis is based on a pooled dataset of all hospitals in the sample for a single year (2006-07). The pooled sample allows for variations in efficiency to be detected on the basis of hospital size, indicating the extent to which scale economies exist across the hospital sector. The pooled sample also allows for the number of observations in the dataset to be preserved, which improves the accuracy of the estimated model.

The Commission intends to undertake further analysis over coming months of hospital performance in terms of both hospital outputs and costs, using a longer dataset from 2003-04 to 2006-07. It is intended that the results from this analysis will be published in March 2010.

The following discussion provides an overview of the techniques the Commission has used for this first stage of its analysis.

Production function

In the first stage of analysis, hospital performance is modelled on the basis of an output-oriented production function, where a hospital’s output (volume and type of services provided) is assumed to depend on its use of inputs (resources such as staff and capital). In the context of an output-oriented production model, hospital performance is measured in terms of the hospital’s capacity to maximise its output for a given set of inputs. This is known as technical efficiency (Coelli et al. 2005).

The efficiency of an individual hospital can be assessed by comparing its actual output to the optimal level of output that could be achieved if the hospital adopted best-practice production techniques. Using the available data in the sample, a production ‘frontier’ is constructed which represents the optimal level of output achievable. In this method of benchmarking hospital performance, in general, production functions are widely used because they do not rely on any assumptions about the behaviour of hospitals in relation to inputs and output prices.

The production model is founded on the following form:

$$y_i = f(x_i) \tag{1}$$

where y_i is the output and x_i is the vector of inputs for hospital i. Following Kumbhakar and Lovell (2000), at this stage of analysis, the production model is expressed as a deterministic function. Random variation will be introduced at a later point.

When applied in a benchmarking framework, the optimal level of output that could be achieved by a best-practice hospital is represented by:

$$y^* = f(x) \tag{2}$$

where y^* is the output of the best-practice hospital, and x is the vector of inputs that generates the optimal level of output.

From these equations, the technical efficiency (TE) of a given hospital can be computed. The efficiency score for a given hospital reflects the extent to which its output falls below the optimal level of output achievable. Specifically, the scope of technical efficiency (TE) of hospital i is measured by the ratio of its actual output (y_i) to the optimal output achievable (y^*), as defined by:

$$TE_i = \frac{y_i}{y^*} \tag{3}$$

The value of TE_i will be between zero and one, where a value closer to one indicates that the hospital is closer to full technical efficiency.

Estimating the frontier

The assessment of hospital performance involves estimating the 'frontier' that benchmarks the optimal level of performance, and then computing the extent to which each hospital falls below this frontier. One of the most commonly applied methods to undertake these steps is stochastic frontier analysis (SFA). This econometric technique was originally developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) to study the efficiency and productivity of firms. A good introductory summary of SFA can be found in Coelli et al. (2005) and a more advanced treatment in Kumbhakar and Lovell (2000).

In SFA, the extent to which each hospital falls short of the benchmarked frontier (that is, the extent of its inefficiency) is captured by the error term of the regression. A key feature of SFA is that the error term is divided into two components:

- random error due to measurement errors, the omission of variables which cannot be measured, and other random factors that affect output
- an error term that captures the extent to which the individual hospital falls short of maximising its output for a given set of inputs (that is, its technical inefficiency).

When introducing the two error components into the production function, the stochastic frontier regression is modelled as:

$$y_i = f(x_i) + (v_i - u_i) \tag{4}$$

where y_i is output, x_i is a vector of inputs, v_i is the random error, and u_i is the measure of technical inefficiency), for hospital i. It is assumed that both v_i and u_i are independently and identically distributed; that v_i follows a normal distribution with a zero mean and constant variance; and that u_i is a non-negative value and follows a non-normal distribution that can be pre-defined as half-normal, truncated half-normal, exponential or gamma.

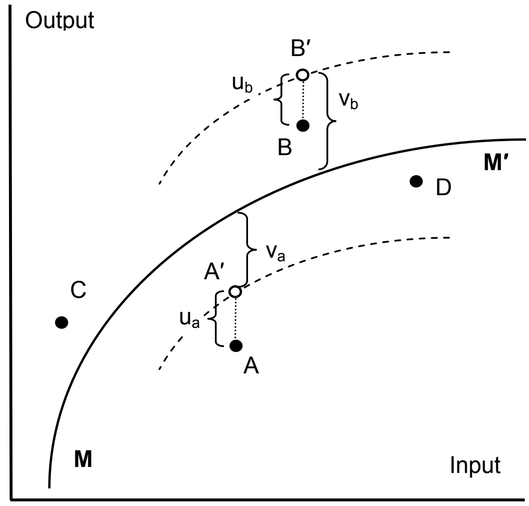
The error component u_i is interpreted to capture the technical inefficiency of each hospital. Although the choice of the distribution for u_i will affect the calculated efficiency scores, there is evidence to suggest that it has a relatively lesser effect on the ordinal rankings of the scores within a sample (Kumbhakar and Lovell 2000). Conventionally, the technical efficiency score of each hospital is expressed in logarithmic form such that the measured effects can be interpreted as proportional changes, as follows:

$$Index_i = \exp(-u_i) \tag{5}$$

Figure E.1 illustrates the estimation of the production model using SFA regression. The estimated function plots the relationship between input and outputs, shaped to reflect diminishing returns to scale. Firstly, the model is estimated to pass through the mean of the data (in this example, observation points *A*, *B, C* and *D*). This generates the deterministic component of the production function, *MM′*.

Next, the production function *MM′* is adjusted for each hospital by the component of the random error that cannot be attributed to technical inefficiency (v_i). This establishes each hospital’s stochastic frontier. In this example, the production function *MM′* is adjusted by the amounts v_a and v_b for hospitals *A* and *B* respectively, establishing their respective stochastic frontier points *A′* and *B′*. If v_i is positive, the stochastic frontier will shift above the deterministic production function (as for hospital *B*). If this random error is negative, the stochastic frontier will shift below it (as for hospital *A*).

Figure E.1 **Illustration of SFA production model**



Source: Adapted from Coelli et al. (2005).

Having established a stochastic frontier for each hospital that accounts for hospital-specific random error, the difference between each hospital's actual output and its frontier can be attributed to its technical inefficiency (as represented by the error component u_i). In this example, the technical inefficiency of hospitals *A* and *B* is represented by u_a and u_b respectively.

SFA offers some recognised advantages of over alternative estimation techniques. Compared to standard ordinary least squares (OLS) regression, SFA formally allows a role for random error in the estimation of efficiency measurements. OLS estimation would construct a production frontier through the mean of the data (as in the initial step of SFA) but would not adjust for hospital-specific random error when computing the distance between the frontier and actual output (as in the next step of SFA). As a further point of difference, SFA allows for a component of the errors to be skewed (that is, non-symmetrically-distributed) whereas OLS imposes the assumption that the whole error term is symmetrically distributed.

Another common technique applied in efficiency measurement is data envelopment analysis (DEA), which uses piece-wise linear programming to estimate the production function. A key difference between DEA and SFA is that SFA generates parameters on the basis of a functional form, whereas DEA generates estimates based on the values of the observations rather than an assumed functional form (Coelli et al. 2005).

The non-parametric approach of DEA may be considered an advantage because it means that fewer restrictions are imposed on the model, and there are less risks associated with misspecified functional forms (Nguyen and Coelli 2009). However, non-parametric estimation presents several drawbacks. First, the significance of the relationship between inputs and outputs cannot be statistically tested (PC 1999a; Siciliani 2006). Without testing their significance, explanatory variables may be inappropriately included in the frontier model. Second, non-parametric estimation is more sensitive to the presence of outliers, which may distort the construction of the production frontier and overstate the computed efficiency scores (Siciliani 2006). Third, non-parametric estimation does not formally allow for technical inefficiency to be distinguished from all other hospital-specific random error (Nguyen and Coelli 2009). For these reasons, the Commission has chosen to undertake SFA in favour over DEA.

Accounting for quality of care

While estimating the volume of output delivered as a function of inputs, the production model also needs to account for hospital resources that are allocated to the quality of care that a hospital delivers, and include appropriate measures of quality in the regression.

Before their inclusion, quality indicators need to be adjusted to control for differences in the risk characteristics of the patients admitted to different hospitals. In this context, risk refers to the extent to which patients' characteristics affect the likelihood of a successful treatment outcome, independent of the actions of the hospital. It may be expected that a hospital which admits relatively 'low-risk' patients will require fewer resources per separation, meaning that it can deliver a relatively larger volume of output for a given level of input. This will gives rise to higher efficiency scores, all other factors equal, compared to a hospital which admits relatively high-risk patients.

To adjust for patient characteristics, the Commission has used hospital-level variables that reflect the composition of each hospital's patient mix. For example, patients' gender is captured by a measurement of the proportion of a hospital's patients who are female.

Many of the available hospital-level quality indicators are measured as rates (for example, mortality rates and readmission rates). This means that the estimated regressors of the model must be specified to fall between pre-determined upper and lower bounds, as estimated by a Tobit model:

$$\begin{aligned} q_i{*} &= f(z_i) + \varepsilon_i \\ q_i &= q_i{*} \quad \text{if } q_L < q_i^* < q_U \\ &= q_L \quad \text{if } q_i^* \le q_L \\ &= q_U \quad \text{if } q_i^* \ge q_U \end{aligned} \tag{6}$$

where q^* is the latent variable of the quality indicator, q_i is the observed value of the quality indicator, z_i are the patient characteristics assumed to influence q^*, q_L and q_U are the lower and upper bounds of the quality indicator, and ε_i is the error term, for hospital *i*. As with other censored regression models, parameters are estimated using maximum likelihood methods.

The estimated results of the Tobit regression are used to compute the standardised value of the quality indicator. This is computed by dividing the observed values by the estimated values. This is commonly applied to mortality rates, where a standardised value less than one indicates that a hospital is performing better than expected (the actual mortality rate is lower than predicted), while a value greater than one indicates an unfavourable performance (the actual mortality rate is higher than predicted) (Ben-Tovim et al. 2009). The standardised values of the quality indicator are included as regressors in the output equation.

Other factors influencing efficiency

The production function estimates a hospital's level of output as a direct function of its inputs. However, it is acknowledged that there are additional factors — known as covariates — that influence a hospital's production process and, therefore, its reported efficiency score. The appropriate method to incorporate such factors into the model depends on whether the factors are considered to be within the control of the hospital or not.

Factors which are considered to be *outside* of the hospital's control contribute to setting the position of the frontier. In this case, the covariates can be included in the production model, regressed directly against output. Factors which are considered to be *within* the hospital's control contribute to variations in efficiency below the benchmarking frontier. In this case, the covariates can be modelled as a function of the random errors of the output model.

The two steps of this regression are defined as:

$$\ln y_i = \beta_0 + \sum_{m=1}^{M} \beta_{mi} \ln x_{mi} + (v_i - u_i) \tag{7}$$

$$\mu_i^u = \delta_0 + \sum_{j=1}^{J} \delta_{ji} \ln z_{ji} + \xi_i \tag{8}$$

where y_{i}, x_i, v_i and u_i are as previously defined, μ_i^u is the conditional mean of u_i, z_i is the vector of additional factors, and ξ_{i} is the error term. Factors which are within the hospital's control are included in x_i, whereas factors which are outside of the hospital's control are included in z_i.

Model specification

Given that hospitals produce a range of outputs (rather than a single output), a stochastic frontier specification which allows for multiple outputs is used. Known as an (output) stochastic distance function, it is defined as:

$$D_{Oi}(x_i, y_i) = \min\{TE : y_i / TE \in P(x_i)\} \tag{9}$$

where y_i is the vector of outputs, x_i is the vector of inputs, and TE is the minimum amount by which output can be reduced and still remain producible with the given set of inputs (Kumbhakar and Lovell 2000).

When applied to the production model, several functional forms are applicable. One of the most basic and widely-applied functional forms is the Cobb-Douglas model, which regresses the terms in first-order form only. The functional form can be expanded with the inclusion of second-order quadratic and cross-terms that allow for interaction effects among the variables, as is applicable for a multi-output, multi-input production model (Paul 2002). The following equation specifies a production model in an expanded multi-input, multi-output form, known as a transcendental logarithmic (translog) distance function:

$$\begin{aligned}\ln D_{Oi}(x_i, y_i) = \alpha_0 &+ \sum_{m=1}^{M} \alpha_m \ln y_{mi} + \sum_{k=1}^{K} \beta_k \ln x_{ki} \\ &+ 0.5 \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln y_{mi} \ln y_{ni} + 0.5 \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} \\ &+ \sum_{k=1}^{K} \sum_{m=1}^{M} \delta_{km} \ln x_{ki} \ln y_{mi}\end{aligned} \tag{10}$$

where D_{Oi} is the distance to the frontier (taking a value between 0 and 1), y_k represents output, x_m represents input, M is the number of outputs, and K is the number of inputs. As is common practice, all terms are specified in natural logarithms, so that the measures represent proportional values rather than absolute levels. The first line of equation (10), comprising first-order variables only, represents the standard Cobb-Douglas form. The inclusion of the higher-order squared terms in the second and third lines represents the complete translog function.

The Cobb-Douglas model is widely applied as it is more parsimonious and computationally simpler to estimate than the higher order, more flexible functional forms. Compared to the more flexible functional forms, the limited number of parameters in the Cobb-Douglas model means there is less risk of multicollinearity and less loss in degrees of freedom. Furthermore, the coefficients of the Cobb-Douglas model are relatively more straightforward to interpret as elasticity values.

However, the simplicity of the Cobb-Douglas model restricts its estimation power. For example, the introduction of the squared terms can be used to detect scale economies, while the further inclusion of cross-terms in the translog model can detect elasticity of substitution between inputs, production coefficients between inputs and outputs, and marginal rates of transformation between outputs (Nguyen and Coelli 2009; Siciliani 2006). All this means is that the Cobb-Douglas model is a relatively inflexible form and is not likely to completely fit the curvature of the production function.

In this analysis, the Commission estimated both the Cobb-Douglas and a restricted version of the translog model and then compared measures of their goodness-of-fit and predictive performance. Higher-order functional forms are expected to provide a more accurate fit of the observed data. These models, therefore, are expected to generate higher efficiency scores because they contain less unexplained variation that would otherwise be attributed to random error or inefficiency. Nguyen and Coelli (2009) presented a meta-analysis of hospital efficiency studies which substantiated this observation. When selecting the model to apply, it is also recognised that higher-order functional forms are likely to incur more computational difficulties, due to the large number of multiplicative parameters contained in the model.

For the models to comply with standard economic regularity properties, and for an empirical equation to be estimated, homogeneity constraints need to be imposed (Coelli et al. 2005; O'Donnell and Coelli 2005). The constraint of homogeneity of degree one in outputs is defined as:

$$\sum_{m=1}^{M} \alpha_m + \sum_{m=1}^{M}\sum_{n=1}^{M} \alpha_{mn} \ln y_n + \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} \ln x_k = 1 \tag{11}$$

This constraint is satisfied if:

$$\sum_{m=1}^{M} \alpha_M = 1, \quad \sum_{m=1}^{M} \alpha_{mn} = 1 \ \text{ for all } n, \quad \text{and } \sum_{k=1}^{K}\sum_{m=1}^{M} \delta_{km} = 0 \ \text{ for all } k. \tag{12}$$

According to Lovell et al. (1994), the homogeneity condition is equivalently satisfied by normalising equation (10) by one of the outputs (y_L), as follows:

$$\begin{aligned} \ln\left(\frac{D_i(x_i, y_i)}{y_{Li}}\right) &= \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln\left(\frac{y_{mi}}{y_{Li}}\right) + \sum_{k=1}^{K} \beta_k \ln x_{ki} \\ &+ 0.5 \sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \alpha_{mn} \ln\left(\frac{y_{mi}}{y_{Li}}\right) \ln\left(\frac{y_{ni}}{y_{Li}}\right) + 0.5 \sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki} \ln x_{li} \\ &+ \sum_{k=1}^{K}\sum_{m=1}^{M-1} \delta_{km} \ln x_{ki} \ln\left(\frac{y_{mi}}{y_{Li}}\right) \end{aligned} \tag{13}$$

This can be condensed to:

$$\ln\left(\frac{D_i}{y_{Li}}\right) = TL(x_i, \frac{y_i}{y_{Li}}, \alpha, \beta, \delta) \tag{14}$$

where $TL(.)$ refers to the translog function.

The expression can be re-arranged and specified as a stochastic distance function with the inclusion of the technical efficiency component and random error term, as follows:

$$\ln D_i - \ln y_L = TL(x_i, \frac{y_i}{y_{Li}}, \alpha, \beta, \delta) \tag{15}$$

$$-\ln y_L = TL(x_i, \frac{y_i}{y_{Li}}, \alpha, \beta, \delta) - \ln D_i \tag{16}$$

$$-\ln y_M = TL(x_i, \frac{y_i}{y_{Mi}}, \alpha, \beta, \delta) + (v_i - u_i) \tag{17}$$

where $-\ln D_i = (v_i - u_i)$ and v_i and u_i are as previously defined.

E.3 Data sources

Data for public and private hospitals, detailed at both patient and establishment levels, had to be sourced from several different data collections and then merged to create the final data set. Details of the data sources and the process of accessing and assembling the dataset are outlined below.

Public hospital data

Establishment-level data for public hospitals were drawn from the National Public Hospital Establishments Database (NPHED), which is held by the Australian Institute of Health and Welfare (AIHW).

Patient-level data for public hospitals were drawn from the National Hospital Morbidity Database (NHMD), which is also held by the AIHW.

Private hospital data

Establishment-level data for private hospitals were drawn from the Private Health Establishments Collection (PHEC), which is held by the Australian Bureau of Statistics (ABS). The collection is drawn from a census of private hospitals (acute and psychiatric) and free-standing day facilities (ABS 2008f).

Patient-level data for private hospitals were drawn from the National Hospital Morbidity Database (NHMD), which is held by the AIHW. Although the PHEC held by ABS contains patient data, the Commission does not regard these data to be useful for this study because they are not casemix-adjusted and do not include the details required on patient morbidity.

Accessing hospital data

To access data for the purpose of this analysis, the Commission obtained the consent of the state and territory health departments for the AIHW to release public hospital patient and establishment data to the ABS. The Commission also obtained the consent of 130 privately-owned hospitals for the state and territory health departments to provide additional information that would allow the private hospital patient data held by the AIHW to be matched with the establishment-level data held by the ABS. After excluding free-standing day facilities and non- and sub-acute facilities, there were 122 private acute hospitals in the sample.

The ABS undertook the analysis with the assistance of the Commission. This arrangement was to facilitate access to the private hospital information held by the ABS, and to safeguard the data drawn from both ABS and AIHW sources.

Assembling the data

The first step in assembling the dataset was to match the patient-level morbidity data needed with each hospital. The morbidity data were then aggregated to the establishment-level data. Hospital-level patient variables were created which represented the shares of patients with given patient-level characteristics.

In the case of private hospitals, the patient-level data contained in the NHMD (held by the AIHW) had to be matched with the corresponding establishment-level data contained in the PHEC (held by the ABS).

Furthermore, several adjustments to the dataset needed to be made to handle reporting inconsistencies.

- A number of Victorian hospitals are incorporated into regional networks. As a result, much of the establishment-level data for these hospitals are available at the network level and needed to be rescaled to match establishment-level data. Rescaling was achieved by disaggregating the networked data on the basis of the number of hospitals contained in the network, and weighting the values on the basis of each hospital's number of casemix-adjusted separations. To capture potential efficiency effects of belonging to a network and indicate networked hospitals, a dummy variable denoting network membership was created.
- A single observation was provided for Tasmanian public hospitals. The names and the number of beds are known for each Tasmanian hospital, but not the number of casemix-adjusted separations. The establishment- and patient-level data of the single Tasmanian observation were disaggregated on the basis of the number of acute and non-acute beds. On the basis of the hospital's name and address, the Australian Standard Geographic Classification – Remoteness Area (ASGC-RA) classification of each hospital was computed. The limitation of this approach is that it blurs the distinction between the functions of Tasmanian acute and non-acute hospitals.

- A single observation was provided for Tasmanian private hospitals. However, since the number of private hospitals in Tasmania was not known with certainty, the observation could not be disaggregated, although the scale of these hospitals is expected to be very small.

Representativeness of the sample

Ideally, the data contained in the sample for analysis should be representative of all Australian hospitals. In this study, however, data on private hospitals was only made available on a voluntary basis and therefore do not necessarily represent the full range of private hospitals in Australia.

In particular, a larger proportion of for-profit private hospitals made their data available to this study than not-for-profit private hospitals. For-profit hospitals accounted for 57 per cent of Australia's 289 private acute hospitals (AIHW 2009a). In contrast, 85 per cent of the private hospital sample comprises for-profit hospitals.

This presents two concerns. First, it means that the not-for-profit hospitals are relatively under-represented compared to for-profit hospitals. Second, it means that the dataset is potentially subject to sample-selection bias, as the private hospitals included in the study are not a random selection. If the factors which affect hospital efficiency also affect the likelihood that a hospital agreed to participate in the study, the efficiency estimates may be biased.

The Commission considered potential methods to overcome this sampling issue, including the Heckman correction procedure (Heckman 1976). However, given that there is no common statistical technique to address this issue in this field of analysis, and given the time constraints of this study, the Commission's analysis proceeded without such sampling correction. It is acknowledged, therefore, that the findings only apply to the hospitals included in the study, and the Commission cautions readers from drawing conclusions for all hospitals in Australia.

In its further analysis, the Commission intends to examine the degree to which the sample of hospitals included in the analysis adequately represents the population of hospitals Australia-wide, and further investigate methods to address potential sampling bias.

Final dataset

The AIHW provided a range of hospital-level data from the NHMD that correspond to 703 public hospital observations in its NPHED and 130 private hospital observations that agreed to participate in this study. After removing acute, sub-acute non-acute, psychiatric hospitals and free-standing day facilities, there were 508 acute hospital observations in the sample. Of these, 368 were public hospitals and another 18 that are ordinarily classified as public hospitals by the AIHW, but which are typically managed by non-government entities to provide public hospital services for state and territory governments. These are referred to as 'public contract' hospitals. There were also 122 private acute hospital observations in the sample (table E.2).

Table E.2 **Hospital sample by size, region and sector, 2006-07[a]**

	Major cities			*Outside major cities*			*All hospitals*
	Public	Private	Public contract	Public	Private	Public contract	
Very large	53	np	np	15	np	–	98
Large	21	16	np	16	6	np	70
Medium	14	26	–	31	12	–	83
Small & very small	8	np	–	210	np	np	257
All hospitals	**96**	**93**	**15**	**272**	**29**	**3**	**508**

a Hospital location is defined by the Australia Standard Geographical Classification (ABS 2001). Hospital size is defined by number of casemix-adjusted separations per year, where *very large* refers to 20 001 or more casemix-adjusted separations; *Large* is defined as 10 001 to 20 000 casemix-adjusted separations per year; *medium* is defined as 5001 to 10 000 casemix-adjusted separations per year; *small* is defined as 2001 to 5000 casemix-adjusted separations per year; and *very Small* is defined as 2000 or fewer casemix-adjusted separations per year. Sample refers to all the acute hospitals included in the Commission's multivariate analysis. **np** Not published due to confidentiality. – Nil or rounded to zero.

Source: Productivity Commission estimates based on unpublished ABS and AIHW data.

E.4 Variables

This section describes the variables selected for use in the analysis and discusses some associated sampling issues. Full details of the variables used in the analysis, including their definitions and summary statistics, are presented at the end of the section in table E.3.

Drawing on the literature review, variables used in the analysis are grouped as:

- outputs
- quality and patient safety
- inputs
- other factors that describe establishment characteristics, hospital roles and functions, financial incentives and patient characteristics.

Outputs

Ideally, a hospital's performance should be measured in terms of patient outcomes. Individuals seek hospital services in order to improve their physical and emotional wellbeing relative to what would otherwise be the case. However, it is not practicable to directly measure changes to patient health outcomes. Instead, the approach used here is to measure health outcomes along two dimensions — hospital outputs and quality of care.

Hospitals are complex entities that provide a wide range of services. This is a strong argument that hospitals should be modelled as multi-input multi-output firms (Butler 1995). Hospitals vary significantly in terms of the surgical and medical procedures they provide. Many provide some sort of outpatient services, emergency departments and a number provide teaching services while others maintain research and development programs.

Inpatient services

The Melbourne Institute of Applied Economic and Social Research suggested that a reasonable compromise would be to model inpatient activity at the major diagnostic category (MDC) level:

> … considering the need to keep model specification parsimonious in empirical analysis, this approach probably represents a reasonable compromise. (sub. 16, p. 4)

However, a concern is that since there are 23 MDCs, this would represent too many variables, particularly when more complex functional forms are considered. The categories of inpatient outputs used in this study are:

- acute separations — casemix-adjusted separations for MDCs 1 to 9, 11 to 13, 16 to 18, 21 and 22)
- pregnancy and neonate separations — casemix-adjusted separations for MDCs 14 and 15
- mental and alcohol separations — casemix-adjusted separations for MDCs 19 and 20
- other separations — casemix-adjusted separations for MDC 23
- endocrine, nutritional and metabolic diseases and disorders — casemix-adjusted separations for MDC 10. This was the dependent variable for the model.

Pregnancy and neonate MDCs were kept separate from the majority of acute care separations, as pregnancy and neonates do not generally constitute a disease or illness. Similarly, mental and alcohol separations were also kept separate because of concerns over the robustness of measuring cost weights for these categories.

Public hospital cost weights were used for both public and private hospitals. In the estimation, each of the output categories (except for the last) were normalised by the dependent variable (MDC 10). All variables were expressed in natural logarithms, and where a natural number was reported as zero, its corresponding natural logarithm was changed to zero.

Non-admitted occasions of service

There is no national casemix classification for outpatient services, so there is a greater need to provide a detailed level of aggregation of these hospital activities than it is for admitted patient care. The output categories are:

- accident and emergency services — the number of accident and emergency department presentations or visits
- allied health and other services — the number of occasions of service for allied health, dental and other outpatient services
- mental and alcohol services — the number of mental, alcohol and psychiatric outpatient services
- dialysis and endoscopy — the number of occasions of service for dialysis and endoscopy
- diagnostic services — the number of pathology and radiology services
- outreach services — the number of community services, district nursing and other outreach services.

Each of these output categories were divided by the reference category. Each output was expressed in terms of natural logarithms.

The Commission included a binary variable to indicate whether a hospital is a teaching hospital ('1' if it is teaching hospital, '0' otherwise). However, no distinction was drawn between medical and nursing teaching functions, or the intensity of the teaching effort. The variable represents all forms of teaching functions — major and minor.

Given the procedure of normalising hospital outputs, the coefficients of the output variables on the right-hand side would be expected to take on a positive value. However, to make interpretation simpler, the dependent variable was multiplied by minus one to ensure that the right-hand side output variables take on a negative value. This assists in the interpretation of the coefficients — each of the output variables are expected to take a negative value (reflecting the marginal rate of transformation between the reference category and outputs) and a positive value for each of the inputs.

Quality and patient safety

A number of variables were available to the Commission to measure hospital quality, including:

- in-hospital mortality
- infection rates
- adverse events.

As noted in chapter 7, there are limits to both adverse events and hospital infections data due to under-reporting and the difficulty in attributing the role of hospital in contributing the cause of those events. As a result, these were not considered in this analysis of hospital performance, though they will be reconsidered in further work. Robust data on re-admissions were not available to the Commission.

Drawing on the practice of previous studies, in-hospital mortality rates were used as a measure of the quality of hospital services. Based on a review of literature into the standardisation of hospital mortality ratios (Ben-Tovim et al. 2009), the following variables were included:

- average comorbidity — the average Charlson Index of comorbidity
- distribution of comorbidity — the proportion of hospital separations that were associated with each of the seven indices of comorbidity (0, 1, 2, 3, 4, 5 and 6 or more) (Charlson et al. 1987)[2]
- age — the proportions of patients who are in youngest and oldest age groups
- gender — the proportion of patients who are female
- socioeconomic status — the proportion of patients who reside in areas of the highest quintiles of socioeconomic disadvantage, as measured by the Socio-economic index for Areas — Index of Relative Disadvantage and Advantage (ABS 2008g)

[2] The Commission explored the possibility of employing the Multipurpose Australian Comorbidity Scoring System (Preen et al. 2006) but chose not to use this approach because the data available to the Commission were neither linked between different hospitals or within the same hospital over time.

- remoteness of residence — the proportion of patients whose usual place of residence was in inner regional, outer regional, remote and very remote communities (as defined by the Australian standard Geographic Classification–Remoteness Area)
- Indigenous — the proportion of patients that identified themselves as Indigenous.

Unlike in other studies, no account was made for differences in the procedures undertaken by hospitals, as these are formally considered in the analysis of hospital production.

The Tobit regression generates the predicted mortality rates for each hospital. Using the estimates, risk-adjusted mortality ratios (RAMR) are derived. Lower ratios indicate lower relative mortalities after adjusting for patient differences. If a hospital faces a trade off between improving the quality of care and producing additional services, it is expected that the coefficient of the RAMR variable will be positive with respect to the output variables.

Inputs

Following common practice in this area of analysis, inputs into the production of hospital services include:

- nursing staff — number of nursing staff (measured in terms of full-time equivalents)
- diagnostic staff — number of diagnostic (pathology and radiology) staff (measured in terms of full-time equivalents)
- other staff — number of domestic, administration and other staff (measured in terms of full-time equivalents)
- medical and surgical supplies — expenditure on medical and surgical supplies used
- pharmaceutical supplies — expenditure on pharmaceuticals
- other inputs — expenditure on other hospital inputs, such as administration and clerical, housekeeping, and repairs and maintenance
- beds — number of beds of the hospital as a proxy for hospital capital. This is given by the number of beds licensed in a private hospital, and the number of beds published by the AIHW for public hospitals.

The total number of beds is not a satisfactory measure of the usage of capital in a hospital. The number of beds does not adequately reflect the change in capital stock over time or between hospitals. Ideally, capital measures should be disaggregated into the main categories of hospital activity — such as the number of ICU beds, non-acute beds, palliative care beds, the number of sameday chairs, the number of operating theatres, and so on. Instead, differences in the capital of hospitals were captured with variables that reflected differences in the roles and functions of hospitals (discussed below).

Since the number of doctors working in private hospitals is not known, the number of medical staff has been excluded from the analysis. All efficiency scores derived from the analysis are to be interpreted as the efficiency of the hospital, and not specifically of the hospital and the medical workforce.

Each of the coefficients of these variables, for a Cobb-Douglas specification, is expected to take a positive sign.

Patient-risk characteristics

Although it is posited above that differences in the level of patient risk might be represented in a measure of quality, it is feasible that patient-risk characteristics might directly influence the level of hospital output. For example, more morbid populations may compel hospitals to undertake additional services, to be more productive with the resources that they have. The patient-risk characteristics explored here include the same set described in the section quality and patient safety.

Hospital roles and functions

A number of other variables were included in the analysis to account for the differences between hospitals in terms of the services they provide, the resources they use and the patients they treat.

Admissions from an emergency department — the number of accident and emergency visits divided by the total number of inpatient separations is used as a proxy for the extent to which emergency patients are admitted hospitals. A number of commentators have said to the Commission that the presence of an accident and emergency department can reduce the throughput of inpatient services, particularly if there are insufficient beds available to accommodate the variability of demand. If this were the case, then the coefficient on this variable would be negative.

Same-day separations as a share of total separations — a number of study participants have said to the Commission that private hospitals would appear to be more technically efficient than public hospitals because the former undertake relatively more same-day separations. If same-day separations constitute best practice, and the variable were included in the main model (equation 7), the coefficient on the variable would be positive. If, on the other hand, same-day separations permit hospitals to reach best practice, the coefficient on the same-day separations variable would be positive in the second model (equation 8).

Proportion of patients treated with surgical and other procedures is a variable that describes the extent to which a hospital specialises in surgical and other DRG cases, or conversely, the degree to which public hospitals undertake medical DRG cases. Some participants to this study have argued that a difference between public and private hospitals is the ability of private hospitals to maximise their productivity by specialising in elective surgery procedures, which permits them to operate with higher levels of productivity. On the other hand, public hospitals are unable to refuse medical treatment, and since medical DRG cases have a greater likelihood of being unplanned, medical DRGs become inherently more difficult for public hospitals to manage. Ignoring the differences between surgical and medical cases has the potential to distort the interpretations of efficiency measures.

As noted earlier, the lack of detailed capital data limits the ability of this type of analysis to distinguish between hospitals on the basis of their inputs. Instead, a number of surrogate variables were used to test the extent to which there were such differences.

Hospital services can also differ in terms of the level of acuity in the services they provide. For example, hospitals that maintain level III intensive care units have different resourcing requirements to those than those that maintain residential aged care units and palliative care units. These three influences are represented with three binary variables (with ‘1’ indicating that these services or units are provided, ‘0’ if they are not).

Proportion of patients who are not treated as public patients is a proxy measure for the different levels of resources used by hospitals to treat public and non-public patients. It includes patients who are funded by private health insurance, Department of Veterans’ Affairs, third-party motor vehicle accident, workers’ compensation patients, and self-funding. Public hospitals are funded with capped budgets, at least when treating public patients. In contrast, the funding of non-public patients is uncapped. It is possible that differences between capped and uncapped funding enables hospitals to provide different service levels to public and non-public patients.

Evans and Walker indices

The Evans and Walker information indices are measures of the relative complexity of work undertaken by hospitals. They are based on work undertaken by Thiel (1967) in the field of information theory. Evans and Walker (1972) postulated a relationship between the complexity of work undertaken by a hospital and the information the hospital learns from undertaking that work. By establishing a link between complexity and information gain, the authors were able to adapt information indexes as proxies for hospital complexity.

In general, the amount of information a hospital learns from an admission is inversely related to the likelihood of that case occurring within the system and the likelihood of that hospital treating that particular case. If an event is almost certain to take place, such as a routine case from which the hospitals learns little, the hospital attracts a relatively low index of information gain (Butler 1988). In contrast, more complex (and presumably rarer cases) attract more information gain.

Evans and Walker offer two indices. They differ in terms of the assumptions about the prior knowledge of probabilities. The first assumes there is no prior knowledge of the distribution of cases among hospitals. This is a measure of the complexity of a hospital's caseload (Evans and Walker 1972). The index X_i^1 is given as:

$$X_i^1 = \sum_j \bar{H}_j^1 p_{ij} \tag{18}$$

which is a weighted average of the standardised complexity indexes $\bar{H}_j^1$ of each AR-DRG, where the weights p_{ij} are the share of the i*th*'s hospital's cases being classified as the j*th* AR-DRG.

To derive $\bar{H}_j^1$, the index of complexity for the j*th* AR-DRG is used:

$$H_j^1 = \sum_i q_{ij} \ln\left(\frac{q_{ij}}{\frac{1}{I}}\right) \tag{20}$$

Equation (20) describes the information gain rising from the probability of the j*th* AR-DRG being treated by the i*th* hospital. The smaller the q_{ij}, the larger will be its natural logarithm. Pre-multiplying gives the probability of that information gain occurring. If in the absence of any information of the actual distribution of cases, the probability of a case going to any hospital is the same for all hospitals, and is equal to the inverse of the number of hospitals 1/I.

H_j^1 is standardised to ensure that the index has a mean of one:

$$\bar{H}_j^1 = \frac{H_j^1}{\sum_j H_j^1 q_j} \tag{21}$$

This second measure of a hospital's relative complexity takes into account the relative differences in hospital size. In this index, it is assumed that the prior probability of a case occurring is equal to the actual proportion of all cases in the system treated by the hospital. This means that the larger the hospital, the higher will be the probability that it will treat a case entering the system (Butler 1995). While larger hospitals may treat more complex cases than smaller hospitals, they are also expected to treat more complex cases.

The second Evans and Walker index X_i^2 resembles the first, insofar that it is equal to the weighted average of standardised complexity cases $\bar{H}_j^2$:

$$X_i^2 = \sum_j \bar{H}_j^2 p_{ij} \tag{22}$$

However, the corresponding measure of information gain differs in that it is now influenced by the probability p_i that a case will go to the i*th* hospital is given by:

$$H_j^2 = \sum_i q_{ij} \ln\left(\frac{q_{ij}}{p_i}\right) \tag{23}$$

As with the first index, equation (23) is standardised to ensure that the index has a mean of one:

$$\bar{H}_j^2 = \frac{H_j^2}{\sum_j H_j^2 q_j} \tag{24}$$

What is the Commission measuring?

In this study, the Commission has compared the performance of all acute hospitals in one sample. That is, all hospitals — large and small, urban and rural — were compared in a single multivariate analysis. The typical practice in benchmarking is to identify relevant 'peers' against which hospital can be compared. For example, large metropolitan teaching hospitals are compared against other large metropolitan teaching hospitals, in order to learn about ways these hospitals might improve their performance. This practice of stratifying the sample according to key hospital characteristics, however, is not necessarily useful in an analytical context, because it cannot address an important research question: how significant are factors such as location and size in determining a hospital's performance? How can the impact of a hospital's size or location on efficiency be assessed if hospitals are only compared with those of the same size or location?

The Commission's analysis therefore is based on a pooled sample of all hospitals in the study, as the econometric model is designed to account for differences in hospitals which would typically be used to define 'peer groups'. For example, the inclusion of the explanatory variables measuring hospital size, location, teaching status and emergency services is designed to control for the effects of these factors on hospital output and efficiency. Using the stochastic frontier regression technique, the model can identify variation in hospital output that is specifically due to the inefficient use of inputs, and not due to differences in a hospital establishment's characteristics.

E.5 The results

Before attempting to estimate the technical efficiencies, the Commission undertook to identify a suitable measure of the quality of hospital care. The approach used here was to risk-adjust in-hospital mortality rates using a Tobit regression, and then to include the estimated risk-adjusted mortality ratios (RAMRs) into the estimation of hospital performance.

Risk-adjustment analysis

As noted earlier, in-hospital mortality is probably the only reliably measured hospital health outcome. Other measures, such as adverse events and infections, are generally not well reported. But, mortality rates do not always provide an indication of the quality of care in a hospital — a number of other factors outside the control of hospitals (such as the patient's comorbidities) can contribute to patient mortality.

Three sets of Tobit regressions were analysed. Model 1 considered each of the major categories of variables — patient comorbidities, socioeconomic status, place of residence, gender, Indigenous status and age profile. Model 2 excludes gender and the younger age profiles which appear to be insignificant as a group. It tests specifically for the effect of place of residence. Model 3 is identical to model 2 apart from replacing the place of residence variables with socioeconomic status of the patient (table E.4).

Table E.3 **Description and summary statistics of variables, 2006-07**[a]

Variable	*Description*	*Mean*	*Std. dev.*
Hospital outputs — Admitted patients			
Number of separations	Total number of separations	11 549.38	15 382.78
Acute separations	Number of casemix-adjusted separations (defined by MDC)	9 526.72	14 786.51
Pregnancy and neonate separations	Number of casemix-adjusted separations (defined by MDC)	1 175.80	2 557.90
Mental and alcohol separations	Number of casemix-adjusted separations (defined by MDC)	536.67	1 021.36
MDC 10 separations	Number of casemix-adjusted separations (defined by MDC)	267.68	427.37
Other separations	Number of casemix-adjusted separations (defined by MDC)	526.80	908.15
Average cost weight	Ratio	0.8953	0.370
Hospital outputs — Non-admitted patient services			
Accident and emergency services	Number of occasions of service	11 436.72	16 190.93
Allied health and dental services	Number of occasions of service	26 842.13	63 441.71
Mental and alcohol services	Number of occasions of service	536.67	1 021.36
Dialysis and endoscopy services	Number of occasions of service	158.19	1 457.82
Community outreach and district nursing services	Number of occasions of service	7 526.32	22 949.87
Pathology and radiology services	Number of occasions of service		
Hospital inputs			
Nursing staff	Number of full-time equivalents	211.96	339.17
Diagnostic staff	Number of full-time equivalents	63.55	145.77
Other staff	Number of full-time equivalents	141.88	243.78
Total beds	Total number	118.03	151.22
Drug costs	$'000s	306.47	13.09
Other hospital costs	$'000s	1 934.16	11.88
Medical and surgical supplies cost	$'000s	606.21	14.58

(Continued next page)

Table E.3 (continued)

Variable	*Description*	*Mean*	*Std. dev.*
Roles and functions			
Teaching	Dummy variable (1=yes; 0=otherwise)	0.3209	0.4673
Network	Dummy variable (1=yes; 0=otherwise)	0.0846	0.2786
Share of patients that were not public patients	Share of total separations	0.3915	0.3804
Surgical and other DRGs	Share of total separations	0.3104	0.2387
Same-day separations	Share of total separations	0.4585	0.1785
Accident and emergency rate	Ratio to total separations	2.1304	2.8140
Transfers to aged care	Share of total separations	0.0102	0.0164
Transfers to acute hospitals	Share of total separations	0.0687	0.0622
Transfers to other hospitals	Share of total separations		
Evans and Walker Index 1	Rate	0.5557	0.5241
Evans and Walker Index 2	Rate	0.4904	0.4211
Palliative-care unit	Dummy variable (1=yes; 0=otherwise)	0.1122	0.3159
High intensive care unit	Dummy variable (1=yes; 0=otherwise)	0.1772	0.3822
Residential care unit	Dummy variable (1=yes; 0=otherwise)	0.0039	0.0627
Patient characteristics			
Female patients	Share of total patients	0.5372	0.0800
Aged less than 1year	Share of total patients	0.0191	0.0325
Aged 1-4 years	Share of total patients	0.0252	0.0438
Aged 5-14 years	Share of total patients	0.0346	0.0526
Aged 50-59 years	Share of total patients	0.1334	0.0511
Aged 60-69 years	Share of total patients	0.1451	0.0516
Aged 70+ years	Share of total patients	0.2866	0.1395
From major city	Share of total patients	0.3880	0.4279
From inner regional	Share of total patients	0.3187	0.3591
From outer regional	Share of total patients	0.2124	0.3250
From remote	Share of total patients	0.0376	0.1427
From very remote	Share of total patients	0.0433	0.1782

(Continued next page)

Table E.3 (continued)

Variable	*Description*	*Mean*	*Std. dev.*
SEIFA 1	Share of total patients	0.3352	0.3464
SEIFA 2	Share of total patients	0.2326	0.2854
SEIFA 3	Share of total patients	0.1819	0.2272
SEIFA 4	Share of total patients	0.1354	0.1851
SEIFA 5	Share of total patients	0.1149	0.1974
Charlson score 1	Share of total patients	0.0819	0.0448
Charlson score 2	Share of total patients	0.0997	0.1014
Charlson score 3	Share of total patients	0.0150	0.0134
Charlson score 4	Share of total patients	0.0133	0.0262
Charlson score 5	Share of total patients	0.0317	0.0523
Charlson score 6 or higher	Share of total patients	0.0050	0.0079
Average Charlson score	Score	0.5396	0.4481
Quality indicator			
Mortality rate	Rate	0.0133	0.0310

[a] Statistics for the minimum and maximum observations were suppressed for confidentiality reasons.

Source: Unpublished ABS and AIHW data; Productivity Commission estimates.

Between the three models, patient characteristics prove to have a significant influence on hospital mortality rates. In particular, hospitals which have proportionally more patients in older age-groups (70 years or older), with higher Charlson scores (5 or over), and that identify with Indigenous status are expected to report higher mortality rates. Hospitals' patient profiles according to patient gender, usual place of residence, and socio-economic status (the latter based on the SEIFA) were not found to be significant in most cases (table E.4).

In terms of overall fit (log likelihood) and parsimony of variable choice (Akaike and Bayesian Information Criteria tests), there is little to separate the three models. The younger age profiles and gender were generally poor explanators, and so were dropped from the analysis altogether. The choice between models 2 and 3 is almost arbitrary. The residuals of the third model were used for the predicted mortality rates in table E.5.

The predicted and RAMRs are reported in table E.5 for private, public and public contract hospitals. A RAMR value less than one indicates that a hospital's actual mortality rate is less than predicted, given its patient profile, while a value greater than one indicates the reverse. On average, the private hospitals in this study reported lower RAMRs than public and public contract hospitals. It is of interest to note that the RAMRs of public contract hospitals are slightly lower than public hospitals, with whom they are likely to share a similar pattern of activity. The RAMRs are further disaggregated in table E.6 according to hospital size.

Care needs to be taken when interpreting RAMRs in relation to hospital quality. For example, the average RAMR for public hospitals (0.632) does not mean that patients die at twice the rate than in private hospitals (0.305) (table E.5). The purpose of the regression is to adjust hospital mortality rates for the profile of patients they treat. The Tobit regression is only intended to provide an indication of the extent to which patient-risk characteristics influence hospital mortality rates, and are not designed to account for the different activities that hospitals undertake (that is, their casemix). The estimated mortality ratios are then used as a control for quality in the output regression. Variables to measure a hospital's casemix are not included in the mortality rates regression, as they are already included as a direct component of the output stochastic frontier regression, and inclusion of these factors in the mortality rates is likely to generate collinearity.

The reported RAMRs should not be compared to other reported mortality measures (such as Hospital Standardised Mortality Rates, HSMRs).

Table E.4 **Results of Tobit regression of mortality rates, 2006-07**

Variable	*Model 1*		*Model 2*		*Model 3*	
Comorbidity						
Share of patients with Charlson 6 or more	2.817	***	2.810	***	2.829	***
Share of patients with Charlson 5	0.142	***	0.146	***	0.156	***
Share of patients with Charlson 4	-0.013		-0.011		0.007	
Share of patients with Charlson 3	-0.295	***	-0.292	***	-0.296	***
Share of patients with Charlson 2	-0.027	*	-0.027	*	-0.023	
Average Charlson score	-0.007		-0.001		-0.004	
Age						
Share of patients aged 70 or more	0.049	***	0.050	***	0.051	***
Share of patients aged between 60 and 69	-0.064	**	-0.064	***	-0.066	***
Share of patients aged between 50 and 59	-0.065	**	-0.061	***	-0.058	**
Share of patients aged between 5 and 14	-0.019					
Share of patients aged between 1 and 4	0.026					
Share of patients aged under 1	-0.017					
Indigenous status	0.008		0.010	***	0.013	**
Female	0.007					
Patient’s usual place of residence						
Proportion of patients from inner regional areas	0.005		0.004	*		
Proportion of patients from outer regional areas	0.009	**	0.008	***		
Proportion of patients from remote areas	0.009		0.008			
Proportion of patients from very remote areas	0.006		0.005			
SEIFA classification of patient’s residence						
Proportion of SEIFA 4	0.002				0.001	
Proportion of SEIFA 3	0.003				0.005	
Proportion of SEIFA 2	0.000				0.005	
Proportion of SEIFA 1	0.002				0.008	*
Constant	-0.004		0.000		0.001	
Sigma	0.018	***	0.017	***	0.018	***
Model criteria						
Log likelihood	1 244.94		1 244.33		1 241.81	
Likelihood Ratio χ^2	591.10		589.89		584.84	
Probability > χ^2	0.0000		0.0000		0.0000	
Akaike Information Criterion	-2 441.9		-2 456.6		-2 450.5	
Bayesian Information Criterion	-2 340.3		-2 388.9		-2 382.8	
No. of observations	508		508		508	

*** Significant at the 1 per cent critical level. ** Significant at the 5 per cent critical level. * Significant at the 10 per cent critical level.

Source: Unpublished ABS and AIHW data; Productivity Commission estimates.

Table E.5 Predicted mortality rates and risk-adjusted mortality ratios, by sector, 2006-07

	Public hospitals	*Public contract hospitals*	*Private hospitals*	*All hospitals*
Predicted mortality rates				
Mean	0.022	0.030	0.022	0.022
Median	0.019	0.017	0.015	0.018
Standard deviation	0.010	0.040	0.041	0.023
Minimum	0.007	0.012	0.006	0.006
Maximum	0.083	0.186	0.434	0.434
Weighted average[a]	0.023	0.032	0.019	0.023
RAMRs[b]				
Mean	0.632	0.540	0.305	0.550
Median	0.593	0.420	0.189	0.517
Standard deviation	0.380	0.563	0.324	0.399
Minimum	–	0.074	–	–
Maximum	2.793	2.583	1.860	2.793
Weighted average[a]	0.530	0.383	0.327	0.471
Number of observations	368	18	122	508

a Weighted average by casemix-adjusted separations. **b** RAMR – Risk-adjusted mortality ratio is equal to the actual (observed) mortality rate divided by the predicted mortality rate. – Nil or rounded to zero.

Source: Unpublished ABS and AIHW data; Productivity Commission estimates.

Table E.6 **Risk-adjusted mortality ratios, by sector and hospital size, 2006-07[a]**

	Very large	*Large*	*Medium*	*Very small and small*	*All*
Public hospitals					
Mean	0.506	0.472	0.532	0.718	0.632
Median	0.506	0.441	0.481	0.685	0.593
Standard deviation	0.195	0.269	0.325	0.431	0.380
Minimum	0.072	–	–	–	–
Maximum	0.889	1.043	1.590	2.793	2.793
Number of observations	68	37	45	218	368
Public contract hospitals					
Mean	np	np	np	np	0.540
Median	np	np	np	np	0.420
Standard deviation	np	np	np	np	0.563
Minimum	np	np	np	np	0.074
Maximum	np	np	np	np	2.583
Number of observations	np	np	np	np	18
Private hospitals					
Mean	0.357	0.316	0.274	0.297	0.305
Median	0.340	0.236	0.185	0.064	0.189
Standard deviation	0.256	0.267	0.270	0.432	0.324
Minimum	–	–	–	–	–
Maximum	0.908	0.908	0.908	1.860	1.860
Number of observations	24	22	38	38	122
All hospitals					
Mean	0.457	0.432	0.414	0.662	0.550
Median	0.469	0.415	0.330	0.636	0.517
Standard deviation	0.221	0.277	0.390	0.465	0.399
Minimum	–	–	–	–	–
Maximum	0.908	1.124	1.691	2.793	2.793
Number of observations	np	np	np	np	508

[a] RAMR – Risk-adjusted relative mortality ratio is equal to the actual (observed) mortality rate divided by the predicted mortality rate. **np** Not published due to confidentiality concerns. – Nil or rounded to zero.

Source: Unpublished ABS and AIHW data; Productivity Commission estimates

Stochastic frontier analysis

Two distinct types of production (distance) functions were modelled using the 2006-07 data — a Cobb-Douglas and a restricted translog function (as it was not technically possible to solve the full version of the translog function). The results for a number of versions of the Cobb-Douglas and a restricted translog are presented in tables E.7 and E.8.

Table E.7 **Results of Cobb-Douglas stochastic frontier analysis, 2006-07**

	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*	
Primary model										
Inpatient services										
Log of acute separations	-0.546	***	-0.542	***	-0.488	***	-0.545	***	-0.506	***
Log of preg. & neonate seps.	-0.057	***	-0.014		-0.066	***	-0.059	***	-0.060	***
Log of mental & alcohol seps.	-0.102	***	-0.108	***	-0.121	***	-0.100	***	-0.106	***
Log of other separations	-0.146	***	-0.186	***	-0.146	***	-0.144	***	-0.151	***
Non-admitted services										
Log of emergency dept. visits	-0.014	*	0.009		-0.022		-0.011		-0.021	
Log of allied & dental services	-0.044	***	-0.080	***	-0.048	**	-0.049	***	-0.050	***
Log of mental & alcohol serv.	-0.011		0.001		-0.006		-0.013		-0.011	
Log of outreach & dist. nurs.	0.002		-0.005		0.003		0.004		0.004	
Log of diagnostic services	-0.038	**	-0.013		-0.041	***	-0.037	**	-0.041	***
Log of dialysis & endoscopy	0.036		0.010		0.057		0.027		0.031	
Quality										
RAMR	-0.035		0.057		0.022		-0.017			
Inputs										
Log of nursing staff	0.177	***	0.268	***	0.187	***	0.188	***	0.241	***
Log of diag. staff	0.033	*	0.092	***	0.024		0.032		0.030	
Log of other staff	-0.147	***	-0.006		-0.120	**	-0.140	**	-0.161	***
Log of beds	0.436	***	0.681	***	0.443	***	0.449	***	0.462	***
Log of drugs	0.064	**	-0.036		0.075	***	0.061	**	0.068	***
Log of med.& surg. supplies	0.025		0.142	***	0.017		0.020		0.015	
Log of other inputs	-0.016		-0.088	***	-0.018		-0.008		-0.012	
Role and functions										
Emergency to admission ratio	0.008									
Teaching hospital	0.100				0.106		0.097		0.116	*
Level III ICU	0.004				0.013					
Palliative care unit	-0.026				0.007					
Residential care unit	-0.187				-0.171					
Evans & Walker Index 1	-1.997	***			-2.030	***	-2.015	***	-2.098	***
Evans & Walker Index 2	3.970	***			4.029	***	3.944	***	4.011	***
% of seps surgical or other	1.117	***			0.958	***	1.152	***	1.131	***
% non-public patients	-1.089	***			-1.118	***	-1.123	***	-1.160	***
Patient characteristics										
% with Charlson 6 +	-0.866		8.763				-1.912		-6.518	**
% with Charlson 5	0.710		2.677				0.825		-1.520	**
% with Charlson 4	-0.584		2.200				-0.712		-2.641	***
% with Charlson 3	0.717		0.021				0.915			
% with Charlson 2	1.025		2.691	**			1.036			
Average Charlson	-0.062		-0.729				-0.072		0.394	***

(Continued next page)

Table E.7 (continued)

	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*	
Patient SEIFA										
% from SEIFA 4	-0.045		0.429	**			-0.045			
% from SEIFA 3	-0.245	*	0.235				-0.251	*	-0.307	***
% from SEIFA 2	-0.228		0.198				-0.233		-0.332	***
% from SEIFA 1	-0.162		0.314	**			-0.173		-0.261	***
Patient place of residence[a]										
Major city	0.378	***	0.137				0.248	**		
Outer regional	0.498	***	0.016				0.114			
Remote	0.826	***	-0.066				0.052			
Very remote	0.475		-0.078				-0.098			
Hospital location[a]										
Major city	-0.078				0.149	**				
Outer regional	-0.350	***			-0.002					
Remote	-0.720	***			-0.102					
Very remote	-0.576	*			-0.163					
State or territory[b]										
NSW	-0.087		-0.054		-0.083		-0.072		-0.090	
Victoria	-0.254	***	-0.161	**	-0.224	***	-0.253	***	-0.277	***
South Australia	-0.244	***	0.104		-0.224		-0.240	***	-0.230	***
Western Australia	-0.077		0.164		-0.037	**	-0.055		-0.069	
Tasmania	0.976	***	0.403		1.050	***	0.977	***	1.176	***
Northern Territory	-0.190		0.211		-0.105		-0.190		-0.217	
ACT	-0.123		-0.161		0.152		-0.129		-0.237	
Constant	3.802	***	2.683	***	3.521	***	3.747	***	3.644	***
Secondary model										
Log σ_v^2										
Constant	-2.664	***	-2.585	***	-2.452	***	-2.654	***	-2.543	***
Log σ_u^2										
Constant	-1.915	***	-1.289	***	-1.953	***	-1.866	***	-1.918	***
Model criteria										
No. of observations	508		508		508		508		508	
Log likelihood	-297.4		-400.6		-319.3		-305.3		-311.3	
Wald χ^2	7 969.7		5 215.4		6 997.2		7 663.4		7 345.2	
Probability $> \chi^2$	0.0000		0.0000		0.0000		0.0000		0.0000	
Akaike Inference Criterion	704.8		885.3		718.6		704.6		700.5	
Bayesian Inference Criterion	937.6		1062.9		887.8		903.4		865.5	
σ_v	0.264		0.275		0.295		0.265		0.280	
σ_u	0.384		0.525		0.376		0.393		0.383	
σ^2	0.217		0.351		0.228		0.225		0.226	
λ	1.454		1.911		1.283		1.483		1.367	

[a] Inner regional is the reference region. [b] Queensland is the reference jurisdiction. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level.

Source: Unpublished ABS and AIHW data; Productivity Commission estimates.

Table E.8 **Results of translog stochastic frontier analysis, 2006-07**

	Model 6	*Model 7*	*Model 8*	*Model 9*	*Model 10*
Primary model					
Inpatient services					
Log of acute separations	-0.302	-0.265	-0.160	-0.171	-0.211
Log of acute seps – sq	-0.015	-0.022	-0.030	-0.029	-0.022
Log of preg. & neonate seps	-0.049 ***	-0.035 ***	-0.049 ***	-0.050 ***	-0.052 ***
Log of preg. & neon. – sq	-0.005	-0.009 ***	-0.005	-0.004	-0.004
Log of mental & alc.	-0.148 ***	-0.167 ***	-0.156 ***	-0.155 ***	-0.151 ***
Log of mental & alc – sq	-0.019 ***	-0.023 ***	-0.020 ***	-0.020 ***	-0.019 ***
Log of other seps	-0.096 ***	-0.095 ***	-0.087 ***	-0.090 ***	-0.103 ***
Log of other seps – sq	-0.017 ***	-0.029 ***	-0.017 ***	-0.017 ***	-0.016 ***
Non-admitted services					
Log of ED visits	-0.061	-0.099 **	-0.073 *	-0.074 *	-0.069
Log of ED visits – sq	0.007	0.016 **	0.006	0.007	0.006
Log of allied & dental	0.128 ***	0.160 ***	0.115 ***	0.117 ***	0.105 ***
Log of allied & denta – sq	-0.027 ***	-0.035 ***	-0.026 ***	-0.026 ***	-0.024 ***
Log of mental & alc	0.035 *	0.029	0.039 **	0.042 **	0.029
Log of mental & alc – sq	-0.005 ***	-0.001	-0.005	-0.005 **	-0.003
Log of outreach & dist.	0.007	0.005	-0.004	-0.001	0.010
Log of outreach – sq	0.001	0.001	0.002	0.002	0.000
Log of diagnostic	-0.034	-0.044	-0.025	-0.029	-0.027
Log of diagnostic – sq	0.003	0.004	0.000	0.001	0.000
Log of dialysis & endoscopy	0.021	-0.013	0.071	0.025	0.014
Log of dial & endo. – sq	-0.008 **	-0.018	0.006	-0.009	-0.018
Quality					
RAMR	-0.256 *	-0.050	-0.200	-0.216	
RAMR – sq	0.109	0.015	0.087	0.090	
Inputs					
Log of nursing staff	0.533 ***	0.708 ***	0.664 ***	0.657 ***	0.678 ***
Log of nursing staff - sq	-0.051 **	-0.058 **	-0.066 ***	-0.066 ***	-0.061 ***
Log of diag. staff	0.032	0.087 ***	0.029	0.030	0.036
Log of diag. staff - sq	-0.004	-0.009	-0.006	-0.006	-0.003
Log of other staff	-0.129	0.028	-0.163	-0.155	-0.152
Log of other staff - sq	-0.002	-0.014	0.007	0.007	0.000
Log of beds	-0.007	0.030 ***	0.032	0.039	0.075
Log of beds - sq	0.075 ***	0.092 ***	0.071 ***	0.069 ***	0.068 ***
Log of drugs	-0.010	-0.073 ***	-0.005	-0.004 ***	-0.005
Log of drugs - sq	0.011 ***	0.014 ***	0.011 ***	0.011 ***	0.011 ***
Log of med.& surg. supplies	0.290 ***	0.175 **	0.246 ***	0.238 ***	0.246 ***
Log of med. & surg. - sq	-0.027 ***	-0.006	-0.023 ***	-0.022 ***	-0.022 ***
Log of other inputs	-0.383 ***	-0.423 ***	-0.380 ***	-0.375	-0.380 ***
Log of other inputs -sq	0.030 ***	0.024 ***	0.029 ***	0.029 ***	0.028 ***
Role and functions					
Teaching hospital	0.168 ***		0.176 ***	0.185 ***	0.196 ***
Level III ICU	0.057		0.062		
Palliative care unit	-0.035		-0.025		

(Continued next page)

Table E.8 (continued)

	Model 6	*Model 7*	*Model 8*	*Model 9*	*Model 10*
Residential care unit	-0.403		-0.610 *		
Evans & Walker Index 1	-2.047 ***		-1.732 ***	-1.574 ***	-1.777 ***
Evans & Walker Index 2	3.658 ***		3.230 ***	3.086 ***	3.246 ***
% non-public patients	-0.962 ***		-0.998 ***	-0.996 ***	-0.993 ***
% of seps surg. or other	0.856 ***		0.767 ***	0.761 ***	0.862 ***
Patient characteristics					
% with Charlson 6 +	-0.374	13.307 **			-7.362 **
% with Charlson 5	1.822	7.850 ***			-1.121
% with Charlson 4	0.692	6.384 ***			-2.079 **
% with Charlson 3	1.235	4.308			
% with Charlson 2	1.424	4.271 ***			
Average Charlson	-0.362	-1.769 ***			0.250 **
Patient SEIFA					
% from SEIFA 4	-0.182	0.080			
% from SEIFA 3	-0.216	0.097			-0.216 **
% from SEIFA 2	-0.272 **	0.037			-0.322 ***
% from SEIFA 1	-0.178	0.167			-0.238 ***
Patient place of residence[a]					
Major city	0.409 ***	0.122	0.190 ***	0.191 ***	
Outer regional	0.423 ***	-0.008	-0.032	-0.034	
Remote	0.837 ***	0.030	-0.147	-0.148	
Very remote	0.499	-0.084	-0.182 *	-0.188 *	
Hospital location[a]					
Major city	-0.070				
Outer regional	-0.332 ***				
Remote	-0.757 ***				
Very remote	-0.637 **				
State or territory[b]					
NSW	-0.089 *	-0.075	-0.088	-0.079	-0.098
Victoria	-0.219 ***	-0.137 *	-0.203 ***	-0.212 ***	-0.249 ***
South Australia	-0.165 **	0.089	-0.141	-0.144 *	-0.134
Western Australia	0.007	0.207 **	0.034	0.026	0.009
Tasmania	0.737 **	-0.411	0.937 ***	0.938 ***	1.001 ***
Northern Territory	-0.356 **	-0.031	-0.227	-0.229	-0.342 *
ACT	-0.171	-0.167	0.054	0.056	-0.253
Constant	3.864 ***	3.578 ***	3.281 ***	3.323 ***	3.318 ***
Secondary model					
Log σ_v^2					
Constant	-2.744 ***	-2.646 ***	-2.500 ***	-2.511 ***	-2.495 ***
Log σ_u^2					
Constant	-2.430 ***	-1.961 ***	-2.553 ***	-2.520 ***	-2.560 ***

(Continued next page)

Table E.8 (continued)

	Model 6	*Model 7*	*Model 8*	*Model 9*	*Model 10*
Model criteria					
No. of observations	508	508	508	508	508
Log likelihood	-305.3	-292.6	-242.9	-244.7	242.2
Wald χ^2	7 663.4	8 637.8	9 650.9	9 584.7	9 830.1
Probability $> \chi^2$	0.0000	0.0000	0.0000	0.0000	0.0000
Akaike Inference Criterion	704.6	705.9	601.8	599.4	596.1
Bayesian Inference Criterion	903.4	959.7	847.2	832.0	833.2
σ_v	0.254	0.266	0.287	0.285	0.287
σ_u	0.297	0.375	0.279	0.284	0.278
σ^2	0.152	0.212	0.160	0.162	0.160
λ	1.171	1.408	0.973	0.996	0.968

a Inner regional is the reference region. **b** Queensland is the reference jurisdiction. **sq** Indicates a squared term. *** Significant at the 1 per cent level, ** Significant at the 5 per cent level, * Significant at the 10 per cent level.

Source: Unpublished ABS and AIHW data; Productivity Commission estimates

Models 1 and 6 include all the variables available for each of the functional forms. Models 2 and 7, respectively, include outputs and inputs as well as the major patient-risk characteristics (such as Charlson comorbidity scores, SEIFA indices). They do not include those variables that describe the roles and functions of hospitals. It is worth noting the high degree of collinearity between these variables and the RAMR (which includes a number of these variables in its estimation).

Models 3 and 8 include the hospital outputs and inputs, the RAMR and all the variables describing hospital roles and functions and hospital location. It is worth observing that dummy variables indicating the presence of intensive care, palliative care and residential aged care units were not significant. The coefficients for both Evans and Walker indices confirm that the complexity of hospital services is a determinant of the dependent variable. Models 4 and 9 are similar to models 3 and 8 but with selected hospital roles and function variables excluded.

In models 5 and 10, the RAMR is replaced by the patient-risk characteristics. Not all of the Charlson and SEIFA variables were included, as collinearity was evident within members of each set. Models 5 and 10 reflect the synthesis of models 3 and 4, and 8 and 9 respectively. The Akaike and Bayesian information criteria tests indicate that models 5 and 10 are to be preferred, followed by models 4 and 9, for the Cobb-Douglas and restricted translog functions respectively.

In interpreting the coefficients (from models 5 and 10), the following observations can be made:

- Hospitals that treat relatively more comorbid partients (Charlson index) and patients from more disadvantage areas (SEIFA index) have lower frontiers (best-practice benchmarks).
- Hospitals that treat relatively more non-public patients (that is, patients who elect to be funded by private health insurance, the Department of Veterans' Affairs, third-party motor vehicle accident schemes or are self-funded) tend to have lower frontiers. This may reflect the additional resources employed by hospitals to treat these patients.
- Hospitals that undertake relatively more surgical and other procedures (as opposed to medical procedures) tend to have higher frontiers. This may be because that medical procedures are inherently more difficult to manage, possibly because of their relatively unplanned nature.
- The coefficients for Victoria and Tasmania remain relatively significant in all specifications. This is likely to reflect the effects of having to disaggregate the data for these jurisdictions from a single public hospital observation.

Other variables, such as average length of stay and the proportion of same-day separations, were not considered in the analysis because shorter lengths of stay and higher turnover of patients is reflected in the greater level of inpatient separations.

Efficiency results

Efficiency results are presented in tables E.9 to E.11 for models 4, 5, 9 and 10. After taking into account the various factors that influence their performance, the average efficiency of all hospitals was broadly similar. The mean technical efficiencies across the major hospital categories (public, private, public contract) were between 0.75 to 0.80 (models 9 and 10) (table E.9). The median efficiencies across the same categories ranged between 0.81 and 0.83 (model 9), and between 0.81 and 0.84 (model 10), suggesting a degree of skewness in efficiency scores (table E.9).

The use of the translog functional form is intended to 'net out' the effects of scale economies, although using the mean efficiency scores, it is possible to discern differences in the technical efficiencies of hospitals of different size. For example, the mean technical efficiency score was about 0.766 for the smallest hospitals (table E.11, model 10) and 0.814 for very large hospitals (table E.10, model 10).

The median is a better measure of central tendency than the mean, given the skewness in the data. There is a perceptible difference between the major hospital categories. The median technical efficiency score for large and very large private hospitals was slightly higher than for public hospitals, except for large hospitals in model 9 (table E.10). For example, the median technical efficiency of large and very large private hospitals was 0.829 and 0.851 respectively, compared to 0.812 and 0.820 for public hospitals of the same size (model 10, table E.10).

Table E.9 **Technical efficiency scores, all hospitals, 2006-07**[a]

	Model 4	*Model 5*	*Model 9*	*Model 10*
All hospitals				
Mean	0.729	0.732	0.783	0.786
Median	0.772	0.776	0.814	0.816
5th percentile	0.366	0.408	0.501	0.553
95th percentile	0.895	0.893	0.904	0.906
No. of observations	508	508	508	508
Public hospitals				
Mean	0.743	0.746	0.794	0.797
Median	0.771	0.774	0.814	0.816
5th percentile	0.478	0.503	0.627	0.643
95th percentile	0.890	0.886	0.902	0.901
No. of observations	368	368	368	368
Private hospitals				
Mean	0.677	0.680	0.746	0.750
Median	0.771	0.785	0.817	0.822
5th percentile	0.092	0.105	0.311	0.313
95th percentile	0.905	0.905	0.913	0.916
No. of observations	122	122	122	122
For-profit hospitals				
Mean	0.663	0.667	0.749	0.751
Median	0.765	0.777	0.816	0.818
5th percentile	0.062	0.079	0.311	0.313
95th percentile	0.911	0.909	0.918	0.917
No. of observations	94	94	94	94
Not-for-profit hospitals				
Mean	0.721	0.722	0.736	0.747
Median	0.797	0.796	0.828	0.838
5th percentile	0.110	0.136	0.175	0.203
95th percentile	0.880	0.888	0.898	0.906
No. of observations	28	28	28	28
Public contract hospitals				
Mean	0.791	0.787	0.801	0.800
Median	0.826	0.814	0.818	0.805
5th percentile	0.511	0.523	0.580	0.583
95th percentile	0.911	0.906	0.907	0.908
No. of observations	18	18	18	18

a Results based on models 4 and 5 (Cobb-Douglas) and models 9 and 10 Logarithmic quadratic. The 5% and 95% percentile values are equivalent to the minimum and maximum scores after removing for the outliers in the estimated distribution.

Table E.10 Technical efficiency scores, large and very large hospitals, 2006-07[a]

	Large hospitals				*Very large hospitals*			
	Model 4	*Model 5*	*Model 9*	*Model 10*	*Model 4*	*Model 5*	*Model 9*	*Model 10*
All hospitals								
Mean	0.776	0.776	0.807	0.809	0.761	0.763	0.814	0.814
Median	0.793	0.799	0.827	0.828	0.765	0.770	0.814	0.827
5th percentile	0.565	0.556	0.656	0.644	0.587	0.585	0.715	0.683
95th percentile	0.892	0.891	0.907	0.908	0.895	0.890	0.908	0.905
No. of obs.	70	70	70	70	98	98	98	98
Public hospitals								
Mean	0.763	0.764	0.808	0.810	0.750	0.754	0.811	0.813
Median	0.785	0.773	0.826	0.812	0.756	0.762	0.810	0.820
5th percentile	0.567	0.581	0.668	0.648	0.557	0.585	0.729	0.708
95th percentile	0.886	0.891	0.917	0.917	0.895	0.893	0.908	0.905
No. of obs.	37		37	37	68	68	68	68
Private hospitals								
Mean	0.788	0.789	0.810	0.813	0.785	0.784	0.823	0.819
Median	0.827	0.827	0.824	0.829	0.805	0.811	0.850	0.851
5th percentile	0.662	0.644	0.751	0.752	0.647	0.645	0.670	0.655
95th percentile	0.881	0.878	0.887	0.878	0.885	0.879	0.894	0.893
No. of obs.	22	22	22	22	24	24	24	24
For-profit hospitals								
Mean	0.780	0.784	0.808	0.810	0.793	0.793	0.839	0.834
Median	0.823	0.823	0.824	0.828	0.827	0.821	0.858	0.863
5th percentile	0.565	0.558	0.465	0.457	0.587	0.586	0.689	0.659
95th percentile	0.892	0.889	0.920	0.918	0.893	0.891	0.918	0.917
No. of obs.	15	15	15	15	15	15	15	15
Not-for-profit hospitals								
Mean	0.807	0.799	0.815	0.819	0.772	0.770	0.797	0.795
Median	0.831	0.832	0.830	0.830	0.801	0.795	0.825	0.846
5th percentile	0.739	0.699	0.751	0.757	0.647	0.651	0.643	0.639
95th percentile	0.851	0.850	0.858	0.868	0.852	0.847	0.876	0.877
No. of obs.	7	7	7	7	9	9	9	9

a Results based on models 4 and 5 (Cobb-Douglas) and models 9 and 10 Logarithmic quadratic. The 5% and 95% percentile values are equivalent to the minimum and maximum scores after removing for the outliers in the estimated distribution.

Table E.11 **Technical efficiency scores, small and very small, and medium hospitals, 2006-07[a]**

	Small and very small hospitals				*Medium hospitals*			
	Model 4	*Model 5*	*Model 9*	*Model 10*	*Model 4*	*Model 5*	*Model 9*	*Model 10*
All hospitals								
Mean	0.701	0.708	0.762	0.766	0.738	0.746	0.791	0.741
Median	0.771	0.766	0.808	0.806	0.765	0.777	0.819	0.780
5th percentile	0.173	0.202	0.378	0.415	0.506	0.499	0.557	0.491
95th percentile	0.890	0.879	0.902	0.899	0.913	0.915	0.915	0.915
No. of obs.	257	257	257	257	83	83	83	83
Public hospitals								
Mean	0.737	0.739	0.786	0.788	0.748	0.754	0.797	0.803
Median	0.776	0.781	0.815	0.816	0.762	0.760	0.812	0.815
5th percentile	0.404	0.408	0.556	0.575	0.528	0.558	0.607	0.622
95th percentile	0.889	0.880	0.895	0.897	0.904	0.901	0.915	0.907
No. of obs.	218	218	218	218	45	45	45	45
Private hospitals								
Mean	0.495	0.505	0.622	0.641	0.725	0.727	0.785	0.780
Median	0.601	0.605	0.694	0.700	0.798	0.803	0.838	0.841
5th percentile	0.046	0.063	0.175	0.203	0.103	0.118	0.448	0.427
95th percentile	0.907	0.909	0.916	0.919	0.925	0.926	0.928	0.931
No. of obs.	38	38	38	38	38	38	38	38
For-profit hospitals								
Mean	0.471	0.480	0.628	0.640	0.732	0.734	0.797	0.791
Median	0.607	0.605	0.716	0.715	0.795	0.802	0.826	0.820
5th percentile	0.046	0.063	0.186	0.208	0.178	0.205	0.503	0.470
95th percentile	0.907	0.908	0.916	0.916	0.925	0.926	0.928	0.931
No. of obs.	31	31	31	31	33	33	33	33
Not-for-profit hospitals								
Mean	0.598	0.614	0.597	0.642	0.679	0.682	0.707	0.707
Median	0.596	0.606	0.634	0.644	0.878	0.883	0.874	0.876
5th percentile	0.110	0.136	0.175	0.203	0.028	0.031	0.029	0.029
95th percentile	0.875	0.875	0.913	0.919	0.905	0.908	0.898	0.906
No. of obs.	7	7	7	7	5	5	5	5

a Results based on models 4 and 5 (Cobb-Douglas) and models 9 and 10 Logarithmic quadratic. The 5% and 95% percentile values are equivalent to the minimum and maximum scores after removing for the outliers in the estimated distribution.

These differences in the means and medians are relatively small, particularly when it is recognised that there are significant variations within each group of hospitals. For example, the range between the 5th and 95th percentile for very large private hospitals is 0.655 and 0.893 (model 10, table E.10). This implies that the differences in the means between very large public and private hospitals may be negligible. That said, in terms of median scores, the relative rankings between public and private hospitals remained the same, regardless of the functional form

(Cobb-Douglas and restricted translog) and choice of variables, with the exception of large hospitals in model 9 (table E.10).

In contrast, the median efficiencies of very small and small private hospitals were lower than for public hospitals (for example, the efficiency scores of very small and small private hospitals efficiency was 0.700 compared to 0.816 for public hospitals, for model 10, table E.11). The greater dispersion of efficiency among small and very small private hospitals, for example with efficiencies between 0.203 and 0.919 in model 10 (compared with public hospitals 0.575 to 0.897) suggests a degree of variability that has not been adequately captured in the model.

Finally, some correlation statistics were calculated for three variables of interest on the efficiency scores (table E.12). Occupancy rates were positively correlated with efficiency scores for all hospitals, public and private, and to some extent, public contract hospitals. Average length of stay (ALOS) is an important contributor to private hospital efficiency — hospitals with higher ALOS were less efficient. Finally complexity, as measured by cost weights, indicated that public hospitals with the higher cost weights were more efficient, while the private hospitals with the lower cost weights were more efficient.

Table E.12 **Correlation coefficients between selected variables and technical efficiency scores**

	Model 4	*Model 5*	*Model 9*	*Model 10*
Occupancy rate				
All hospitals	0.1616*	0.3222*	0.2162*	0.3361*
Publics	0.2264*	0.2333*	0.2386*	0.2555*
Privates	0.1855*	0.1964*	0.2899*	0.3051*
Public contract	0.3517	0.3279	0.5356*	0.4973*
ALOS				
All hospitals	-0.2749*	-0.3530*	-0.2411*	-0.3913*
Publics	0.0981	0.0752	0.0725	0.0920
Privates	-0.4564*	-0.4478*	-0.3954*	-0.3606*
Public contract	0.1809	0.1762	0.3313	0.3720
Cost weight				
All hospitals	-0.0800	-0.2390*	-0.0186	-0.1890*
Publics	0.2151*	0.1799*	0.2236*	0.2344*
Privates	-0.3242*	-0.3254*	-0.2005*	-0.1847*
Public contract	-0.0934	-0.1333	0.0186	0.0924

*Significant at the 5 per cent level.

Source: Unpublished ABS and AIHW data; Productivity Commission estimates

E.6 Proposed future analysis

Given the data delays faced by the Commission, the multivariate analysis presented in this report estimates hospital production functions and technical efficiency based on a single year of data (2006-07). Given the large number of hospital observations in this data set, the results are expected to be robust.

Nevertheless, the Commission intends over coming months to replicate this analysis using a larger data set that includes data from the earlier years of 2003-04 to 2005-06. Future analysis will also focus on examining the performance of hospitals for different peer groups (say, to compare the performance of very large hospitals). The Commission will also extend this analysis to examine the determinants of hospital costs.

The Commission intends to publish the results from this further analysis in March 2010.