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## Foreword

The Commission recently completed a Research Report for the Government on the performance of public and private hospitals. The report examined relative costs, hospital-acquired infections and other aspects of hospital performance. It also dealt with informed financial consent and the indexation of the income threshold for the Medicare Levy Surcharge.

As part of that study, the Commission undertook a 'multivariate analysis' of the relative efficiency of public and private hospitals. Such analysis can take account of differences in the characteristics of a hospital's patients and activities undertaken. Due to delays in accessing data, the analysis was confined to the single year 2006-07. This supplementary report includes three additional years of data, as well as some methodological enhancements. While still 'experimental', the present estimates of the relative performance of public and private hospitals are consequently more reliable.

A number of parties assisted the Commission in this study. The Australian Bureau of Statistics and the Australian Institute of Health and Welfare provided data and undertook some analysis. Others participated in a roundtable or provided referee comments. The Commission thanks all who contributed.

The study was overseen by Commissioner David Kalisch. The staff research team was headed by Ilias Mastoris and based in the Commission's Melbourne office.

Gary Banks AO Chairman

May 2010

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## **Abbreviations**





**X** ABBREVIATIONS AND EXPLANATIONS

## **Glossary**

- Acute care Clinical services provided to admitted or non-admitted patients, including managing labour, curing illness or treating injury, performing surgery, relieving symptoms and/or reducing the severity of illness or injury, and performing diagnostic and therapeutic procedures. Most episodes involve a relatively short hospital stay.
- Acute hospital Establishments which provide at least minimal medical, surgical or obstetric services for admitted patient treatment and/or care, and which provide round-the-clock comprehensive qualified nursing service as well as other necessary professional services. They must be licensed by a state/territory health department, or controlled by government departments. It also includes hospitals specialising in dental, ophthalmic aids and other specialised medical or surgical care.
- Admitted patient A patient who has undergone a formal admission process in a hospital to begin an episode of care. Admitted patients may receive acute, sub-acute or non-acute care services.
- Adverse event The unintentional harm arising from an episode of healthcare and not due to the disease process itself.

Allocative efficiency How well resources are allocated across different uses so as to generate the greatest community wellbeing at a given point in time.

- Average length of stay The average number of patient days per admitted patient episode. Patients admitted and separated on the same day are allocated a length of stay of one day.
- Australian Refined Diagnosis-related Groups An Australian system of Diagnosis-related Groups (DRGs). Version 5.0/5.1 is based on the fifth edition of ICD-10-AM. See Diagnosis-related groups.



- Elective surgery Any surgery that a patient's doctor or health professional considers to be necessary but which can be delayed by at least 24 hours. In Australia, elective surgical procedures are defined in the Medicare Benefits Schedule.
- Episode of care The period of admitted patient care between a formal or statistical admission and a formal or statistical separation, characterised by only one care type.
- Hospital A healthcare facility established under Commonwealth, state or territory legislation as a hospital or a freestanding day procedure unit and authorised to provide treatment and/or care to patients.
- Hospital-acquired infection An infection that appears during the course of care at a hospital or healthcare facility and is the result of that care. Also referred to as nosocomial infection.
- Hospital Casemix Protocol A data collection of the episodes of admitted patient care, benefits and charges for privately insured patients. It includes clinical, demographic and financial information for privately insured admitted patient services.
- Hospitalstandardised mortality ratio The ratio of the actual number of in-hospital mortalities to the number of in-hospital mortalities predicted for a hospital with the same characteristics.
- Hospital cost index An index of hospital costs published by the Australian Bureau of Statistics.
- Input-oriented technical efficiency The extent to which the quantity of inputs can be reduced without also reducing the quantity of outputs or increasing the use of another input.
- Intensive-care unit An area or environment in a hospital that provides the highest level of critical care and monitoring.
- International Classification of Diseases The World Health Organisation's internationally-accepted classification of diseases and related health conditions. The current version ICD-10 forms the basis of Australia's ICD-10-AM.
- Length of stay The period from admission to separation, less any days spent away from the hospital.



services provided by the hospital and relevant medical and paramedical practitioners.

- Private patients Patients admitted to a hospital who decide to choose the doctor(s) who will treat them and/or to have private ward accommodation. They are charged for medical services, food and accommodation.
- Procedure A clinical intervention that is surgical in nature, carries a procedural risk, carries an anaesthetic risk, requires specialised training, and/or requires special facilities or equipment available only in an acute-care setting.
- Public contract hospital For this study, a health care provider facility established under state or territory legislation as a hospital and on behalf of the government, to provide hospital services free of charge to all eligible patients.
- Public hospital For this study, a health care provider facility established under state or territory legislation as a hospital and operated by the government, to provide hospital services free of charge to all eligible patients.
- Public patient A patient admitted to a hospital who has agreed to be treated by doctors of the hospital's choice and to accept shared accommodation. This means the patient is not charged.
- Quality A measure of the quality of clinical care and patient safety in a hospital, and is measured by indicators such as in-hospital mortality and unplanned re-admission rates. It is synonymous with 'effectiveness' in this study.

Technical efficiency A measure of the efficiency that relates a hospital's outputs to its input use. Can be specified as 'input-oriented technical efficiency', and 'output-oriented technical efficiency'.

- Total operating expenditure Expenditure on a hospital's goods and services which are used up during the year. Includes salaries and wages, expenditure on drug, medical and surgical supplies, and repairs and maintenance. Does not include investment expenditure, or the depreciation of capital.
- Same-day establishments Day centres, hospitals and freestanding day surgery centres that provide a course of acute treatment on a full-day or

part-day non-residential attendance basis at specified intervals over a period of time. Freestanding day surgery centres are approved by the Commonwealth for the purposes of basic table health insurance benefits.

Separation An episode of care for an admitted patient, which can be a total hospital stay (from admission to discharge, transfer or death), or a portion of a hospital stay beginning or ending in a change of type of care (for example, from acute to rehabilitation).

> Separation also means the process by which an admitted patient completes an episode of care either by being discharged, dying, transferring to another hospital or changing type of care.

Stochastic frontier analysis A statistical regression technique used to determine the frontier of best-practice entities such as firms and hospitals.

- Sub-acute and non-acute care Clinical services provided to patients suffering from chronic illnesses or recovering from such illnesses. Services include rehabilitation, planned geriatric care, palliative care, geriatric care evaluation and management, and services for nursing home type patients. Clinical services delivered by designated psychogeriatric units, designated rehabilitation units and mothercraft services are considered non-acute.
- Unplanned hospital readmission An unexpected hospital admission for treatment of: the same condition for which the patient was previously hospitalised; a condition related to one for which the patient was previously hospitalised; or a complication of the condition for which the patient was previously hospitalised.
- Unplanned hospital readmission rate The number of unplanned readmissions to the same hospital that occur within a given period after separation, divided by the total number of separations (excluding deaths), including day stay patients.
- User cost of capital The opportunity cost of the capital used to deliver hospital services. That is, the return that could be generated if the funds were employed in their next best use.

**OVERVIEW** 

#### **Key points**

- The Commission recently completed a Research Report on the performance of public and private hospitals which compared costs, infection rates and other indicators (PC 2009). That report also considered rates of, and impediments to, informed financial consent; and assessed potential indexation factors for the Medicare Levy Surcharge income thresholds.
- A part of that study used multivariate techniques which estimated that hospital output was typically around 20 per cent below best practice. This was based on preliminary analysis of just a single year of data because of significant delays in accessing data.
	- The modelling in this supplement draws on three additional years of data, as well as improved data quality and estimation methods, and finds that hospitals are operating around 10 per cent below best practice. While this estimate is more reliable, it remains an estimate given the limitations to the data.
- In this supplement, the Commission has compared hospital performance in terms of:
	- $-$  hospital-standardised mortality ratios  $-$  as a measure of the effectiveness and 'quality' of hospital care
	- $-$  efficiency  $-$  measured by the extent to which hospitals made best use of their resources to provide services.
- Hospital-standardised mortality ratios were estimated to be generally similar between very large public and private hospitals. However, smaller private hospitals had noticeably better mortality ratios than similar-sized public hospitals.
	- While this might indicate differences in management and clinical competence, it could also indicate the tendency for smaller public hospitals to be the only major source of clinical care in remote and very remote areas.
- Australian acute hospitals were estimated to have scope to improve their efficiency by about 10 per cent under the existing policy environment.
	- For-profit and 'public contract' hospitals were estimated to be more efficient than public hospitals on average, in terms of their potential to increase output for a given set of inputs.
	- However, for-profit, not-for-profit and public hospitals were found to be similarly efficient with respect to their potential to economise on input use for a given level of output.
- Smaller public hospitals, many of which are located in more remote communities, were found to be less efficient than similar-sized private hospitals, possibly due to lower occupancy rates.
- The Commission also sought to measure the determinants of hospitals costs, but the available financial data, such as capital and medical costs, were inadequate.
- There are various other shortcomings in data quality and availability. These would need to be overcome if policy analysts and other researchers are to produce improved estimates of efficient costs of providing hospital care.

## **Overview**

The Commission recently completed a Research Report on the performance of public and private hospitals which compared hospital and medical costs, infection rates and other indicators; considered rates of, and impediments to, informed financial consent; and assessed potential indexation factors for the Medicare Levy Surcharge income thresholds (PC 2009). The report also reported the estimates from a preliminary multivariate analysis of the efficiency of public and private acute hospitals. Due to a lack of timely access to data, however, that analysis had to be based on a single year of data (2006-07) and examined only one aspect of efficiency. The Research Report noted that the Commission would be revisiting the multivariate analysis in early 2010.

This supplement improves on the multivariate analysis in the Research Report by:

- including three additional years of data (2003-04 to 2005-06)
- addressing the poor quality of some of the data
- improving the measurement of effectiveness and quality of hospitals
- considering alternative approaches to modelling hospital efficiency
- addressing the under-representation of not-for-profit hospitals in the dataset.

Overall, these enhancements have yielded more reliable estimates of the relative effectiveness and efficiency of public and private hospitals, but should still be understood as estimates produced using the best available data and modelling techniques at this time. However, a number of data limitations persist.

## **Measuring hospital performance**

In this study, hospital performance is examined in terms of both quality and efficiency. Hospital quality is proxied by the hospital-standardised mortality ratio (HSMR) for each hospital. The relative performance of hospitals in reducing mortality is a potentially useful measure, as it represents the basic tenet of a hospital — to heal the sick and provide for their safety. Nonetheless, HSMRs are only one of a range of quality indicators.

The second measure of performance, hospital efficiency, relates the services a hospital provides to its input use or costs incurred. Hospital efficiency is important, because improvements can free up resources for use elsewhere, either within the hospital or broader health care sector, to improve the community's wellbeing.

Hospital efficiency in this study is principally concerned with the activities within hospitals. The study does not seek to consider the issue of *allocative efficiency* the efficiency with which the health sector as a whole is providing the appropriate mix of hospital and other healthcare services. Such a study would need to focus on the way a hospital's services are priced, and account for the operation of public and private health insurance and the asymmetries of information within the health sector. These are beyond the scope of this analysis.

The data made available for this study contain 1806 observations for 459 acute overnight hospitals between 2003-04 to 2006-07. These comprised:

- public hospitals  $-343$  hospitals contributing 1354 observations
- for-profit private hospitals 75 hospitals contributing 295 observations
- not-for-profit private hospitals  $-24$  hospitals contributing 94 observations
- public contract hospitals  $-17$  hospitals contributing 63 observations.

As noted in the Commission's Research Report (PC 2009), permission to access public hospital data was obtained from the health departments of each state and territory. Permission to access private hospital data was obtained from a number of hospital owners and operators. The Australian Institute of Health and Welfare (AIHW) was the source of morbidity data for both public and private acute hospitals, and establishment data for public hospitals. The Australian Bureau of Statistics (ABS) was the source of establishment data for private hospitals. For commercial-in-confidence reasons, the analysis was undertaken by the ABS under the direction of the Commission.

The sample of public hospitals includes all public acute hospitals in Australia. According to the AIHW, there were 768 public hospitals in 2007-08. However, many of these were sub-acute, non-acute and psychiatric hospitals. To ensure maximum comparability, these were excluded from the sample. Other observations were also removed because of concerns about the quality of the data, leaving 343 public acute hospitals in the dataset.

A distinction is made between for-profit and not-for-profit hospitals. Not-for-profit hospitals include both religious and non-religious charitable hospitals. For-profit and not-for-profit hospitals operate under different taxation arrangements, and are likely to have different profit and pastoral care motivations. Those arrangements

and other factors may sufficiently influence their relative performance and justify explicitly testing for such differences.

A distinction is also made between public and 'public contract' hospitals. Public contract hospitals are managed by non-government entities to provide public hospital services either under contract or, if they are deemed to be public health organisations (for example, as under the *Health Services Act 1997* (NSW)), with a subsidy. Public contract hospitals are operated by for-profit and not-for-profit organisations. The Commission made this distinction to test whether ownership or management structure affects the performance of hospitals.

## **Hospital-standardised mortality ratios**

There are a number of potential indicators that describe different aspects of the effectiveness and quality of a hospital's care. Some of the more notable indicators include the rates of hospital-acquired infections, adverse events, unplanned readmissions and in-hospital mortality.

The Commission used the rate of in-hospital mortality as a measure of effectiveness and quality for two reasons. First, it is relatively accurately measured. Second, it is a reasonable proxy for some other aspects of hospital quality. Some of the underlying factors that contribute to unplanned re-admissions, for example, may also influence a hospital's incidence of mortality. That said, in-hospital mortality is only a partial measure of a hospital's effectiveness and quality, and may not fully reflect variations in other quality dimensions such as hospital-acquired infection rates and adverse events in hospitals.

In-hospital mortality rates vary substantially according to the ownership and size of hospitals. Rates were over two-and-a-half times higher for public hospitals (1.48 per cent of separations) than for private hospitals (0.54 per cent of separations) (table 1).

In-hospital mortality, however, is influenced by a number of observable factors that are outside the control of hospitals, such as the characteristics of patients and the role of the hospital itself. Patients in public hospitals were reported to have more comorbidities than in private hospitals (with an average Charlson comorbidity score of 0.58 compared to 0.54) (table 1). Significantly, more of a public hospital's patient workload also comes from the most disadvantaged socioeconomic quintile (40.5 per cent of separations compared to 15.2 per cent of separations for private hospitals).



#### Table 1 **Selected patient characteristics, by owner and hospital size, 2003-04 to 2006-07a**

**<sup>a</sup>** Very large hospitals have 20 001 or more casemix-adjusted separations per year, Large hospitals have between 10 001 and 20 000, Medium hospitals have between 5001 and 10 000, Small hospitals have between 2001 and 5000, and Very Small hospitals have up to 2000 separations per year. **b** In-hospital mortality is the percentage of separations that involved an in-hospital death. **c** Patient comorbidity is based on the Charlson comorbidity score calculated at admission, and is an odds-ratio of the probability of dying within a year from admission. Thus a score of 0.50 indicates a 0.50:1 or 33 per cent chance of dying within a year. **d** The percentage of a hospital's separations from a geographic area rated as the most disadvantaged socioeconomic quintile. **np** Not published due to ABS confidentiality concerns.

To ensure that the comparisons between different hospitals reflect their underlying performance, as distinct from their roles, functions and characteristics of their patient population, the Commission risk-adjusted each hospital's mortality rate.

The process of risk adjustment involved undertaking a multivariate analysis of in-hospital mortality. In-hospital mortality rates were found to increase where hospitals offered palliative care services, treated more patients that were aged 70 and over, treated more patients with the most number of comorbidities, treated more medical rather than surgical cases, and treated more patients for circulatory, respiratory, digestive diseases and disorders and burns.

Conversely, in-hospital mortality rates decreased where hospitals offered rehabilitation services, treated more patients aged between 5 and 19 years, provided relatively more surgical than medical cases, and specialised in a narrower range of services. Furthermore, in-hospital mortality was also found to increase as hospitals decreased in size, and to decline over the four years of the data.

The Commission then calculated the HSMR for each hospital in the dataset. The HSMR is the ratio between the observed and predicted in-hospital mortalities. It reflects unobservable characteristics of the hospital — including management and clinical competence. Hospitals with HSMRs below 100 perform better than predicted, and those with HSMRs above 100 have mortality outcomes worse than predicted. A score of 90, for example, indicates that the incidence of mortality of that hospital is 10 per cent below what would be expected for a hospital with the same observable patient and hospital characteristics.

The estimated mean HSMRs of private hospitals are lower than those of public hospitals by almost 12 percentage points (table 2). This overall difference was statistically significant in aggregate. There was no statistically significant difference, however, between the estimated HSMRs of very large public and private hospitals.



#### Table 2 **Estimated mean hospital-standardised mortality ratios, by owner and hospital size, 2003-04 to 2006-07a,b**

**a** Very large hospitals have 20 001 or more casemix-adjusted separations per year, Large hospitals have between 10 001 and 20 000, Medium hospitals have between 5001 and 10 000, Small hospitals have between 2001 and 5000, and Very Small hospitals have up to 2000 separations per year. **b** The hospital-standardised mortality ratio is equal to the actual (observed) mortality rate divided by the predicted mortality rate, multiplied by 100. **c** There is no statistical difference in the scores of 'very large' hospitals, but there is a relatively small group of not-for-profit hospitals. **d** Statistically different from public hospitals of 'all sizes'. **e** Not statistically different from not-for-profit hospitals of 'all sizes'. **f** Results combined for small and very small hospitals because of ABS confidentiality concerns. **g** Not statistically different from public hospitals, but there is a relatively small sample of public contract hospitals of 'all sizes'. **np** Not published due to ABS confidentiality concerns.

These findings suggest that the differences between very large public and private hospitals are largely explained by their observable factors — that is, there is little to distinguish them in terms of their underlying HSMR performance. However, the divergence in HSMRs between smaller public and private hospitals suggests the presence of unexplained factors. These might include management performance, though they could also reflect other factors. For example, smaller public hospitals tend to be predominant sources of clinical care in remote and very remote areas, and other factors such as the availability primary care may also be important. It might also reflect differences in the ability of hospitals to specialise in a narrow range of procedures. Even though the Commission sought to take into account the effect of specialisation, this effect may still be present in the data. Since private hospitals have greater scope to specialise, they may better able to reduce in-hospital mortality rates as procedures become more routine.

## **Hospital 'efficiency'**

The Commission sought to estimate both the technical efficiency and the determinants of hospital costs. Technical efficiency is the extent to which hospitals make best use of their resources to achieve a desired output or outcome. It is an attractive approach to measuring efficiency because it does not require data on prices or costs, reliable estimates of which can be difficult to obtain.

Hospitals are also commonly compared in terms of their costs. However, hospital costs, at least in Australia, are dogged by incomparable and poor quality financial data, which limit the ability to produce robust estimates of the influences on costs. The remaining discussion accordingly focuses on technical efficiency.

Technical efficiency represents the gap between a hospital's actual output and its potential output, without changing input use or quality (the output-orientation approach). It can, conversely, be measured as the gap between its actual resource use and its potential input use, without changing outputs or quality (the input-orientation approach).

While the two approaches are expected to yield similar estimates of efficiency in aggregate, they need not yield the same estimates of efficiency for individual hospitals, as in figure 1. Technical efficiency in the output-orientation approach is the distance between a hospital at *A* and its potential output at *B*, while technical efficiency under the input-orientation approach is given by the distance between a hospital at *A* and its potential input use at *C*.



#### Figure 1 **Illustration of the measurement of technical efficiency**

The choice between the output and input-orientation approaches to measuring efficiency in part depends upon which approach best reflects the operational practices of hospitals. The output-orientation approach assumes that hospitals have the flexibility to increase their outputs, whereas the input-oriented method assumes

that hospitals have little or no flexibility to change their output but seek to minimise their input use.

A variant of stochastic frontier analysis (SFA), stochastic distance functions, was used to determine each hospital's best-practice frontier (box 2).

#### Box 2 **The Commission's approach to measuring hospital frontiers**

The Commission used stochastic frontier analysis (SFA) to determine the best-practice frontiers against which hospital technical efficiency was measured. SFA is an econometric technique, similar to ordinary least squares (OLS). As with OLS, a variety of factors that are thought to determine hospital production are included in the model.

A lack of data means that hospital efficiency cannot be measured directly and must be inferred. If there is a strong a priori expectation that efficiencies differ across hospitals, it is possible to use the information contained from the residuals of a regression estimation to distinguish between genuine random error and unobservable hospital efficiency.

SFA can be graphically represented as a two-step regression. In the first step, a regression equation is estimated to pass through the mean of the data, much like OLS (in this example, between hospitals *A*, *B, C* and *D*). This gives the production function *MM-*.



The curve *MM'* is then shifted for each hospital by the amount that reflects the genuine random error. For example, the curve MM' is shifted by amounts Shift b and Shift c for hospitals *B* and *C*. The distances between the actual positions and projected frontier are the efficiency gaps *Gap b* and *Gap c* for hospitals *B* and *C*.

SFA represents a significant improvement on earlier techniques, such as data envelopment analysis, for benchmarking hospitals. By explicitly accommodating for random error, the technique is less prone to overstating the presence of inefficiency. Moreover, as an econometric technique, it allows for the statistical relationships between variables to be estimated and tested.

#### **Determinants of technical efficiency**

Hospital technical efficiency is influenced by the variety of inputs used by hospitals and the diversity of services they produce. A detailed description of the differences in the services provided by hospitals can be found in the Commission's Research Report on public and private hospitals (PC 2009). For example, there are significant differences between public and private hospitals with their inpatient, accident and emergency department, and occupancy rates (table 3).



#### Table 3 **Selected hospital characteristics, by owner and hospital size, 2003-04 to 2006-07a**

**<sup>a</sup>** Very large hospitals have 20 001 or more casemix-adjusted separations per year, Large hospitals have between 10 001 and 20 000, Medium hospitals have between 5001 and 10 000, Small hospitals have between 2001 and 5000, and Very Small hospitals have up to 2000 separations per year. **b** Number of casemixadjusted separations per non-medical staff member. **c** Number of accident and emergency department visits per non-medical staff member. **d** Defined as (the number of patient days) divided by (the number of staffed beds multiplied by 365). **np** Not published due to ABS confidentiality concerns.

To ensure that the estimated hospital technical efficiency results actually report efficiency rather than some other factor, measures of hospital efficiency should also take into account the influence of factors outside the control of hospitals — such as the average severity of patient illness or injury, and the quality of services provided by hospitals. The Commission took into account an extensive range of inputs, outputs and control variables (box 3).

#### Box 3 **Factors included in the measurement of hospital technical efficiency**

A large number of variables were included to control for the differences between hospitals, including:

- *admitted patient outputs* the number of casemix-adjusted separations for acute diseases and disorders, pregnancy and births, mental disorders and drug and alcohol cases, and other separations (including mostly rehabilitation and long-term aged care)
- *non-admitted patient outputs*  most categories of non-admitted services such as accident and emergency services, diagnostic services, allied health and dental services, district nursing and community outreach services, and dialysis and endoscopy services
- *output control variables*  such as the percentage of separations that were surgical rather than medical, the relative ratio of emergencies to admitted patients, the extent to which a hospital's admitted patients have been transferred to or from another hospital
- *hospital quality* as measured using the hospital-standardised mortality ratio
- *inputs* including the number of full-time equivalent nurses, diagnostic and allied health staff, and other staff, as well as the number of staffed beds, and the expenditure on medical and surgical supplies, pharmaceutical supplies, and other hospital costs
- *patient characteristics* such as the patient's age, acuity of illness, number of comorbidities, socioeconomic status, and gender
- *financial incentives*  such as the patient's public patient status
- *hospital characteristics* such as the hospital's remoteness, teaching status, complexity of its work, as well as whether it was part of a network, and whether it had a number of specialist units, such as palliative care and level III intensive-care units.

Medical staff (doctors) were not included in the determination of technical efficiency, and medical costs were excluded from the attempts to estimate the determinants of hospital costs, because data were not readily available for the majority of doctors in private hospitals or for doctors exercising rights of private practice in public hospitals (box 4).

#### Box 4 **Medical workforce and hospital beds: selected data issues**

#### **What is the effect of excluding medical staff?**

Care needs to be taken when interpreting the efficiency scores since medical staff are not included in the estimation of technical efficiency in this supplement. The exclusion of medical staff may influence the estimated efficiency scores of hospitals, depending on the use of doctors across hospitals.

If, however, the intensity of use of doctors is the same across hosptials, then the resulting efficiency scores are expected to be reasonably representative of hospitals and the medical workforce. Information is not available to allow a firm conclusion to be drawn on this matter.

#### **How was capital measured?**

For the calculation of technical efficiency, a hospital's capital stock should ideally be represented in terms of the physical units of capital in the hospital — such as the number of operating theatres, birthing suites, acute and non-acute beds and so on.

Such data are not available on a consistent basis nationally. Instead, the number of staffed beds was used as a proxy for capital. Since public and private hospitals counted beds differently, the Commission estimated the number of staffed beds for private hospitals.

Since using the number of beds does not adequately distinguish between the different types of hospital capital (for example, between acute and non-acute beds) and the presence of particular facilities (such as operating theatres), a number of other control variables were included. These variables represented the presence of particular units or functions (such as whether the hospital is a teaching facility, or has level III intensive care, rehabilitation and palliative care units) or represented the relative differences in the complexity of a hospital's workload.

There were also limitations with the measure of capital employed in this study. In the absence of detailed and robust capital data, the number of beds was used as a proxy for a hospital's capital stock. Furthermore, private and public hospitals report their beds differently. Public hospitals report the number of *staffed* beds while private hospitals report the total number of *available* beds, whether they are staffed or not. The Commission endeavoured to overcome this discrepancy by estimating the number of staffed beds for private hospitals and by introducing a range of variables to account for the different roles and functions of hospitals (box 3).

Factors that were estimated to be significant in influencing hospital output and input use included:

- the complexity of cases provided by the hospital
- the extent to which the hospital treated medical rather than surgical cases
- the degree of comorbidity in the patient population
- the age profile of patients (particularly the presence of more older patients)
- the presence of level III intensive care and other specialist units
- the remoteness of the hospital
- the extent to which a hospital treated public patients
- whether the hospital was a recognised medical teaching hospital
- whether the hospital was part of a network.

The estimation results also showed a strong relationship between a hospital's quality and its efficiency. The most efficient hospitals were also those with the lowest in-hospital mortality. This was apparent with both the output-oriented and input-oriented efficiency approaches. This suggests that the factors that contribute to a well-managed hospital also improve health outcomes.

### **Estimates of technical efficiency**

After accounting for the range of observable factors, the remaining unobserved differences in performance can be interpreted as measuring a hospital's efficiency — the potential for management to improve hospital performance under the existing policy environment.

Across the hospital sector, output-oriented efficiency was estimated to be 90 per cent, suggesting there was scope to improve output, on average, by 10 per cent (for a given level of input use). Input-oriented efficiency was estimated, on average, to be just below 90 per cent of the estimated potential, suggesting that input use could be reduced by just over 10 per cent (for a given level of output) (table 4).

The results also indicate that for-profit and public contract hospitals had the highest *output-oriented* technical efficiency among Australian hospitals, and not-for-profit hospitals the lowest. These differences were statistically significant.

Public contract hospitals were estimated to have the highest *input-oriented* technical efficiency. There was no statistically significant difference between public, for-profit and not-for-profit private hospitals. Public and not-for-profit hospitals had similar scope to for-profit hospitals to reduce their input use while still producing the same level of outputs.

The differences in estimated efficiency between private and public hospitals were most noticeable between smaller for-profit private and public hospitals. There also appeared to be considerable scope for large and medium-sized not-for-profit hospitals to improve their efficiency.



#### Table 4 **Summary of estimated technical efficiency scores, by ownership and hospital size, 2003-04 to 2006-07a**

**a** Very large hospitals have 20 001 or more casemix-adjusted separations per year, Large hospitals have between 10 001 and 20 000, Medium hospitals have between 5001 and 10 000, Small hospitals have between 2001 and 5000, and Very Small hospitals have up to 2000 separations per year. **b** Statistically significantly different from public hospitals, "all sizes". **c** Statistically significantly different from public hospitals and from not-for-profit hospitals, "all sizes". **d** Statistically significantly different from other public and private hospitals, "all sizes". **e** Not statistically significantly different from public hospitals, "all sizes". **f** Not statistically significantly different from not-for-profit hospitals, "all sizes". **g** Results combined for small and very small hospitals because of ABS confidentiality concerns. **np** Not published due to ABS confidentiality concerns.

### **Overall assessment**

In weighing up both HSMRs (as a quality measure) and technical efficiency, for-profit hospitals were estimated in the model to be the best performing among very large hospitals, followed by public contract hospitals. For-profit hospitals had among the highest estimated technical efficiency (whether using the output or input-oriented approaches) and among the lowest estimated HSMRs.

Very large public hospitals were estimated to be the best performing public hospitals. They recorded relatively high technical efficiencies (under the output-oriented approach) and comparatively low HSMRs. Very small public hospitals were estimated to be the worst performing among public hospitals, having both very high HSMRs and lowest technical efficiency (under the output-oriented approach).

The best performing for-profit hospitals were estimated to be the smaller hospitals — these had consistently high technical efficiency scores (under both output and input-oriented approaches) and comparatively low HSMRs. Very large for-profit hospitals were estimated to have similar levels of efficiency but slightly worse HSMRs. The best-performing not-for-profit hospitals were estimated to be the smaller hospitals (under the input-oriented approaches). Their technical efficiency was similar to that of public hospitals, and they had comparatively low HSMRs.

Smaller private hospitals were estimated to outperform smaller public hospitals, in terms of HSMRs and output-oriented technical efficiency. The observed lower efficiency performance of very small public hospitals might simply be due to their comparatively low occupancy rates. If there is a minimum size for a hospital, and there is comparatively low demand for hospital services in more remote communities, this would contribute to lower observed occupancy rates, and therefore lower comparative efficiency. For example, the occupancy rates for small and very small public hospitals (most of which are outside major cities) were 67 and 49 per cent respectively. In contrast, the occupancy rates for small and very small private hospitals (most of which are inside major cities) were 74 and 63 per cent respectively (table 3).

## **Limits to estimating hospital costs**

As noted, the Commission also sought to estimate the determinants of public and private hospital costs. Hospitals are commonly compared in terms of their costs, so estimating the performance of hospitals in managing the costs of providing patient care is an attractive performance measure.

Even though this study made some advances in developing an appropriate methodology for the estimation of hospital costs, particularly through the use of factors explaining patient and hospital characteristics, the Commission lacks confidence in the results because of data deficiencies:

- First, there was an absence of capital costs (including both the depreciation cost of building, plant and equipment, as well as the opportunity cost of capital) for public hospitals. The Commission was unable to estimate the capital costs for individual hospitals.
- Second, medical costs were not included in the cost analysis. Such data are readily available for public hospitals. Though they are, in principle, available for

doctors in private hospitals through the Commonwealth's *Hospital Casemix Protocol*, the Commission could not obtain access to private hospital medical costs data.

• Third, there were limited data on the prices paid by hospitals for their inputs. The prices for pharmaceutical supplies, medical and surgical supplies, and other hospital costs were unavailable for individual hospitals and therefore needed to be estimated using nation-wide deflators. There was, as a result, no price variation between states and territories, within states and territories, and between hospital sectors. The absence of capital costs also meant that it was not possible to obtain estimates on the cost per unit (that is, price) of capital for public hospitals.

### **How do these results compare with other studies?**

The results in this supplementary analysis differ somewhat from those reported in Chapter 8 of the Commission's Research Report (PC 2009). In that report, the model estimates suggested that — based on one year's data — there was little to separate private and public hospital efficiency, and that hospitals could on average increase their outputs by 20 per cent given their current set of inputs. While the results reported in this supplement are likely to be more reliable, they remain estimates, and could be improved further with more comprehensive and accurate data.

There are very few other Australian studies with which these results can be directly compared. There has been no study, to the Commission's knowledge, that directly compared public and private hospital HSMRs using a common method and dataset. Jensen, Webster and Witt (2007) found that Victorian private hospitals had significantly better outcomes at treating acute myocardial infarction than did Victorian public hospitals, although Chua, Palangkaraya and Yong (2008) using the same dataset, found that better health outcomes were achieved among larger hospitals. There is no study comparing public and private hospital technical efficiency at a national level. A study by Webster, Kennedy and Johnson (1998) found that for-profit hospitals were technically more efficient than not-for-profits, although the authors did not account for casemix differences and the patient and hospital characteristics of each hospital.

There are few overseas studies that compare the performance of public and private hospitals. Among those that are available, there are differences in the modelling techniques employed, datasets, variables used, including the treatment of quality, and hospital and patient-risk characteristics. Some of the more notable studies include Herr (2008), Grosskopf, Margaritis and Valdmanis (1995), Burgess and Wilson (1995) and Zuckerman, Hadley and Iezzoni (1994). The average gaps in efficiency range between 10 and 20 per cent. In two of these studies, public hospitals were found to be more efficient than private hospitals. Differences in these findings can be explained in part by methodological differences of the studies and institutional differences of the countries being studied.

## **Areas for further work**

The Commission found a number of challenges in undertaking this study as well as the analysis in the preceding Research Report.

First, there was reluctance among a number of parties to grant access to data needed for the analysis. Reasons put forward included protecting the privacy of individuals, and commercial-in-confidence arrangements for individual hospitals and owners of hospitals. This has led to an under-representation of not-for-profit hospitals in the dataset.

In the Commission's view, these impediments to accessing data were greater than would reasonably be expected to address legitimate privacy and confidentiality concerns. Making data more accessible could help drive improvements in health care, especially as competitive markets have a limited role. It could also encourage future improvements in data collections (PC 2009).

Second, to meet the commercial-in-confidence concerns of various parties, the analysis needed to be undertaken by ABS staff under the direction of the Commission. Commission staff were not permitted to observe data items which could identify individual hospitals. This meant that there were delays, as the analysis was necessarily undertaken remotely in a two-step process.

Third, the Commission used HSMRs as a proxy for hospital quality. While HSMRs are a significant improvement on unadjusted in-hospital mortality rates, they are only one measure of quality. Improvements to the reporting of other indicators, such as unplanned re-admission rates, infection rates and adverse events would substantially contribute to our understanding of hospital quality.

Fourth, there are significant limitations to the financial data of hospitals, particularly public hospitals. Efficiency estimates accounting for costs would be substantially improved if:

• both capital costs and capital leasing costs were more accurately reported

- the medical costs of doctors practicing privately in both private and public hospitals were available and accessible
- more detailed estimates of the price components of hospital resources, such as pharmaceutical, medical and surgical supplies, were available.

Fifth, there are also deficiencies in certain hospital establishment data. Estimates of technical efficiency would also be improved if:

- the number of doctors practicing privately in both private and public hospitals were made available and accessible
- private and public hospitals counted their beds in the same manner
- there were consistent and detailed estimates of the various types of capital in hospitals (such as level III intensive care unit beds and non-acute beds).

Finally, there are well known deficiencies in the quality of hospital outpatient data. Both cost and technical efficiency estimates would be improved if there were greater consistency in the reporting of outpatient services and if these estimates were adjusted for differences in casemix.

Each of these areas for data improvement would greatly assist in any future work seeking to measure efficient costs of providing hospital care.

# 1 Introduction

#### **Key points**

- The Productivity Commission recently completed a study comparing the relative performance of public and private hospitals.
- This included a multivariate analysis of technical efficiency using 2006-07 data.
- This supplementary report extends that analysis by:
	- using three additional years (2003-04 to 2005-06)
	- addressing the poor quality of some of the data
	- exploring alternative ways to model technical efficiency
	- expanding the scope of the analysis to include cost efficiency
	- accounting for the under-reporting of not-for-profit hospitals in our sample.

## **1.1 What is this study about?**

The Commission was asked by the Australian Government to report the costs of public and private hospitals, and to report on hospital-acquired infections as well as other indicators that might inform comparisons of hospital performance. The Commission published its findings in its report (PC 2009) drawing on a number of partial indicators that describe hospital performance.

The Commission also undertook a multivariate analysis of hospital efficiency because partial indicators suffer from two broad limitations. First, since they are by definition partial, no one indicator provides an overall assessment of a hospital's performance. Instead, a large number of indicators that cover costs, quality and patient safety need to be read in conjunction to infer an overall assessment of hospital performance.

Second, there is a large range of factors outside the control of a hospital that can influence its performance. These include the characteristics of its patients (such as the patient's socioeconomic status, gender, age and comorbidities), and the roles and functions of the hospital (such as whether it provides teaching and emergency department services, its location and size).

To overcome the limitations of partial indicators, the Commission compiled a dataset comprising 459 public and private hospitals for the period 2003-04 to 2006-07. To the Commission's knowledge, this is the first time such a dataset has been assembled at the national level. However, due to a range of delays in constructing the dataset, the multivariate analysis reported in PC (2009) was confined to a single year (2006-07) and only examined the technical efficiency of public and private hospitals. As a result, the multivariate analysis results of the Research Report are preliminary.

This supplement re-examines the multivariate analysis terms of:

- hospital-standardised mortality ratios (HSMRs) a measure of a hospital's performance in reducing in-hospital mortality after accounting for differences in patient and hospital characteristics
- technical efficiency which is a measure of the extent to which a hospital is able to increase its output without producing less of another output or using more of some input.

The key differences with the supplement are that it:

- includes three additional years of data (2003-04 to 2005-06)
- explores alternative approaches to measuring technical efficiency
- seeks to examine the determinants of cost efficiency the extent to which the hospital is delivering services to the community at the least possible cost, for a given level of output and/or hospital quality
- explicitly accounts for the under-representation of private hospitals (especially not-for-profits) in the dataset.

The results of this supplement replace the preliminary multivariate analysis results of the Research Report.

## **1.2 Structure of study**

This supplementary report is structured as follows:

• Chapter 2 provides a brief review of the literature concerning the multivariate analysis of public and private hospitals. It also provides a brief description of the techniques used to estimate the HSMRs, and technical and cost efficiencies. Detailed descriptions of the literature reviews and analytical techniques are given in appendices B and C respectively.
- Chapter 3 provides a description of the Commission's dataset, including the sources of data and how it was constructed. It also provides a discussion of how representative the Commission's dataset is of the population of Australian hospitals.
- Chapter 4 reports the results of techniques to measure HSMRs which are also subsequently used in the multivariate estimation of technical and cost efficiencies. More detailed results of the HSMRs are presented in appendix D.
- Chapters 5 and 6 report estimates of the technical and cost efficiencies for public and private hospitals. More detailed results of the technical and cost efficiency analyses are presented in appendix D.

# **1.3 Conduct of the study**

Consistent with its practices, the Commission consulted and sought feedback from relevant experts and interested parties. In addition to the consultation processes in PC (2009), the Commission:

- held a teleconference with interested parties from a number of organisations on 12 March 2010 (listed in appendix A)
- engaged two external referees to review the Commission's methods and findings, and to provide independent written comments on the Commission's analysis (appendix E).

# 2 The Commission's approach

#### **Key points**

- The Commission used hospital-standardised mortality ratios (HSMRs) to measure the effectiveness and quality of hospital care.
	- HSMRs describe how effectively hospitals reduce in-hospital mortality relative to how well they are predicted to perform, after accounting for patient and other factors affecting mortality.
- The Commission also assessed hospital performance by measuring the efficiency with which hospitals use their resources to provide services and to contribute to the quality of health care.
- The Commission measured hospital efficiency in three ways:
	- output-oriented technical efficiency the extent to which a hospital is able to produce more of any output without producing less of some other output or using more of some input
	- $-$  input-oriented technical efficiency  $-$  the extent to which a hospital is able to reduce the use of any input without producing less of some output or using more of some other input
	- cost efficiency the extent to which a hospital produces its outputs at least possible cost.
- In calculating the various performance measures, the Commission took into account a range of factors including:
	- patient characteristics that were outside the control of hospitals
	- financial incentives faced by hospitals
	- other hospital characteristics, such as the hospital's teaching status, location, the presence of emergency departments and intensive care facilities, and the presence of specialist facilities.

The Commission benchmarked the performance of public and private hospitals in terms of:

- hospital-standardised mortality ratios (HSMRs), which are measures of hospital effectiveness and quality
- the efficiency with which hospitals provide their services.

The approach to measuring hospital effectiveness and quality is outlined in section 2.1. Key concepts of hospital efficiency are described in section 2.2. The Commission's approach to estimating efficiency is outlined in section 2.3. Other issues for estimating hospital efficiency are outlined in section 2.4. A more detailed description of the methods for estimating HSMRs and efficiency are outlined in appendix C.

# **2.1 Measuring hospital effectiveness and quality**

Patients seek hospital services in order to improve their physical and emotional wellbeing relative to what would otherwise be the case. The effectiveness of a hospital's health care is an important aspect of a hospital's performance because it is a major contributor to the key purpose of a hospital — to heal the sick and injured and to provide for their safety.

Considerable effort, in Australia and overseas, has been put into measuring hospital effectiveness and quality. In Australia, for example, a number of reporting frameworks have been developed (including ACHS 2008; AIHW 2009b and SCRGSP 2009, as well as the National Healthcare Agreement reporting) to assist policy makers and hospital administrators to understand and assess the extent to which they are meeting those objectives.

# **Some measures of hospital effectiveness and quality**

The ideal measure is one which captures the incremental improvement to a patient's health status after an episode in hospital care. Theoretical measures of incremental improvements include the improvements to the disability-adjusted life years or quality-adjusted life years of a patient. However, as noted by the Centre for Health Economics (Monash University) (cited in PC 2009), such measures of patient outcomes are not generally available.

The community also places value on other aspects of hospital services — such as accessibility and waiting times for services. These dimensions are included in many definitions of hospital quality (for example, ACSQHC 2009; Campbell, Roland and Buetow 2000). A number of organisations in Australia and overseas have sought to identify and measure various dimensions of hospital quality (for example, ACHS 2008; AHRQ 2009; AIHW 2009b; Department of Health (Victoria) 2009; Kelley and Hurst 2006). It was not possible, however, to incorporate these measures in the estimation of hospital effectiveness and quality.

A review of Australian and overseas studies of hospital efficiency (appendix B) suggests that potential measures of hospital quality include:

- adverse events
- hospital-acquired infections
- unplanned re-admissions
- in-hospital mortality.

Data for each these variables are included in the National Hospital Morbidity Database (NHMD) in Australia. However, the current reporting of these variables suffer from a number of limitations. In the case of adverse events, there are two problems. First, the categories for classifying adverse events do not fully reflect the true incidence of hospital error. Other classification categories in the NHMD may also report an incidence of adverse events, but these are not routinely collected (AIHW 2009a). For example, published Australian Institute of Health and Welfare (AIHW) data indicate that the rate of adverse events varied between 3.4 and 3.7 per cent for private hospitals and over 5 per cent for public hospitals in 2007-08. However, Wilson et al. (1995) estimated that approximately 8.3 per cent of all separations involved in-hospital adverse events, while Jackson (2008) used Victorian and Queensland data (which at the time were the only data that contained a flag to indicate if a diagnosis arose during hospitalisation) and found that adverse events occurred in 12.3 per cent of separations. This suggests that available data under represent the true incidence of adverse events by an unknown margin.

The second problem is whether the adverse event originated in hospitals or in the wider community. The NHMD classifications for adverse events do not distinguish where the adverse event took place — in a hospital or elsewhere.

Similar problems exist with the NHMD data on hospital-acquired infections. The Commission notes that there is some debate as to whether existing morbidity data can feasibly distinguish between hospital-acquired and community-acquired infections. One view is that the ICD-10-AM codes can be used to distinguish infections (such as *staphylococcus aureus*) that are either *methicillin* or multi-antibiotic resistant, and which are believed to have occurred within a hospital setting. The AIHW advised the Commission that NHMD data from 2007-08 and previous years cannot accurately identify whether an infection arose during hospital stay or in the community (PC 2009).

There are also similar measurement issues with unplanned re-admissions within 28 days of discharge. Re-admission rates are likely to substantially underestimate the true re-admission rate because NHMD data are not linked to individual patients,

and so it is not possible to determine if discharged patients are re-admitted to another hospital, which would not be captured by these data.

## **Which measure to use?**

The Commission is of the view that the in-hospital mortality rate is the most reliable indicator in this circumstance. That said, there are two issues that should be recognised. First, in-hospital mortality rates are only a partial measure of patient outcomes. However, there is some evidence that in-hospital mortality is correlated with the processes of care for a range of conditions (chapter 4). Second, random variation in the incidence of mortality may still exist from year-to-year, such as the outbreak of influenza epidemics. Mortality rates would be unsuitable as a quality measure if they varied greatly from year to year in a random fashion. Several authors reviewed the incidence of random variation with in-hospital mortality data (Ben-Tovim, Woodman, Harrison et al. 2009; ACSQHC 2009) and concluded that such variation was not significant.

# **Standardising in-hospital mortality**

To use the incidence of in-hospital mortality as a quality measure, three other limitations to this variable had to be addressed.

First, the incidence can vary between hospitals for reasons that are beyond their control. For example, some hospitals may specialise in treating higher or lower-risk patients, a factor that is likely to impact on observed mortality rates.

Second, mortality rates are likely to vary according to the range of services provided by different hospitals. Hospitals that provide palliative care facilities, for example, are more likely to experience higher mortality rates.

Third, in-hospital mortality rates can raise a problem of *collinearity* when they are used in an estimation of technical or cost efficiency. Since in-hospital mortality is a factor included in the measurement of cost and technical efficiency, and that many of the factors that are thought to influence in-hospital mortality also influence hospital efficiency (such as the services provided by hospitals), there is the likelihood that collinearity will emerge as a problem in the estimation process. When collinearity arises, it is difficult to determine whether in-hospital mortality has a significant bearing on the estimated cost and technical efficiency of a hospital.

These three problems are addressed in this study by risk adjusting mortality rates. Risk adjustment is the process by which a number of explanatory factors (such as the patient's age, gender, degree of comorbidity, and other variables influencing the probability that a patient died or lived in hospital) are used to account for differences in the incidence of in-hospital mortality.

Once predicted values of hospital mortality rates were obtained from the risk adjustment regressions, the Commission then estimated HSMRs for each hospital. Ben-Tovim, Woodman, Harrison et al. (2009) report three variants of the definition of the HSMR. The version adopted for this study, and the only one feasible given the data available to the Commission, is the ratio of the actual number of acute inhospital deaths to the expected number of in-hospital deaths, for all conditions accounting for in-patient mortality.1

The estimates of adjusted mortality rates are included in the subsequent analysis of technical efficiency and hospital costs. Risk adjustment has been used in a number of efficiency studies that have used re-admission rates (Chua, Palangkaraya and Yong 2009), mortality rates (Paul 2002) and both re-admission and mortality rates (Clement et al. 2008).

The Commission used negative binomial regression analysis to risk adjust mortality rates, since only hospital-level data were available to the Commission. The Commission explored several approaches to risk adjusting these data, including Tobit regressions, and weighted logistic regression. The Tobit regression approach is described in PC (2009).2 The negative binomial approach used for this study and the results are described in detail in chapter 4 and appendix C.

# **2.2 Concepts of hospital efficiency**

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The subject of hospital efficiency is about identifying how well hospitals are using their scarce resources (medical and nursing staff, beds, and medical and pharmaceutical supplies, for example) to provide hospital services and improve patient health outcomes and patient safety.

<sup>&</sup>lt;sup>1</sup> The second definition is the HSMR calculated on 20 per cent of diagnoses that account for 80 per cent of in-hospital mortalities. The third definition includes the remaining 80 per cent of cases that account for 20 per cent of deaths (Ben-Tovim, Woodman, Harrison et al. 2009). These are not feasible as the Commission does not have access to data on the number of mortalities for different types of cases.

 $2$  The Commission notes that the average risk-adjusted mortality rate using the Tobit regression was found to be approximately 0.55, which is less than the expected average of 1.0.

# **Definitions of hospital efficiency**

Efficiency, in its broadest sense, refers to how well a community's resources are used to improve its wellbeing. If resources are wasted or not put to their best use, community welfare will be not maximised. This broad interpretation is known as 'economic efficiency'. Economic efficiency has three major components:

- cost efficiency  $(CE)$  the degree to which a community's outputs are produced at the least possible  $\cos t^3$
- allocative efficiency how a community's resources are allocated across different uses so as to generate the greatest wellbeing at a given point in time
- dynamic efficiency the allocation of a community's resources over time, including allocations designed to improve economic efficiency and to generate more resources (PC 2009) (figure 2.1).



Cost efficiency itself comprises:

• technical efficiency  $(TE)$  — which is usually defined to be the extent to which a hospital is able to produce more of any output or patient health outcome without producing less of some other output, outcome or using more of some input

 $\overline{a}$ 

 $3$  The terminology of cost efficiency used in this study is used extensively in the benchmarking literature and is synonymous with the definition of productive efficiency used in PC (2009).

• input allocative efficiency  $-$  the extent to which a hospital is using the appropriate mix of inputs, given the input prices it faces (figure 2.1).

The above definition of technical efficiency is often referred to as 'output-oriented technical efficiency'. Technical efficiency can alternatively be defined as the degree with which a hospital can reduce its use of inputs to produce a given set of outputs or quality.

Efficiency is an important concept for hospitals because any resources saved can be used towards providing additional services elsewhere in a hospital or within the healthcare system, or put towards other useful purposes (including individual consumption or saving), ultimately promoting the wellbeing of the community.

The study does not, however, contend with the broader issue of *allocative efficiency* — the efficiency with which the health sector as a whole is providing the appropriate mix of hospital and other healthcare services. A study on allocative efficiency would need to focus on the pricing of hospital services, recognising the peculiarities of the operation of public and private health insurance and the asymmetries of information within the health sector. A study on the allocative efficiency of hospitals is beyond the dataset and scope of this analysis.

# **Illustration of the concepts of efficiency**

In this study, the Commission assessed hospital performance on the basis of three measures:

- output-oriented technical efficiency
- input-oriented technical efficiency
- cost efficiency.

Each of these approaches are illustrated in figure 2.2. The first approach measures hospital efficiency in terms of how much additional output a hospital must produce to be technically efficient, that is, on the best-practice frontier *MM'*. This is the distance from its position at *A* to its frontier at *B*.

In contrast, the second approach measures the hospital efficiency in terms of how much fewer resources the hospital could employ and still produce the same level of output. This is given as the distance *A* to *C* (figure 2.2).





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

While the output and input-oriented technical efficiencies are expected to be similar in aggregate, there is no reason to suggest that for an individual hospital this should be the case. It is also possible to calculate the average of the output and inputoriented approaches. This assumes that hospitals face some degree of flexibility in terms of their choice of inputs and outputs, but are not entirely restricted in either case. In terms of figure 2.2, this would represent the distance from its position at *A* to its frontier at *D*.

Cost efficiency is defined as the extent with which a hospital can reduce its costs and still produce the same level of output. This is given as the distance between hospital *E* and its frontier estimated at *F* in figure 2.2. Cost efficiency is a commonly used to compare hospital performance, even though there are significant problems associated with obtain in comparable measures of prices and costs.

# **Why distinguish between output and input-oriented efficiency?**

The distinction between output and input-oriented technical efficiency was made to account for the different behavioural assumptions of public and private hospitals. One of the challenges is to accurately represent mathematically the motivations and behaviours of public, for-profit and not-for-profit hospitals. It is clear that these groups of hospitals have different motivations, and as a consequence, exhibit different behaviours when providing medical and surgical care. This in turn has implications for how these hospitals are to be modelled.

For-profit hospitals, for example, are mainly concerned with maximising the return to shareholders. They are concerned with jointly maximising their revenues and minimising their costs. This in turn means that they have the incentive to change

both the inputs they employ and the type and level of services they offer, although the degree to which they can influence their outputs and inputs depends on their individual circumstances.

Not-for-profit hospitals, like for-profit hospitals, appear to have some freedom to choose their level of input use and outputs too. Even though they do not necessarily maximise their financial returns for the benefit of their owners, they nonetheless have incentives to maximise their level of output and quality, as this is consistent with their charter of providing care to the community (Newhouse 1970). Any returns arising from their service provision are reinvested in order to further increase their capacity and quality of care or donated to charitable causes.

Public hospitals, on the other hand, do not appear to have the same degree of flexibility in choosing their output mix for two reasons. First, under the National Healthcare Agreement, public hospitals are not able to refuse medical treatment to the public. Second, public hospitals tend to be funded for a target level of services — funding allocations are determined at the beginning of each year for, but not beyond, a target level of activity (DHS nd; NSW Health 2008). This funding method applies even in jurisdictions that pay hospitals on a casemix basis.

The distinction between output and input-oriented technical efficiency is useful in this regard. Output-oriented technical efficiency is more likely to be more representative of for-profit hospitals, while the input-oriented technical efficiency is more likely to be representative of public hospitals.

# **2.3 Techniques for estimating hospital efficiency**

A literature review of the techniques used to determine the best-practice frontier suggests that the majority of studies employed data envelopment analysis (DEA) and stochastic frontier analysis (SFA) (appendix B). Twenty-seven studies employed DEA (including those that estimated Malmquist productivity indexes) and twenty-two employed SFA (including the closely related stochastic distance functions). While DEA and SFA are conceptually similar at a broad level — they both establish best-practice frontiers given a set of observations — differences in how they determine those frontiers can lead to noticeable differences in the observed results.

Drawing upon the advice of external referees, SFA appears to be the superior technique in this circumstance because, as an econometric method, it permits the significance of variables to be statistically tested. The technique, with a suitably flexible functional form, is likely to exhibit lower sensitivity than DEA which does not account for outliers and random effects. This in turn is likely to yield more conservative efficiency estimates than if DEA were used.

# **Graphical illustration**

SFA was first developed to study the efficiency of firms. It was originally developed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) and later generalised by Schmidt and Sickles (1984) for use with time-series cross-section panel data.

A good introductory summary of SFA can be found in Coelli et al. (2005) and a more advanced treatment in Kumbhakar and Lovell (2000). SFA frontier estimation can be graphically represented as a two-step regression. In the first step, a regression equation is estimated to pass through the mean of the data, much like OLS (in this example, between points *A*, *B, C* and *D*) (figure 2.3). This gives the average function *MM-*. In SFA, unlike OLS, the curve *MM-* is then shifted *for each hospital*. For hospitals *A* and *B*, the curve is shifted by amounts  $v_a$  and  $v_b$ respectively. These shifts establish the *stochastic frontiers A'* and *B'* respectively, against which the efficiency scores are calculated.



#### Figure 2.3 **Illustration of SFA approach**

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

Even though SFA resembles classical ordinary least squares (OLS), it differs from OLS in the treatment of the residual. In OLS, the random error term is assumed to be symmetrically distributed. If, however, the residuals are skewed (that is, they are not symmetric), SFA can be used to partition the error terms into a non-normally distributed component and a pure random error term that is normally distributed.

#### **Mathematical expression**

Mathematically, inefficiency is measured as a component of the stochastic frontier regression equation:

$$
y_i = f(\mathbf{x}_i) - u_i + v_i \tag{1}
$$

where  $y_i$  is the dependent variable,  $x_i$  is the independent variables,  $v_i$  is the random error term, and  $u_i$  is the inefficiency component, for hospital *i*. The term  $v_i$  captures random variations across hospitals reflecting random events that might include:

- measurement error in the variables
- other random events that affect costs or output
- the combined effects of other omitted factors, many of which are not amenable to quantification (Coelli et al. 2005).

In the context of a cost function, *ui* is a measure of cost efficiency, and in the case of a multi-input multi-output production function (distance function), it is a measure of technical efficiency.

Both of the terms  $v_i$  and  $u_i$  are assumed to be independent and identically distributed. It is assumed that the random error (*vi*) adopts a normal distribution with a zero mean and a constant variance. In the Aigner–Lovell–Schmidt models, the inefficiency component (*ui*) can be assumed to have a half-normal, truncated half-normal, exponential or gamma distribution, with a positive mean.

In the output and input-oriented distance functions, the distribution of the technical efficiency term was assumed to have a half-normal distribution, because it was found to generate the most plausible distribution of efficiency scores. An exponential distribution was adopted in the cost function because it was the distribution that was most likely to solve, and because the reported levels of efficiency scores were less susceptible to change, especially when variables were included in the efficiency effects model.

The choice of distribution for  $u_i$  affects the estimated efficiency scores of each observation. However, there is some evidence to suggest that the ordinal ranking of the scores are less sensitive to those distributional assumptions (Kumbhakar and Lovell 2000).

When the estimated function is in natural logarithmic form, efficiency is simply:

$$
Index_i = \exp(-u_i) \tag{2}
$$

#### *Estimating technical efficiency*

When applied to the output-oriented distance (production) function, the equation becomes:

$$
-y_{ik} = f(\mathbf{y}_i, \mathbf{x}_i, q_i, \mathbf{z}_i) - u_i + v_i
$$
\n(3)

where  $y_{ik}$  is the base output of hospital *i*, which is a function of other outputs  $(y_i)$ , inputs  $(x_i)$ , quality  $(q_i)$  and  $z_i$  (factors outside the control of hospitals). The error term is divided into purely random error term (*vi*) and a measure of output-oriented technical efficiency (*ui*).

When applied to the input-oriented distance (production) function, equation (1) is specified as:

$$
-x_{iM} = f(\mathbf{y}_i, \mathbf{x}_i, q_i, \mathbf{z}_i) - u_i + v_i
$$
 (4)

where  $x_{iM}$  is use of the base input of hospital *i*, which is a function of other inputs  $(x_i)$ , outputs  $(y_i)$ , quality  $(q_i)$  and  $z_i$  (factors outside the control of hospitals). The error term is divided into purely random error term  $(v_i)$  and a measure of input-oriented technical efficiency (*ui*).

The factors outside the control of hospitals include a range of patient and establishment characteristics. These include a hospital's assigned function in the healthcare system and the type of patients that seek treatment. The inclusion of these control variables in the frontier equation means that the resulting efficiency scores are net of their effect.

Details of all the variables included in both the cost and technical efficiency equations are explained in chapter 3. A more detailed derivation of the equations presented in this section is provided in appendix C.

#### *Estimating cost efficiency*

In the context of a cost function, equation (1) is specified as:

$$
c_i = f(\mathbf{w}, \mathbf{y}_i, q_i, \mathbf{z}_i) - u_i + v_i
$$
\n<sup>(5)</sup>

where  $c_i$  is the total cost of hospital *i*, which is a function of input prices  $(w)$ , <sup>4</sup> outputs  $(v_i)$ , quality  $(q_i)$  and  $z_i$  (factors outside the control of hospitals). The error term is comprised of purely random error term  $(v_i)$  and a measure of cost efficiency  $(u_i)$ .

A more detailed derivation of these equations is given in appendix C.

# *Testing for differences in efficiency between hospitals*

To test whether any differences in the efficiency scores for different ownership groups are statistically significant, the hospital efficiency scores are regressed as a function of three binary variables:

- *Private / Public or contracted —* to test whether there was a statistically significant difference between all private hospitals (assigned a value of '1') and public and contracted hospitals (assigned a value of '0')
- *For-profit / Not-for-profit* to test whether there was a statistically significant difference between for-profit private hospitals (assigned a value of '1') and not-for-profit private hospitals (assigned a value of '0')
- *Contract / Other* to test whether there was a statistically significant difference between public contract hospitals (assigned a value of '1') and all other hospitals (assigned a value of '0').

The coefficient values of these binary variables cannot be reported due to ABS commercial-in-confidence concerns, but their sign and statistical significance can be reported.

The method of the second-stage regression of the efficiency scores is covered in appendix C.

# *Functional form*

 $\overline{a}$ 

The estimation applies a full transcendental logarithmic (translog) function. In addition to first-order values, the translog contains squared and cross-terms of all inputs, output, price and cost variables, as appropriate. An alternative functional form is the Cobb-Douglas model, which only contains the first-order values. Due to its expanded set of variables, the translog function generates a more precise fit of the model than the Cobb-Douglas (Nguyen and Coelli 2009). More details of this functional form is provided in appendix C.

<sup>4</sup> Input prices are constant across hospitals in the same sector and jurisdiction (chapter 3).

# **2.4 Other modelling issues**

A large number of multivariate studies of hospital efficiency have been undertaken worldwide, although only a few examined the efficiency of Australian hospitals. For example, O'Neill et al. (2008), in a detailed study of 79 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). Of the small number of Australian studies available, there are thirteen commonly cited studies that have been 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). The Commission's preliminary stage of analysis added to this body of literature (PC 2009).

A comprehensive review of the modelling approaches and findings of previous studies is presented in appendix B, yet a cursory examination of Australian studies suggests that:

- private hospitals are less costly than public hospitals (when medical costs are excluded) (for example, Butler 1995)
- private hospitals give rise to better health outcomes than public hospitals (for example, Chua, Palangkaraya and Yong 2008)
- for-profit private hospitals are more technically efficient than not-for-profit private hospitals (for example, Webster, Kennedy and Johnson 1998)
- metropolitan public acute hospitals are more technically and cost efficient than smaller rural hospitals (for example, SCRCSSP 1997; Wang and Mahmood 2000a) (table 2.1) .

There are, however, several reasons to believe that these conclusions need to be further tested. First, a variety of methods was used to estimate the efficiency scores. For example, several studies employed DEA while others employed SFA for a production function. See section 2.4 and appendix C for a discussion of SFA. DEA is described in Coelli et al. (2005).

Second, the studies often measured different aspects of hospital efficiency which are not always comparable. It is inappropriate, for example, to directly compare technical efficiencies with cost efficiencies.

Third, many of the studies compared different samples of hospitals — some have focused on only a few major hospitals in each state (for example, Mortimer 2002;

Yong and Harris 1999) while others focused the all of the hospitals in a state (for example, Paul 2002), while another focused on all acute private hospitals in Australia (Webster, Kennedy and Johnson 1998).

Authors and year published	No. of hospitals and years	Measure of
		efficiency <sup>b</sup>
Data envelopment analysis - multi-output production		
<b>SCRCSSP (1997)</b>	109 Victorian public hospitals for 1994-95	OTE=0.581
		TE=0.775 SE=0.751
	Webster, Kennedy & Johnson 301 private hospitals in 1994-95	OTE=0.282-0.861
(1998)		TE=0.393-0.898
		SE=0.757-0.970
Wang and Mahmood (2000a)	113 NSW public hospitals (in two peer groups - large and small) 1997-98	OTE=0.457 TE=0.834 SE=0.547
Mortimer (2002)	38 Victorian public hospitals in 1993	PTE=0.81
Queensland Department of Health (2004)	Queensland public hospitals for 2000-01 to 2002-03	TE=0.963
Stochastic frontier analysis - single-output production		
Webster, Kennedy & Johnson (1998)	300 private hospitals in 1994-95	$TE=0.71-0.79$
Mortimer (2002)	38 Victorian public hospitals in 1993	$TE=0.80$
Mangano (2006)	116 Victorian public hospitals 1992-93 to 1995-96	$TE=0.75$
Gabbitas and Jeffs (2007)	State-level observations for 1996-97 to 2004-05	$TE = 0.87$
Stochastic frontier analysis - cost function		
Webster, Kennedy & Johnson (1998)	280 private hospitals in 1994-95	CE=0.77-0.96
Yong and Harris (1999)	35 large Victorian acute public hospitals for 1994-95	CE=0.95-0.97
Wang and Mahmood (2000b)	113 NSW public hospitals (in two peer groups - large and small) 1997-98	$CE=0.90-0.92$
Stochastic distance function - multi-output production		
Paul (2002)	223 NSW public hospitals in 1995-96	TE=0.735

Table 2.1 **Summary of efficiency scores from selected Australian studiesa**

**a** Some studies distinguish overall technical efficiency (OTE) from technical efficiency. OTE is technical efficiency under the assumption of constant returns to scale. In this study, technical efficiency is assumed to be based on variable returns to scale, which means that the derived estimates will be net of any effects of scale economies.**b** Efficiency scores are fractions, that 0.50 represents 50 per cent efficiency. **TE** Technical efficiency, **OTE** Overall technical efficiency, **CE** Cost efficiency, **SE** Scale efficiency.

Finally, there were differences between the studies in the variables used to measure hospital quality and to control for a variety of factors outside the control of hospitals.

These issues are addressed in this study from the use of a single estimation technique (stochastic frontier analysis), the separate estimation of technical and cost efficiency, the use of a consistent sample of public and private hospitals, and a

comprehensive treatment of variables for the treatment of quality and factors outside the control of hospitals.

The issues of the measurement of hospital quality and the role of factors outside the control of hospitals, are covered below.

# **Relationship between quality and efficiency**

Hospitals vary significantly in terms of the services they provide. Correctly specifying the measurement of the quality of hospital care is important to ensure that the estimated efficiency scores are as accurate as possible.

A review of Australian and overseas literature on hospital efficiency suggests three broad approaches to take account of variations in the quality of hospital health care (appendix B). The first approach compares a hospital's performance solely in terms of the quantity of (intermediate) outputs provided by the hospital (for example, Dor and Farley 1996; Jacobs 2001; Rosko and Chilingerian 1999; Scott and Parkin 1995; Webster, Kennedy and Johnson 1998). Such services include the number of separations, procedures, emergency department visits, and outpatient department services. The attraction of this approach is that it permits, through the use of casemix-adjustment, a hospital's activity to be differentiated across procedures and diagnoses. Another attraction is that it is comparatively easy to attribute a hospital's resource use to its outputs, whereas attributing cause and effect is far more difficult for health outcomes (Hollingsworth and Peacock 2008).

A disadvantage of only using quantity as a measure of hospital activity is that it assumes that there is no relationship between hospital quality and the level of activity. If a hospital faces a trade-off between quantity of services provided and outcomes and quality of its services, then this modelling assumption would penalise those hospitals that focus on achieving better outcomes and higher quality of services.

The second approach is to compare hospital performance solely in terms of a clearly identifiable patient health outcome, such as unplanned re-admission rates and mortality rates (for example, Chua, Palangkaraya and Yong 2008; Jensen, Webster and Witt 2007). The attraction of this approach is that it provides a clear measure of the resources used to achieve a particular health outcome. Its disadvantage is that it does not provide any information about which we can judge the efficient use of scarce resources in a hospital environment.

A third approach is to compare hospital performance in terms of both the quantity of outputs and partial indicators of patient health outcomes. The attraction of this approach is that it enables researchers to explore the relationship between hospital activity and the quality of its services. The disadvantage of this technique is that its usefulness will depend upon the availability and quality of patient outcome data.

#### *What is the relationship between hospital output and quality?*

The approach of representing hospital activity in terms of quantities of services and partial measures of health outcomes and quality gives rise to another question: what is the relationship between input use, outputs and patient outcomes?

A number of overseas studies have found that increases in hospital activity may improve patient outcomes or at worst may have no effect on the quality of patient outcomes (box 2.1). Chirikos, French and Luther (2004) argued that 'learning by doing', scale economies, and comparative advantage can provide an explanation of why increasing output can lead to improved patient health outcomes.

A number of authors cautioned against using the volume of hospital activity as a measure of hospital quality (Gruen et al. 2009; Hewitt 2000). As Halm, Lee and Chassin (2002, p. 517) said:

The magnitude of the [volume–outcome] relationship varies greatly among individual procedures and conditions. The clinical and policy significance of this finding is complicated by methodological shortcomings of many studies. Even when a significant association exists, volume does not predict outcome well for individual hospitals or physicians.

Other authors have noted that insufficient effort was placed on identifying other contributing factors. For example, Carson (2009, p. 1566) noted:

The evidence supporting a causal effect — high volume surgeons or institutions lead to better surgical outcomes — is not as conclusive as it may seem from the large number of published studies purporting to show such a connection. Case mix and statistical bias is not accounted for in many studies and when taken into account often minimizes apparent differences.

Even if increases to output were correlated with improvements to quality, it may not be possible for an individual hospital to increase its output and improve its quality simultaneously. High volume surgical hospitals are more likely to have specialised units that provide related non-surgical care. For example, a hospital that performs a large volume of cancer surgery is more likely to also have radiation and medical oncologists and cancer specialist nurses. It is therefore difficult to separate the volume of cancer surgery performed by such a hospital from the effects of the specialised oncology and cancer nursing care (Hogan and Winter 2008) or other structures and processes specific to each hospital (Christian et al. 2005).

#### Box 2.1 **The 'volume–outcome' relationship**

An inverse relationship between surgical volume and mortality was described by Luft, Bunker and Enthoven (1979). Since then, many studies have considered the possibility of a 'volume–outcome relationship' for various procedures and treatments, and found better outcomes for patients who are treated by hospitals and/or medical practitioners who conduct a greater volume of that procedure or treatment.

The US Institute of Medicine examined evidence from 88 studies concerning eight conditions and procedures, and found that higher volume (whether assessed by hospital or by physician) was associated with better health outcomes in three quarters of the studies reviewed (Hewitt 2000). No studies found a negative relationship between volume and outcome. Other systematic reviews had very similar findings:

Twenty years of research have established that, for some procedures and conditions, higher volume among hospitals and physicians is associated with better outcomes. (Halm, Lee and Chassin 2002, p. 517)

Overall, the studies in this review, when combined, demonstrate a quantifiable and statistically significant inverse association between case volume and mortality. (Gruen et al. 2009, p. 208)

All other things being equal, a higher volume provider will have a marginally better mortality rate than a lower volume provider. This is probably more significant, both in terms of effect size and clinical importance, for complex procedures. (Campbell et al. 2006, p. 162)

Moreover, Birkmeyer, Dimick and Staiger (2006) demonstrated that the volume-outcome relationship is stable over time. Historical measures of procedural volume can therefore identify hospitals that are likely to have better outcomes in the future.

#### *What is the relationship between input use and quality?*

A number of other authors have argued that it is the intensity of input use that determines hospital quality rather than the quantity of services. For example, McCue, Mark and Harless (2003) argued that observed improvements to patient outcomes were due to increased hospital resources and therefore operating costs rather than economies of scale. Conversely, reducing hospital resources are thought to worsen the quality of health care.

A number of studies examined the interaction between staffing, and in particular nursing levels, and patient outcomes. Needleman et al. (2002) drew on the 1997 administrative data of 799 hospitals in 11 US states (covering 5 million medical and 1.1 million surgical discharges). The authors found that:

• among medical patients, a higher proportion of hours per care per day by registered nurses and a greater number of hours of care provided by registered nurses was associated with shorter lengths of stay, lower rates of urinary tract infection, upper gastrointestinal bleeding, pneumonia and cardiac arrest, and lower rates of 'failure to rescue' (which was defined as death from pneumonia, shock, cardiac arrest, upper gastrointestinal bleeding, sepsis or deep venous thrombosis)

• among surgical patients, a higher proportion of care provided by registered nurses was associated with lower rates of urinary tract infections, and a greater number of hours of care provided by registered nurses was associated with lower rates of 'failure to rescue'.

The authors did not find any association between the levels of registered nursing and in-hospital mortality, or between licensed nurses and nurses' aides and the rates of adverse outcomes.

Aiken et al. (2002) examined the relationship between patient-to-nurse ratios and the incidence of dying within 30 days of admission, and failure-to-rescue (defined as deaths following complications) among surgical patients. The authors drew on a survey of 10 184 staff nurses and 232 000 discharged patients from 168 non-federal general hospitals in Pennsylvania in 1998-99. The authors found, after adjusting for patient and hospital characteristics (such as whether it was a teaching hospital, and the available technologies), that an incremental increase in the patient-to-nurse ratio increased the odds-ratio of in-hospital mortality and failure-to-rescue by 7 per cent.

Finally, Kane et al. (2007), in a review of other studies, also concluded that higher registered nurse staffing was associated with less hospital-related mortality, failure to rescue, cardiac arrest, hospital acquired pneumonia, and other adverse events. The effect of increased registered nurse staffing on patients safety was strong and consistent in intensive care units and in surgical patients.

These two views form the bases of hypotheses that can be tested in this study. The output-oriented distance function permits the testing of the volume–outcome relationship and the input-oriented distance function permits the testing of the input–outcome relationship.

#### **Factors outside the control of hospitals**

Some of the observed differences in the services that hospitals provide and patients they treated do not reflect decisions by the hospitals themselves, but rather are factors outside their control. 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.

Most past Australian studies did not sufficiently account for factors outside the control of hospitals (appendix B). For example, Queensland Department of Health (2004), SCRCSSP (1997), Wang and Mahmood (2000a and 2000b) and Webster, Kennedy and Johnson (1998) did not take into account any such characteristics. Yong and Harris (1999), Mangano (2006) and Paul (2002) accounted for whether the hospital had a teaching status and whether it was in a metropolitan area. Only Jensen, Webster and Witt (2007) and Paul (2002) took into account the socioeconomic status of the patient population and the amount of research undertaken at the hospital. And, only Chua, Palangkaraya and Yong (2009) took into account the effects of competition for hospital services. A similar pattern can be observed for many overseas studies (for example, Färe, Grosskopf and Valdmanis 1989; Maniadakis and Thanassoulis 2000).

Where external factors have been taken into account in Australian and overseas studies, 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)
- hospital characteristics that include geography, roles and functions, such as:
	- hospital location (for example, Granneman, Brown and Pauly 1986; Herr 2008)
	- whether it is a teaching or university hospital, and 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).

# 3 Data used in this analysis

#### **Key points**

- The Commission obtained the permission of state and territory health departments, and private hospital owners to access data of public and private hospitals for the years 2003-04 to 2006-07.
	- There were 343 public, 99 private and 17 public contract acute overnight hospitals that contributed 1806 observations to the dataset.
- The dataset captures virtually all public acute hospitals, and approximately 42 per cent of all private hospitals in Australia.
	- The Commission weighted the known private hospital observations to compensate for the under-representation of not-for-profit hospitals in the dataset.
- The dataset provides a rich picture of the patient activity within hospitals:
	- medical separations comprise 78 per cent of public hospital inpatient activity and 42 per cent of private hospital inpatient activity
	- public hospitals provide significantly more outpatient services including emergency departments, pathology and radiology, mental and alcohol services, and allied health and dental services
	- private hospitals serve relatively more patients from major cities, whereas the patients for public hospitals are largely from outside major cities
	- private hospitals serve patients from relatively more socioeconomically advantaged communities
	- the comorbidity of patients is highest for public contract hospitals, followed by public and private hospitals.
- There are, however, some limitations with the data:
	- non-admitted occasions of care are not casemix adjusted
	- public hospitals do not adequately report the depreciation and other costs of land, buildings, plant and equipment
	- medical staff and medical staff costs were excluded because data were not available for doctors exercising their rights of private practice in public and private hospitals
	- public and private hospitals counted hospital beds differently.

The Commission accessed data from a number of databases to create a unique dataset on the care provided and the facilities available in public and private acute hospitals from 2003-04 to 2006-07. Details of data sources, and the processes by which consent was obtained to access those data sources, are provided in section 3.1. The variables used in the analysis are described in section 3.2. A description of the hospitals used in the sample, and their representativeness of the population of Australian hospitals, is discussed in section 3.3.

# **3.1 The Commission's dataset**

For this study, the Commission treated hospital establishments (and in some instances, campuses) as the principal subject of measurement. In doing so, it was assumed that decisions made to use 'inputs' (such as nurses, administration and clerical staff, medications, and technologies) to produce a range of 'outputs' (such as medical and surgical procedures, emergency department episodes of care) occurred at the hospital level.

Acute overnight-stay hospitals were the focus of this analysis. Psychiatric hospitals, free-standing day hospitals and sub-acute and non-acute facilities were considered to be sufficiently different from these hospitals to exclude them from the analysis, because they generally offer a more limited range of services compared to acute overnight hospitals. Likewise, free-standing day hospitals often focus on a small number of procedures at the exclusion of many other activities undertaken by acute hospitals which have overnight stays.

#### **Data sources**

Data on public hospital establishments were drawn from the National Public Hospital Establishments Database (NPHED) held by the Australian Institute of Health and Welfare (AIHW). The NPHED contains information on public hospital staffing levels, expenditure, revenues and other hospital characteristics, including bed numbers and geographical location.

Data on private hospital establishments were drawn from the Private Health Establishments Collection (PHEC) 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 2008a). It includes information about private hospital staffing, finances, patients, facilities (such as beds or special units) and activities (such as days of hospitalisation provided and bed occupancy rates).

Patient-level data on morbidity for both public and private hospitals were drawn from the National Hospital Morbidity Database (NHMD) held by the AIHW. In Australian hospitals:

 … the medical notes, laboratory reports and other relevant information are integrated into an individual patient's ongoing medical record and 'coded' after the patient is discharged, transferred or dies. Trained medical coders assign codes for principal and other diagnoses, procedures, and other events to a coded electronic summary of that admission. This coded record then goes into a hospital database which eventually populates, via state, territory or private hospital ownership chain aggregation, a national data collection called the NHMD. (ACSQHC 2009, p. 82)

Although the PHEC contains some patient data, the Commission does not regard these data to be useful for this study because they are not patient-level, and therefore are not casemix-adjusted and do not include the necessary details of patient morbidity.

## **Accessing hospital data**

The Commission obtained the consent of the state and territory health departments for the AIHW to release public hospital morbidity and establishment data to the ABS for the years 2003-04 to 2006-07.

The Commission also obtained consent from 130 for-profit and not-for-profit private hospitals to use their hospital-level morbidity data in this study. After consent was obtained, state and territory health departments provided information that allowed the private hospital patient morbidity data held by the AIHW to be matched with the establishment-level data held by the ABS.

After the AIHW undertook some preliminary analysis to prepare the morbidity and public hospital establishment data, the empirical analysis was undertaken at the ABS under direction from the Commission. The latter arrangement was to facilitate access to the private hospital information held by the ABS, and from the perspective of both data providers, to protect the identity and commercial-in-confidence arrangements of hospitals and hospital groups.

This data access arrangement, however, meant that the analysis was considerably delayed and restrictions were imposed on the analytical results that could be reported (PC 2009). The Commission considered these delays and restrictions to be greater than what would be reasonably expected to address legitimate privacy and confidentiality issues. Making these data more accessible to a range of users could drive improvements in health care, especially as competitive markets have only a limited role in the health sector. It could also encourage future improvements in data collections (PC 2009).

# **Assembling the data**

The first step in assembling the dataset was to group the patient-level morbidity data by hospital. The morbidity data were then aggregated to create hospital-level patient variables (for example, the total number of casemix-adjusted separations of endocrine, nutritional and metabolic diseases and disorders).

A number of modifications to the dataset were made in order to adjust for reporting inconsistencies. Many Victorian hospitals operate as part of a hospital network. This meant, however, that some data items were reported at the network level while others were reported at the hospital level. Similarly, a single observation was reported for all Tasmanian public hospitals and another observation was provided for all Tasmanian private hospitals. To overcome these problems, grouped data were apportioned to the hospital (establishment) level on the basis of casemix-adjusted separations. Binary variables denoting the state and territory of the hospital and whether the hospital belonged to a hospital network were introduced to account for possible biases that might arise from this process.

Other adjustments were required to remove invalid data, such as hospitals that were recorded as incurring negative costs, or having no staff, beds or deaths in a given year. While it is feasible that some acute hospitals did not experience any deaths, some of the 'zero deaths' were found to have occurred in medium and large hospitals. It was concluded that these were missing values that were inadvertently classified as zero deaths. Ninety-six observations in total with erroneous data were removed from the dataset.

From time to time, hospitals open, merge or close down, or change from public to private ownership and vice versa. For instance, the Mersey Community Hospital was categorised as a private hospital until 2003-04 and a public hospital from 2004-05 to the end of October 2007 (AIHW 2009a). Because of such changes, some hospitals were not included in the dataset for some of the years in the period 2003-04 to 2006-07.

The requirement to maintain the confidentiality of hospitals and hospital groups meant that the two-step modelling process with the ABS resulted in noticeable delays. Due to these delays, the Commission chose to model the data as a pool rather than a panel, even though the data spanned multiple years.

### **Scope of the dataset**

The dataset excludes the number and cost of medical staff, because data were not available for doctors exercising their rights of private practice in public and private hospitals. As a result, the dataset is limited to hospital nursing, diagnostic, allied health, administrative and ancillary staff. This scope is consistent with the scope of the multivariate analysis reported in PC (2009).

The 343 public hospitals covered in this dataset cover virtually all public hospitals in Australia. Even though the AIHW noted that there were 768 public hospitals in 2007-08 (AIHW 2009a), many of these are sub-acute, non-acute and psychiatric facilities (AIHW 2009a).

The Commission re-classified some public hospitals as 'public contract' hospitals. These are hospitals managed by non-government entities to provide public hospital services. They are either contracted or, if they are deemed to be public health organisations (as under the *Health Services Act 1997* (NSW)), subsidised. The Commission identified 17 such hospitals operated by for-profit and not-for-profit organisations. The Commission made this distinction to test whether there are differences in the effect of ownership or management structure on the performance of public hospitals.

The final dataset consists of 1806 observations comprising:

- public hospitals 343 hospitals contributing 1354 observations
- private hospitals 99 hospitals contributing 389 observations
- public contract hospitals  $-17$  hospitals contributing 63 observations.

# **3.2 Variables used in this study**

The variables used in this study are grouped into:

- costs
- volume of outputs
- quality and patient safety
- volume of inputs and input prices
- patient characteristics
- hospital roles and functions, and incentives
- other factors (table 3.1).

The following discussion defines these variables and posits the expected relationships in the estimation of technical and cost efficiency.

# **Costs**

Hospital costs, ideally, should reflect the costs of all inputs used in the provision of hospital services. This would include the operating expenditures (the costs of nursing and other health service staff, clerical and administration, hotel services, and medical, surgical and pharmaceutical supplies) and capital costs (the costs associated with the operation of land, buildings and equipment). Public hospitals pose a challenge in this regard, since funding and accounting systems have rarely accounted for the depreciation and opportunity cost of capital. In contrast, private hospitals tend to record capital costs.

Consistent with other studies, hospital costs are limited to operating expenditures to ensure a consistency of measurement between public and private hospitals. This estimate will inflate the costs of some private hospital owners who occasionally enter into leasing arrangements for land and buildings and thereby incur leasing costs (operating expenditures) and not interest and depreciation costs.

Total operating expenditure, however, does not include any medical costs. Public hospitals routinely collect data on the medical costs of doctors who are employees of the hospital. They typically do not collect data on the charges of visiting medical officers or those exercising their rights of private practice in private practice. While some private hospitals employ salaried doctors, the majority of doctors are selfemployed and charge patients separately. Data on medical charges to private health insurers are, in principle, available from the Commonwealth's *Hospital Casemix Protocol* dataset. However, given the delays in obtaining other hospital-related data for this study, the Commission did not collect these data for this study.

Hospital operating costs were deflated using the ABS *Hospital Cost Index* (ABS 2008c). In the analysis, hospital costs were converted to natural logarithms and mean centred.1

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<sup>&</sup>lt;sup>1</sup> Mean centering is the process by which the mean of a vector of variables is subtracted from every component of the vector.



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Table 3.1 (continued) (Continued next page)



Table 3.1

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Table 3.1

a MDC Major diagnostic category. - Nil or rounded to zero. **a** MDC Major diagnostic category. – Nil or rounded to zero.

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

# **Outputs**

Hospitals are complex entities that provide a varied range of services. In addition to acute inpatient care, many hospitals provide some sort of outpatient services or emergency departments. This provides a strong argument for hospitals to be modelled as multi-input multi-output firms (Butler 1995).

## *Inpatient services*

There is a wide variation in the type and severity of acute inpatient care provided by different hospitals. To account for this variation, the Melbourne Institute of Applied Economic and Social Research (cited in PC 2009) suggested that it would be reasonable to model inpatient activity at the major diagnostic category (MDC) level (box 3.1).

However, separately specifying all 23 MDCs would result in a large number of variables that would reduce the interpretability of the results, particularly when more complex functional forms such as the translog are considered. Therefore, the categories of inpatient outputs used in this study are:

- normalising variable casemix-adjusted separations for MDC 1 (diseases and disorders of the nervous system)2
- acute separations casemix-adjusted separations for MDCs 2 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.

MDC 1 served as the normalising output variable in the output-oriented distance function as it had the lowest count of zero observations (that is, the fewest number of hospitals not offering that service) and therefore minimised the effects of the adjustments that needed to be made for zero observations. It was also included in both the cost and input-oriented distance functions as its own output.

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 $2$  The normalising variable was inverted in the output distance function. This has the effect of reversing the signs of the coefficients of the output distance function.

#### Box 3.1 **Major Diagnostic Categories and the Australian Refined Diagnosis-Related Group system**

The Australian Refined Diagnosis-Related Group (AR-DRG) system categorises separations according to the patient's condition and the hospital resources expected to be used. The system provides a way to record the number and type of separations administered by a hospital in relation to the resources required.

Version 5.1 of the classification system defines 665 individual AR-DRGs. Each separation is assigned to an AR-DRG mainly on the basis of the medical diagnosis or surgical procedure involved, but also according to a patient's age, length of stay, mode of separation, the level of clinical complexity and the existence of complicating diagnoses or procedures.

Individual AR-DRGs are grouped under 23 Major Diagnostic Categories (MDCs) that are mostly defined by body system or disease type:

- MDC 1 Diseases and disorders of the nervous system
- $MDC 2$  Diseases and disorders of the eve
- MDC 3 Diseases and disorders of the ear, nose, mouth and throat
- MDC 4 Diseases and disorders of the respiratory system
- MDC 5 Diseases and disorders of the circulatory system
- MDC 6 Diseases and disorders of the digestive system
- MDC 7 Diseases and disorders of the hepatobiliary system and pancreas
- MDC 8 Diseases and disorders of the musculoskeletal system and connective tissue
- MDC 9 Diseases and disorders of the skin, subcutaneous tissue and breast
- MDC 10 Endocrine, nutritional and metabolic diseases and disorders
- MDC 11 Diseases and disorders of the kidney and urinary tract
- MDC 12 Diseases and disorders of the male reproductive system
- MDC 13 Diseases and disorders of the female reproductive system
- MDC 14 Pregnancy, childbirth and the puerperium
- MDC 15 Newborns and other neonates
- MDC 16 Diseases and disorders of the blood and blood forming organs and immunological disorders

(Continued next page)

Box 3.1 (continued)

- MDC 17 Neoplastic disorders (haematological and solid neoplasms)
- MDC 18 Infectious and parasitic diseases
- MDC 19 Mental diseases and disorders
- MDC 20 Alcohol or drug use and alcohol or drug induced organic mental disorders
- MDC 21 Injuries, poisoning and toxic effects of drugs
- $\bullet$  MDC 22 Burns
- MDC 23 Factors influencing health status and other contacts with health services.

Within each MDC, individual AR-DRGs are assigned to a 'surgical', 'medical' or 'other' partition on the basis of the type of treatment involved. A separation is classified as surgical if it includes an operating-room procedure, medical if it does not include any type of procedure, and other if it includes a procedure performed outside of an operating room (such as dental extractions and colonoscopies). In this context, a procedure is defined as a clinical intervention that carries a procedural or anaesthetic risk, and/or requires specialised training, facilities or equipment available only in an acute-care setting.

*Sources*: AIHW (2009a); DOHA (2004).

Pregnancy and neonate MDCs were kept separate from the majority of acute care separations, as pregnancy separations do not generally involve acute illness. Similarly, mental and alcohol separations were also kept separate because these MDCs do not contain any diagnoses requiring surgical treatment, and therefore require a different mix of hospital resources to other acute diagnoses.

Casemix-adjusted data were based on public hospital cost weights supplied by the AIHW. As is common practice, all input and output variables terms are specified in natural logarithms except shares and binary variables, so that the measures represent proportional values rather than absolute levels.3 All logarithmic variables were mean centred.

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 $3$  Where a natural number was reported as zero, its value was set to the natural logarithm of one. Additional adjustments were made, as per Battese (1996), which are outlined in appendix C.
### *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 for admitted patient care. The output categories used were:

- accident and emergency services number of accident and emergency department presentations or visits
- allied health and other services number of occasions of service for allied health, dental and other outpatient services
- mental and alcohol services number of mental, alcohol and psychiatric outpatient services
- dialysis and endoscopy number of non-admitted occasions of service for dialysis and endoscopy4
- diagnostic services number of pathology and radiology services provided to non-admitted patients
- outreach services number of community services, district nursing and other outreach services
- pharmaceutical services the number of visits to the hospital's pharmacy.

### *Other output variables*

A number of other variables were used to describe in greater detail the differences in the types of services provided by hospitals. These included:

• emergency ratio

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• proportion of patients treated with surgical and other procedures.

*Emergency ratio —* the number of accident and emergency visits divided by the number of casemix-adjusted separations — is used as a surrogate for data on the proportion of inpatients that were admitted through emergency department, and is intended as a measure of the acuity of a hospital's workload. Ideally, the preferred measure should be the proportion of patients that were admitted as emergency cases — whether through an emergency department or not. However, this is not collected consistently at a national level.

<sup>4</sup> Some jurisdictions admit patients who are undergoing dialysis or endoscopy, while other jurisdictions commonly perform these procedures as non-admitted services. Dialysis and endoscopy are grouped together to account for these different admission practices.

*Proportion of patients treated with surgical and other procedures describes the* extent to which a hospital specialises in surgical and other diagnosis-related group (DRG) cases (box 3.1). Some private hospitals seek to maximise their productivity by specialising in elective surgery procedures. Since medical DRG cases have a greater likelihood of being unplanned, they tend to be inherently more difficult for hospitals to manage. Ideally, this variable should be defined in terms of elective surgery, since some surgical and other procedures captured by this variable will be emergency in nature.

Two other variables which were used in the estimation of hospital-standardised mortality ratios (HSMRs) included the proportion of patients that were transferred from another hospital, and the proportion of patients discharged that were transferred to another hospital. These were included in that analysis to account for the activities of surgical specialisation that is thought to occur among hospitals.

## *Expected signs of the coefficients*

In the output-oriented distance function, the coefficient of each output is expected to be negatively signed, reflecting that as a hospital's outputs increase for a given set of inputs, so does its productivity (and therefore efficiency). In the input-oriented distance function, outputs are expected to be positively signed, reflecting that as a hospital's outputs increase for a given set of inputs, and a decline in resource intensity (which is equivalent to an increase in productivity). In the cost function, each of the output variables is expected to be positively related with costs — that is, increases in outputs are associated with increases to total operating costs.

The variable describing the proportion of patients who undergo surgical and other procedures is expected to be negatively related with costs (since surgical and other procedures are thought to be less expensive than medical cases), positively related in the output distance function, and negatively related with the input-oriented distance function.

# **Hospital quality**

The HSMR is used as a measure of the quality and effectiveness of hospital services (the process of risk-adjustment is described in chapters 2 and 4). Its sign is expected to differ with each of the models:

• Output-oriented distance function — if the coefficient of the HSMR variable is negatively signed, hospitals with higher than expected HSMRs (worse quality) are associated with lower productivity and therefore worse efficiency.

- Input-oriented distance function if the coefficient of the HSMR variable is positively signed, hospitals with higher than expected HSMRs are associated with a increased resource intensity and therefore worse efficiency.
- Cost function  $\frac{d}{dx}$  if the HSMR is negatively correlated with costs, then hospitals can only achieve improvements to mortality outcomes with increases to costs. If however, it is positively correlated with costs, this suggests that improvements in mortality outcomes will lead to reductions in costs.

## **Inputs**

Following common practice, inputs into the production of hospital services included:

- nursing staff number of full-time equivalent nursing staff
- diagnostic and allied staff number of full-time equivalent diagnostic (pathology and radiology) and allied health staff
- other staff number of full-time equivalent domestic, administration and other staff
- medical and surgical supplies constant price expenditure on medical and surgical supplies used
- pharmaceutical supplies constant price expenditure on pharmaceuticals
- other inputs constant price expenditure on other hospital inputs, such as administration and clerical services, housekeeping, and repairs and maintenance
- beds number of beds in the hospital (as a proxy for hospital capital).

As noted, the number of doctors exercising their rights of private practice in public and private hospitals is not known. Hence the number of medical staff has been excluded from the analysis. This exclusion is equivalent to assuming that each hospital employs its doctors in a fixed proportion to its other inputs over time that is, it does not substitute between doctors and other inputs. The extent to which this is the case, however, is unknown. Otherwise, all efficiency scores derived from the analysis can be interpreted as the efficiency of the hospital, and not specifically of the hospital and its medical workforce.

Medical and surgical, pharmaceutical and other input supplies were each deflated by their respective components from ABS *Hospital Cost Index* (ABS 2008c).

The number of beds is used as the normalising variable in the input-oriented distance function. This variable was inverted in the input-oriented distance function, which has the effect of reversing the signs of the coefficients of that function.

## *Some limits to using beds as a measure of capital*

The number of beds presents two challenges as a measure of capital. First, public and private hospitals do not define the number of beds in the same manner. Public hospitals report the number of *staffed beds* (AIHW 2009), which is defined as the number of beds for which staff are on hand to attend to a patient. At any point in time, a staffed bed may be occupied or unoccupied with a patient (AHRQ nd). In contrast, private hospitals report to the ABS the number of *total available beds* (ABS 2007), which generally means the number of beds that are physically set up and ready for use even if they are not staffed (AHRQ nd).

The different definitions mean that, on average, private hospitals report more beds than if they had to comply with the staff beds definition. This in turn means that, in the absence of any data adjustment, private hospitals would appear to be less productive or more resource intensive — and therefore less efficient — than public hospitals.

The Commission estimates that there are approximately 4 to 5 per cent more available beds in the private sector than there are staffed beds, and public contract hospitals maintain approximately 3 to 4 per cent more available beds than staffed beds (appendix C).

To ensure that the number of beds in the two sectors are comparably measured, the Commission estimated the number of staffed beds for private hospitals. The method is outlined in appendix C.

The other challenge is that the count of beds is not an ideal measure of the usage of capital in a hospital 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. As these data were not available, differences in the capital of hospitals were captured with variables that reflected the roles and functions of hospitals — such as the presence of palliative care units, rather than the number of palliative care beds, for example. The variables which reflect differences in hospital roles and functions are discussed below.

## *Expected signs of the coefficients*

The sign of the coefficient of each input is expected to differ according to the model being estimated, so that for the:

- output-oriented distance function each input is expected to be positively signed, indicating that increases in the use of an input reduces productivity and therefore efficiency
- input-oriented distance function each input is expected to be negatively signed, indicating that increases in the use of an input increases resource intensity (for a given level of output), and therefore reduces efficiency
- cost function each input is expected to be positively correlated with total operating expenditure, since increasing input use typically increases overall costs.

## **Input prices**

Input prices are used in estimating the cost function. The five input prices that were considered are:

- wages and salaries of nursing staff
- wages and salaries of diagnostic and allied health staff
- wages and salaries of other staff (including administration and clerical, and hotel staff)
- price index for medical and surgical supplies
- price index for pharmaceutical supplies.

Wages and salaries were set to be equal across each broad hospital sector within each state or territory. Wages and salaries included superannuation and other on-costs and were deflated by the wages and salaries index of the ABS *Hospital Cost Index* (ABS 2008c).

The calculation of wage rates in this way is intended to reflect the possibility that there exists a unique market for hospital staff within each jurisdiction and hospital sector.

The average price of medical and surgical supplies and pharmaceutical supplies was drawn from the price indices for medical and surgical supplies and pharmaceutical supplies from the ABS *Hospital Cost Index* (ABS 2008c). These indices are national, so this assumes that there is single market (and market price) for these inputs.

Input prices are expected to be positively correlated with costs, since increases in input prices contribute to increased total operating expenditures.

# **Patient-risk characteristics**

Patient-risk characteristics used in the HSMR and efficiency analyses included:

- age
- gender
- socioeconomic status based on the *Socio-economic Index for Areas Index of Relative Disadvantage and Advantage* (SEIFA index) (ABS 2008b)
- remoteness of residence based on the *Australian Standard Geographic Classification — Remoteness Area* (ASGC-RA) (ABS 2005)
- distribution of the Charlson index of comorbidity (Charlson et al. 1987).<sup>5</sup>

Unlike PC (2009), patient Indigenous status was not used as a variable because of concerns regarding the reliability of estimates of Indigenous status (AIHW 2010).

At least some patient-risk characteristic variables are expected to be statistically significant because private hospital separations were casemix-adjusted using public hospital cost weights and both private and public hospital outpatient services were not casemix-adjusted.

# *Expected signs of the coefficients*

Patient-risk characteristics can influence hospital costs, outputs and the use of inputs. Patient groups with more complex needs are expected, for the:

- output-oriented distance function to be negatively signed indicating that they reduce a hospital's productivity
- input-oriented distance function to be positively signed indicating that they increase a hospital's resource use

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<sup>5</sup> The Charlson index (Charlson et al. 1987) is an odds-ratio of the risk of mortality within one year. Thus a Charlson score of 6 indicates a 6:1 (or 86 per cent) chance of the patient dying within one year. The Charlson index for this study was prepared using patient morbidity data, based on codes from the International Statistical Classification of Diseases and Related Health Problems, Tenth Revision, Australian Modification — ICD-10-AM (Quan et al. 2005; Sundarajan et al. 2004). The Commission considered using the Multipurpose Australian Comorbidity Scoring System (Preen et al. 2006) but chose not to use this approach because the data available for this study were neither linked between different hospitals nor within the same hospital over time.

• cost function — to be positively correlated with costs.

The signs and statistical significance of each of the patient-risk characteristic variables will depend in part upon their interaction with other patient-risk characteristic variables, including the default variable of a group of common variables. For example, the coefficient of the Charlson comorbidity score of 6 will depend upon the influence of the default Charlson score (such as patients with a score of 0).

# **Hospital roles and functions, and incentives**

To account for differences between hospitals in the services they provide, the resources they use and the patients they treat, a number of other variables were included in the analysis:

- hospital remoteness
- specialist units
- teaching status
- proportion of patients that are public
- Evans and Walker indices of complexity.

*Hospital remoteness* is defined by ASGC-RA (ABS 2005). A hospital is classified as being in a major city, inner regional, outer regional, remote or very remote area. In parts of this analysis, the latter four areas are grouped as 'outside major cities'. Hospitals in more remote communities of Australia are thought to operate a lower levels of capacity.

*Specialist hospital units* are six variables that describe whether a hospital maintains particular facilities. These variables are used to augment existing data on the number of hospital beds as a measure of hospital capital.

*Teaching status* as included to indicate whether a hospital is a teaching hospital affiliated with universities providing undergraduate medical education. However, the available data did not allow the Commission to measure the intensity of the teaching effort. The variable therefore represents all declared university affiliations, irrespective of the hospital resources involved. Data were not available from the ABS or AIHW on the status of nursing education of hospitals.

*Proportion of patients who are treated as public patients* is a proxy measure for the different incentives faced by hospitals when treating public and non-public patients. Non-public patients include patients who are funded by private health insurance, Department of Veterans' Affairs, third-party motor vehicle accident insurance and workers' compensation funds, and patients who are self-funding.

The *Evans and Walker information indices* are measures of the relative complexity of work undertaken by hospitals. Evans and Walker (1972) put forward 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 indices as proxies for the complexity of hospital services.

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 learn little, the hospital attracts a relatively low index of information gain and therefore complexity (Butler 1988a). In contrast, cases that are rarer and provide more information gain are classified as more complex. A mathematical exposition of the Evans and Walker indices is given in appendix C.

## *Expected signs of the coefficients*

The coefficients of the hospital remoteness variables will depend on their relative degree of remoteness. Hospitals that operate in more remote locations are thought to operate at lower levels of capacity. The coefficients for more remote hospitals in the output-distance function are expected to be negatively signed, and positively signed in the input-distance and cost functions.

Level III intensive care units (ICUs) are expensive to operate relative to most other hospital wards and are expected to be negatively signed in the output distance function, and positively signed in the input-distance and cost functions. Though the other five variables are less capital intensive and more labour intensive, their effect on costs and distance functions is unclear.

To the extent that the financial incentives encourage hospitals to treat public and non-public patients differently (for example, public patients share common wards rather than private rooms), this variable is expected to be positively signed in the output-oriented distance function and negatively signed in the input-distance and cost functions.

The sign of the teaching status of a hospital may is unclear. If a teaching hospital's productivity is lower because of the lower productivity of medical trainee staff, then the coefficient in the output-oriented distance function should be negative. If teaching functions are more resource intensive, then the input-oriented and cost functions will have positively signed coefficients. Care must be exercised when interpreting this variable as the number of medical staff and medial costs are not included in the distance and cost functions.

Finally, both of the Evans and Walker indices are expected to be positively with costs — as hospital complexity increases so do hospital costs. The first Evans and Walker index, which as an absolute measure of complexity, is expected to be negatively signed in the output-oriented distance function, since this reflects the effect that the complexity of a hospital's workload has on decreasing its productivity. It is also expected to be positively signed in the input-oriented and cost functions because of the effect that increased complexity has on resource use.

It is unclear what the sign will be for the second Evans and Walker index, since this measure of complexity recognises that larger hospitals are expected to be able to address more complex procedures.

## **Other variables**

Another possible determinant is the policy and regulatory environment in which hospitals operate. These are factors outside the control of hospitals and need to be included in any assessment of hospital performance. Since data on policy and regulatory environments are not available, a set of proxy variables were used. These are binary variables for each state and territory. For example, the New South Wales binary variable took on a value of '1' if a hospital was located in that state, and '0' if not. A variable was not defined for Queensland, because it was used as the reference category.

# **Reporting categories**

Summary statistics, including efficiency scores, are reported for the various reporting categories, including public hospitals, private hospitals (including for-profit and not-for-profit), and public contract hospitals.

Data are also reported according to hospital size. Hospital size is based on number of casemix-adjusted separations per year, in which:

- very large refers to 20 001 or more casemix-adjusted separations per year
- 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
- very small is defined as 2000 or fewer casemix-adjusted separations per year.

Where relevant, data are reported according to a hospital's remoteness: whether a hospital is in a major city, or outside a major city (including inner regional, outer regional, remote and very remote).

# **3.3 Profile of hospitals in the sample**

As noted above, the Commission's dataset includes 1806 observations, with 1354 public acute hospital observations, 389 private hospital observations and 63 public contract hospital observations (table 3.2).



### Table 3.2 **Observations in the sample, by hospital location, size and year, 2003-04 to 2006-07a,b**

**a** Sample refers to all the acute overnight hospitals included in the Commission's multivariate analysis.<br>**b** Hospital location is defined by the Australia Standard Geographical Classification — Remoteness Structure (ABS 2005). 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. **np** Not published because of ABS confidentiality concerns. – Nil.

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

### **Representativeness of the sample**

Ideally, the data should be representative of all Australian hospitals. Data for public hospitals were representative, as virtually all public acute overnight hospitals were included in the study.

However, private sector data may not be representative of the private hospital sector for two reasons. First, there is an under-representation of not-for-profit hospitals. They comprise approximately 43 per cent of the total number of private hospitals in Australia (AIHW 2009a), yet comprise only 15 per cent of the Commission's private hospital dataset. The Commission's dataset was also relatively under-represented in terms of smaller private hospitals — many of which are not-for-profit hospitals. For example, only about 33 per cent of hospital separations from small and very small private hospitals (outside major cities) were represented in the sample (table 3.3).



### Table 3.3 **Profile of private acute hospitals in the samplea,b,c**

**a** Sample refers to all the acute overnight hospitals included in the Commission's analysis. **b** Hospital location is defined by the Australia Standard Geographical Classification — Remoteness Structure (ABS 2005). **c** 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. **d** All separations (not casemix-adjusted).

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

Second, the nature of the for-profit and not-for-profit hospitals in the sample may differ from those in the community. The private hospitals in the dataset were not drawn as a random sample and it is possible that those hospitals that agreed to participate may be different in ways that affects their efficiency compared to those

that did not agree to be included in the study. In particular, if the factors that affect hospital efficiency also affect the likelihood that a hospital agreed to participate in the study, the efficiency estimates may be biased.

To address the first of these issues, sampling weights were applied to the private hospital observations. The weights were designed to capture the extent to which hospitals of different sizes and from different locations are represented in the private sector sample. Specifically, observations from hospitals of different sizes and locations were weighted by the inverse of the share of separations from hospitals of that size and location that were included in the Commission's sample. For example, 62 per cent of separations from large hospitals in major cities are included in the sample (table 3.3). Therefore, observations for this hospital category are assigned a sampling weight of  $(1/0.62 = 1.613)$ . The weights were based on non-casemix-adjusted separations, because casemix-adjusted data are unavailable for hospitals outside of the sample.

The Commission considered potential methods to overcome the issue of non-random selection using methods analogous to the Heckman correction procedure (Heckman 1976). This procedure would involve modelling the likelihood that a hospital chose to participate in the study, before computing the efficiency scores. The Commission did not employ this method because there were insufficient data about the hospitals outside the sample which would be needed to model their likelihood of participation, and that it was not clear that the technique was sufficiently developed for use with stochastic frontier analysis. As a result, the analysis proceeded without this additional sampling correction.

The Commission's approach means that the efficiency scores should be less biased by the under-representation of different sizes or locations, though it does not control for the possibility that hospitals with different efficiencies may also have a different likelihood of participating in the study.

# **Profile of sample hospitals**

Hospital and patient characteristics, as well as the outputs, inputs and partial productivity measures of hospitals are summarised in tables 3.4 and 3.5. These characteristics are based on the Commission's sample and are not population estimates.

### *Establishment characteristics*

Under the Australian Revised Diagnosis Related Groups (AR-DRG) classification system, each episode of hospital care is classified as being medical, surgical or other. Surgical procedures are invasive in nature and take place in an operating theatre, while other procedures, while also surgical in nature, take place within the doctors' suites or rooms. Medical separations comprise 78 per cent of inpatient activity in public hospitals, but around 42 per cent of separations from private hospitals in the sample. The average share of medical separations for public contract hospitals, at 64 per cent, is larger than for private hospitals but smaller than for public hospitals.

Over half of the separations from large and very large public hospitals are same-day separations. The share of same-day separations is lowest in small and very small public hospitals (35 per cent).

Proportionally more private hospitals in the sample are reported to be teaching hospitals than is the case for public hospitals. However, three-quarters of very large public hospitals are teaching hospitals compared to 48 per cent of very large private hospitals.

Very large, large and medium public hospitals are more likely to have palliative-care units, rehabilitation units and high-level intensive-care units than private hospitals of the same size. Public contract hospitals were most likely to have such palliative-care and high level intensive care units than public hospitals.

### *Patient-risk characteristics*

The patients who had the most comorbidities (Charlson score of 6 or more) collectively constitute a larger share of patients in private hospitals than in public hospitals, on average. Public contract hospitals treated patients with the most comorbidities (based on the average Charlson score).

Patients from the most disadvantaged socio-economic areas constituted a larger share of patients in public hospitals than in private hospitals. This differential is particularly apparent in the small and very small size category. With respect to patients' socio-economic status, public contract hospitals treat a similar patient profile to private hospitals. This may reflect the catchment populations of public contract hospitals, which tend to be located in areas of comparative socio-economic advantage.



Profile of sample hospitals, by establishment and patient characteristicsa  **Profile of sample hospitals, by establishment and patient characteristicsa**  Table 34 Table 3.4

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requirements. Private hospital data disaggregated by size refers to both for-profit and not-for-profit hospitals. – Nil or rounded to zero. **b** Defined as the number of cases in which staphylococcus aureus (ICD-10-AM B95.6) is the cause of disease and which is Methicillin resistant (ICD-10-AM BZ06.32). <sup>C</sup> Defined as the number of cases in which<br>staphylococcus aureus (ICD-10-AM B95.6) is the cause which *staphylococcus aureus* (ICD-10-AM B95.6) is the cause of disease and which is *Methicillin* resistant (ICD-10-AM BZ06.32). **c** Defined as the number of cases in which *staphylococcus aureus* (ICD-10-AM B95.6) is the cause of disease and which is resistant to multiple antibiotics (ICD-10-AM Z06.8). **d** Defined as the number of cases in which *streptococcus group D* (ICD-10-AM B95.2) is the cause of disease and which is *Vancomycin* resistant (ICD-10-AM Z06.41). **e** Defined as the number of separations with requirements. Private hospital data disaggregated by size refers to both for-profit and not-for-profit hospitals. - Nil or rounded to zero. <sup>D</sup> Defined as the number of cases in ICD-10-AM Y92.22 place of occurrence code. **np** Not published due to ABS confidentiality concerns. ICD-10-AM Y92.22 place of occurrence code. np Not published due to ABS confidentiality concerns.

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



Profile of sample hospitals, by output, input and partial productivity measures<sup>a</sup>  **Profile of sample hospitals, by output, input and partial productivity measuresa** 

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Table 3.5

Table 3.5

(continued)

(continued)

requirements. Private hospital data disaggregated by size refers to both for-profit and not-for-profit hospitals. **b** Public hospital beds are reported staffed beds and private and pinane din public contract hospital beds are estimated staffed beds. **np** Not published due to ABS confidentiality concerns. **..** Not applicable. – Nil or rounded to zero. nequirements. Frivate nospital beds are estimated staffed beds. **np** Not published due to ABS confidentiality concerns. .. Not applicable. – Nil or rounded to zero.<br>public contract hospital beds are estimated staffed beds

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

Public hospitals treat a relatively larger proportion of patients aged less than 20 years, while private hospitals treat a relatively larger proportion of patients aged 20 to 69 years.

### *Output measures*

On average, public hospitals report a lower volume of casemix-adjusted separations than private or public contract hospitals. The extent of variation among public hospitals, however, is much larger than the variation among private hospitals in the sample. Public contract hospitals report higher average volumes of activity than all other hospitals included in the sample.

Emergency department services are concentrated in the public hospital sector, and a similar pattern of activity is observed for outpatient services. A high volume of outpatient service activity, on par with public hospitals, is reported for public contract hospitals.

### *Input measures*

The average public contract hospital employs more nursing, diagnostic and allied health and more other staff than the average public and private hospitals. Compared to public hospitals, private hospitals in the sample employ fewer nurses, diagnostic and allied health and fewer other staff. Very large and large public and private hospitals recorded higher costs than smaller hospitals, across all cost types.

## *Partial productivity measures*

The number of separations per non-medical staff member and separations per bed are higher among private hospitals than among public hospitals. This differential is consistent across all hospital sizes and also applies to private hospitals. For these partial productivity measures, the public contract hospitals in the sample generally report rates that are higher than public hospitals yet lower than other private hospitals.

Occupancy rates of 95 per cent or more were reported for very large public and private hospitals. Large, small and very small private hospitals had higher occupancy rates than public hospitals, while the reverse was true in medium hospitals. Public contract hospitals had higher overall occupancy rates than both public and private hospitals, on average.

# 4 Hospital mortality

## **Key points**

- Mortality rates are often used as a partial indicator of the safety and quality of practice within hospitals. They can also be used as a measure of the effectiveness of a hospital's services. Mortality is straight forward to measure, but does not necessarily capture quality differences unrelated to patient death.
- When comparing mortality across hospitals, it is necessary to adjust for differences in the characteristics of the patients treated and the services offered by different hospitals to ensure an accurate comparison across hospitals.
- A hospital-standardised mortality ratio (HSMR) is the ratio of observed mortality to the level of mortality that is predicted on the basis of hospital and patient characteristics. The ratio may be used as an indicator of a hospital's underlying quality of service.
- A hospital's predicted mortality involves a process of risk adjustment that takes into account the patient characteristics and other aspects of the hospital's operations.
- Using hospital-level data, the Commission's risk-adjustment process shows that the key patient characteristics that influence in-hospital mortality include the relative number of older patients, particularly aged 70 plus, the relative number of highly co-morbid patients, the average length of stay, the principal diagnosis, and the socioeconomic status of the patient.
- The key hospital characteristics affecting mortality include the degree to which a hospital specialised in surgical procedures, its size, the extent to which it specialises in a narrow range of activities, and whether the hospital had a palliative care unit.
- The Commission found that HSMRs vary according to the hospital owner, the size of the hospital and where it is located.
	- Overall, private hospitals tend to have lower HSMRs than public hospitals, although there is no significant difference between very large public and private hospitals.
	- As the size of hospitals decreases, HSMRs for public hospitals tend to increase, while the HSMRs for private hospitals decrease.
- Even though the Commission sought to account for both specialisation and the effects of size, the wide dispersion of HSMRs for smaller private and public hospitals suggests that such patterns may still be present in the HSMRs.

When assessing the efficiency of a hospital, the quality of the care provided needs to be taken into account to ensure an accurate comparison of hospital outputs. As discussed in chapter 2, hospital mortality is used in this study as an indicator of hospital quality.

This chapter outlines the Commission's approach to estimating hospital-standardised mortality ratios (HSMRs). HSMRs are used in two ways in this study. First, they permit a partial comparison of the quality of hospital services. Second, they provide a necessary variable to account for differences in hospital quality in the subsequent analysis of technical and cost efficiency.

An overview of the calculation of HSMRs is given in section 4.1, with the factors that are likely to affect the mortality rate of a hospital outlined in section 4.2. Results from the process of risk-adjusting mortality rates are presented in section 4.3. HSMRs for both public and private hospitals across Australia are presented in section 4.4. While individual HSMRs for Australian public hospitals have been previously published (Ben-Tovim, Woodman, Harrison et al. 2009), this is the first time a comparison of public and private HSMRs has been undertaken using a common method and dataset. Section 4.5 outlines how HSMRs may be improved for future use as a measure of hospital quality.

# **4.1 Hospital-standardised mortality ratios**

The incidence of mortality is used in this study as a measure of the quality and patient safety of a hospital's health care as well as a measure of the effectiveness of a hospital's service provision (chapter 2). For brevity, 'hospital quality' is used hereafter to refer to both quality and effectiveness. As a measure of safety and quality, mortality is useful because hospital deaths are a well-defined and generally accurately reported outcome, and HSMR scores are regarded as a reasonable indicator of hospital performance (Ben-Tovim, Woodman, Harrison et al. 2009). An attraction of HSMRs is that they are based on routinely collected administrative data which may be as good at predicting risk as more expensive and less-accessible clinical databases (Aylin, Bottle and Majeed 2007; Miyata et al. 2008).

Unadjusted mortality rates are not readily comparable between different hospitals for two main reasons. First, the incidence can vary between hospitals for reasons that are beyond their control, including the type of patients presenting. For example, some hospitals may specialise in treating higher or lower-risk patients, a factor that is likely to impact on observed mortality rates. Second, mortality rates are likely to vary according to the range of services provided by different hospitals — the services offered determine to a large extent the types of patients that are admitted. Hospitals that provide palliative care facilities, for example, are expected to report higher mortality rates.

In order to use mortality statistics as a comparative measure of hospital safety and quality, it is therefore necessary to control for differences in the characteristics of patients treated and the activities of hospitals through a process of risk adjustment (ACSQHC 2009).

Comparing risk-adjusted in-hospital mortality rates involves two steps. First, a predicted mortality rate is derived for each hospital. This is either done via direct standardisation or, as is more common at present, by using patient-level logistic regression as a means of predicting the likelihood of mortality (Heijink et al. 2008). The second step involves calculating a HSMR from both the observed and predicted mortality rates (see box 4.1).

# Box 4.1 **What is a hospital-standardised mortality ratio?**

The hospital-standardised mortality ratio (HSMR) is an indicator that compares the number of observed deaths in a given hospital with the number of deaths that would have been expected, after adjusting for factors that affect the likelihood of in-hospital death.

That is, for any hospital:

*x100 Number of deaths expected Number of deaths observed HSMR* <sup>=</sup>

A ratio greater than 100 indicates that a hospital's mortality rate is greater than expected on the basis of the risks associated with its patients and services. The expected number of deaths for a given hospital is determined by firstly estimating the determinants of in-hospital mortality using a form of regression. Regression parameters are then used to predict the total number of expected deaths for each hospital, given patient and hospital characteristics. This number of expected deaths is then used as the denominator for the HSMR.

*Source*: Shojania and Forster 2008; CIHI 2009.

# **HSMRs as an indicator of hospital quality**

Even though HSMRs are a potentially useful measure of hospital quality, their use as an indicator of quality has been subject to wide discussion, particularly in both Canada and the United Kingdom, where HSMRs are routinely reported (CIHI 2009; Dr. Foster Health 2010). Mortality is a useful indicator of hospital quality both

because of its intrinsic nature and its relationship with other quality measures. A sustained increase in HSMRs or a persistence of HSMRs above 100 is recognised as a useful trigger for further investigation into hospital practices that may affect mortality (Zahn et al. 2008).

A number of studies have demonstrated that lower HSMRs are associated with better performance in quality indicators. For example, HSMRs are shown to have an inverse relationship with adherence to processes of care across a range of conditions, although this effect is often relatively small (Jha et al. 2007; Werner and Bradlow 2006).

Other authors, however, have cautioned that HSMRs are limited in their ability to reflect hospital quality (Brien and Ghali 2008) because HSMRs:

- are too broad to readily identify the source of any problems within a facility
- do not directly account for variations in care between hospitals such as differences in admission and discharge strategies
- do not take into consideration differences in the underlying morbidity rates within the population
- do not provide direct evidence on other aspects of hospital quality, such as the incidence of unplanned readmissions
- are of little use as a measure of adverse events or unexpected death (Penfold et al. 2008)
- are of little value if variation in mortality is largely random.

Mohammed et al. (2009) also raised the possibility that HSMRs might be biased because risk-adjustment processes are premised on the assumption that risk factors are constant across hospitals, when this may not actually be the case. This is referred to as the 'constant risk fallacy', and could arise if coding practices differed across hospitals.

These criticisms can be addressed if HSMRs are estimated and interpreted appropriately. For example:

- while they are broad indicators, HSMRs can provide a suggestion of whether or not there is a problem of quality of care to be investigated by the hospital
- concerns regarding underlying morbidity rates can be addressed through an appropriate risk-adjustment process
- HSMRs are not intended to be used to measure adverse events or unexpected deaths (Wen et al. 2008)

• risk adjustment provides an acceptable level of discrimination so that the residual variation between hospitals has 'a substantial systematic element' that justifies the use of HSMRs (Ben-Tovim, Woodman, Harrison et al. 2009).

Ben-Tovim, Woodman, Hakendorf and Harrison (2009) tested the constant-risk hypothesis for Australian public hospitals using a procedure similar to that used by Mohammed et al. (2009). They concluded that it is generally valid to assume constant risk across hospitals for many factors. However, the authors did find that the risk associated with being an emergency patient or being admitted from another hospital did vary across hospitals, and it was not clear as to whether risk was constant across diagnostic coding categories.

# **4.2 Factors affecting hospital mortality**

The premise of risk adjustment is that rates of in-hospital mortality are systematically influenced by the characteristics of patients presenting and the services offered at each hospital. Ben-Tovim, Woodman, Harrison et al. (2009) provide a review of recent literature covering the risk-adjustment of mortality rates, and note that age, sex, clinical diagnosis, and any comorbidities noted upon admission need to be considered.

Additional information about the admission can also indicate the possible risk associated with a patient, including arrival and discharge dates, whether or not the admission was an emergency or planned, and the nature of discharge (CIHI 2010). Length of stay is also used as a possible indicator of severity of illness (Jarman et al. 1999; Heijink et al. 2008; CIHI 2010). Information about whether or not the patient was transferred from an acute institution can also provide information about risk of mortality (CIHI 2010). Examining mortality from a hospital level necessitates the use of averages across the patient population for these variables.

Risk adjustment may often take into account the characteristics of the institution at which a patient is being treated (Jarman et al. 1999; Heijink et al. 2008; Shahian and Normand 2008). This entails including information about hospital type and size, the services provided by the hospitals, and teaching status, on the grounds that this affects the quality of treating personnel and the types of patients attracted by the institution. Other hospital characteristics considered include staffing levels and discharge procedures (Heijink et al. 2008; Jarman et al. 1999). Hospital staffing levels were not taken into account in risk adjusting the mortality rates presented here, as they are explicitly considered as a hospital input in the estimation of efficiency in the following chapters.

### *Patient characteristics and hospital treatment*

Drawing on recent studies estimating the determinants of within-hospital mortality (Ben-Tovim, Woodman, Harrison et al. 2009; Heijink et al. 2008), the following variables were used to estimate the likelihood of patient mortality:

- *Age* the percentage of patients who are in youngest and oldest age groups, with the default category being those aged 20–59.
- *Gender* the percentage of patients who are female.
- *Indigenous status* the percentage of patients who identify as Indigenous.
- *Comorbidity* the percentage of patients with a Charlson index of comorbidity in different ranges. The share of patients with a score below two is the default category.
- *Average length of stay* the average length of stay (ALOS) for medical, surgical or otherwise categorised patients (CIHI 2010).
- *Socioeconomic status* the percentage 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 (SEIFA) (ABS 2008b). The percentage of patients in the highest quintile (most advantaged) was treated as the default.
- *Major Diagnostic Category* the percentage of casemix-adjusted separations in each Major Diagnostic Category (MDC) (see chapter 3). The percentage of patients with diseases and disorders of the central nervous system were treated as the default category.
- *Transfers* the percentage of admissions that were transfers from other hospitals (Wen et al. 2008). Similarly, the percentage of separations that concluded with a transfer to another acute hospital was also included.

In addition to the variables above, a number of nonlinear and interactive terms were also considered. For example, the transfer variable was interacted with hospital size variables, to account for the possibility that transfers are made between hospitals for different reasons (Wen et al. 2008). Severely-ill patients — with a higher likelihood of death — may be transferred from smaller to larger hospitals for treatment in specialised facilities, such as intensive care units. Conversely, patients recovering from severe illness, and at a lower risk of mortality, may be transferred to smaller hospitals. However, the Commission found that these variables did not significantly impact on mortality and did not improve the fit of the model, so they were not included in the final model specification.

Remoteness of residence was also considered as a factor likely to affect mortality. However, this was found not to improve the fit of the model, given the inclusion of the SEIFA variables. Remoteness was therefore not included in the final model specification.

## *Hospital characteristics*

A number of hospital characteristics were also included to account for the fact that not all individual patient-risk characteristics are observable, but hospital characteristics are known. Hospital characteristics used in estimating expected mortality include:

- *Hospital services* binary indicators as to whether or not a hospital operates neonatal intensive care, obstetric, level-III intensive care, coronary care, palliative care, rehabilitation, and domiciliary care units were included so as to provide further information about the types and severity of illnesses treated.
- *Teaching status* included as an indicator of the potential complexity of cases treated in a given hospital.
- *Admissions from an emergency department* the ratio of emergency department visits to inpatient admissions as a proxy for the share of patients admitted as emergency patients.
- *Hospital size* variables reflecting hospital size were included.
- *Specialisation* the percentage of total separations accounted for by the five most common MDCs was included as an indicator of the degree of specialisation of treatment. The percentage of total separations that are non-medical (classified as 'surgical' or 'other') was also included as an indicator of specialisation.

The relative complexity of work undertaken by hospitals was also taken into account by including an Evans and Walker information index in the regression (Evans and Walker 1972). The index is a measure of the complexity of hospital work that takes into account differences in hospital size. This means that, while larger hospitals generally treat more complex cases than smaller hospitals, due to their size, they are also expected to treat more complex cases, due to a higher degree of capacity (see chapter 3).

Time variables were also included so as to account for national variations in mortality over time.

# *Other factors affecting in-hospital mortality*

It is important to note that a number of factors likely to impact on the mortality rate of a hospital were not able to be taken into consideration. For example, access to both general practitioners (Heijink et al. 2008) and other forms of primary care (Jarman et al. 1999) are likely to effect levels of within-hospital mortality. Similarly the level of access to hospitals themselves is likely to influence mortality rates. It has been demonstrated that, in an urban environment in the United Kingdom, a 10 km increase in the distance from the hospital is associated with a one per cent increase in mortality (Nicholl et al. 2007). It is likely that a patient's proximity to hospital care could impact significantly on the mortality rates observed in regional and remote hospitals in Australia.

# **4.3 Risk adjusting hospital mortality rates**

As the number of deaths observed in a hospital over a given time period is by definition a non-negative integer, it is appropriate to apply a statistical model that takes these restrictions into account. A negative binomial regression was used to predict the expected number of deaths for a given hospital within a given time frame (see appendix C). This is a similar approach to that taken by Korda et al. (2007) in modelling the effect of health care on avoidable mortality rates in Australia.

The negative binomial is based on the assumption that there is an underlying mortality rate within a population that can be multiplied by an 'exposure' to determine the expected number of deaths for that population. A characteristic of the negative binomial is that in the instance of small exposures, the probability of observing more than one death will be small compared with the size of the exposure. The number of deaths for each hospital in each year is regressed over a vector of independent variables, with the number of casemix-adjusted separations used as the 'exposure' variable.

It is worth noting that, by necessity, this approach to risk adjustment is different to that used in other studies (see for example, Ben-Tovim, Woodman, Harrison et al. 2009; CIHI 2007, 2010; Heijink et al. 2008). Normally, the expected mortality of a hospital is predicted from a logistic regression using patient-level data. This was not possible because patient-level data were not available for this study.

The Commission compared the HSMRs resulting from the negative binomial approach with a logistic regression using hospital-level data. The hospital-level data were used to create a pseudo patient-level dataset, with each individual separation for each hospital being ascribed the average patient characteristics for the hospital in which they were treated. The rank correlation between the HSMRs derived from the pseudo patient-level dataset and those produced using the negative binomial approach was in excess of 0.9, suggesting that both approaches produce very similar HSMRs. However, the lack of within-hospital variation inherent in the pseudo patient-level data means that the logistic regression results overstate the statistical significance of mortality determinants. It is for this reason that the negative binomial approach was preferred.

In order to closely adhere to established practice, a range of model specifications were tested, following the patient-level studies of Ben-Tovim, Woodman, Harrison et al. (2009), CIHI (2007) and Heijink et al. (2008). The coefficients were generally of the expected sign. Results from the specification which had the greatest explanatory power are presented as incidence rate ratios — the effect on the mortality rate of an incremental change in the explanatory variable. Estimates from the preferred specification are also the basis for the summary statistics and the HSMR indicator that is used in the following chapters.<sup>1</sup>

### **Incidence rate ratios**

Results from the preferred regression of hospital mortality can be presented as incidence rate ratios (IRRs) for the individual factors that affect in-hospital mortality (table 4.1) Negative binomial regressions model mortality levels as a rate that is subject to a level of exposure — in this case, the number of total separations. The IRR represents the percentage increase in the incidence of mortality given a one-unit increase in the independent variable.2 For example, an IRR of 1.10 indicates that a one unit increase in the independent variable would lead to a 10 per cent increase in the mortality rate. An IRR of 0.90 indicates that a one-unit increase in the independent variable leads to a 10 per cent decline in the mortality rate.

The interpretation of categorical 'share' variables requires care. These are categorical variables that represent the share of patients, as a percentage, that

$$
IRR_i = \frac{E(y_i \mid x_i = 1)}{E(y_i \mid x_i = 0)}.
$$

 $\overline{a}$ 

<sup>&</sup>lt;sup>1</sup> The preferred model was the specification with the greatest log-likelihood and the lowest Akaike Information Criterion score (Hilbe 2007). Coefficients for both the preferred model, as well as an alternative specification that included only variable groups that resulted in a significant increase in the log-likelihood, are presented in appendix D.

<sup>&</sup>lt;sup>2</sup> That is, the incidence rate ratio (*IRR*) for hospital *i* for a binary variable  $x_i$  that affects mortality rate *y*i can be expressed as:

correspond to that category. As with other regressions, any marginal effect of an increase in a categorical variable is relative to the default category for that group of variables.

For example, the IRR for the share of patients aged over 70 is the ratio of expected mortality following a one percentage point increase in the share of those aged over 70 to the level of expected mortality without that increase. It is important to remember that a one percentage point increase in the share of those aged over 70 is relative to the default age category, and therefore simultaneously corresponds to a decrease in the share of those aged between 20 and 59.

As expected, a higher proportion of younger patients is generally associated with a lower expected mortality rate. That is, hospitals that treat a greater number of older patients are likely to experience higher levels of mortality, all else being equal. This is consistent with patient-level studies that demonstrate that the likelihood of mortality increases with age (Ben-Tovim, Woodman, Harrison et al. 2009).

ALOS is associated with increased mortality for medical procedures. In contrast, for surgical procedures the likelihood of death decreases as ALOS increases. This suggests that the relationship between mortality risk and length of stay is not linear, as shown by Ben-Tovim, Woodman, Harrison et al. (2009).

Differences in the effect of ALOS variables on mortality also reflect the different risks associated with medical and surgical procedures. The strength of this effect is reinforced by the significance and magnitude of the specialisation variables. Hospitals with a higher concentration of separations in the five diagnostic categories in which they perform the most separations have a noticeably lower IRR. Importantly, this effect is contingent on size, and is no longer significant when the sample is restricted to large and very large hospitals (appendix D).

Contrary to expectations, an increase in the proportion of admitted patients who were transferred from another hospital is associated with a significant reduction in mortality. This is in contrast to the findings of Ben-Tovim, Woodman, Harrison et al. (2009). A possible explanation for this is that transfers between hospitals of different sizes and capacities occur for different reasons. To examine this explanation, the share of transferred admissions was interacted with the hospital size variables, with the result being that the share of admitted patients was no longer significantly related to mortality for all hospital sizes.



### Table 4.1 **Effects of patient and hospital characteristics on mortality**  Incidence rate ratios

**\*\*\*** p<0.01, **\*\*** p<0.05, and **\*** p<0.1

*Source*: Productivity Commission estimates.

# **4.4 Comparing HSMRs across public and private hospitals**

The HSMRs for different sub-groups of hospitals are summarised in table 4.2. It is useful to consider both the mean and median HSMR scores as aggregate quality indicators. Mean HSMR scores are prone to influence by outliers, as is evidenced by the high mean relative to the median score for public contract hospitals. However, relying solely on the median scores does not acknowledge the persistence of a number of very low HSMR scores for private hospitals.



## Table 4.2 **Hospital-standardised mortality ratios summary statistics, 2003-04 to 2006-07a,b**

**a** Hospital-standardised mortality ratio is equal to the actual (observed) mortality rate divided by the predicted mortality rate multiplied by 100.

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

Over all hospitals, the mean HSMR score for private hospitals is lower than for public hospitals by around 12 percentage points, averaged over 2003-04 to 2006-07. The difference in mortality between public and private hospitals was shown to be significant at the aggregate level by including binary variables indicating management type in a specification of the mortality equation (appendix D).

However, when disaggregated by size, there is little difference between the HSMRs for very large public and private hospitals (table 4.3). If the sample is restricted to include only large and very large hospitals, there is no significant difference between the HSMRs for public and private hospitals (appendix D).



### Table 4.3 **Hospital-standardised mortality ratios, by owner and hospital size, 2003-04 to 2006-07a**

**a** The hospital-standardised mortality ratio is equal to the actual (observed) mortality rate divided by the predicted mortality rate, multiplied by 100. **b** *Very large* hospitals report more than 20 000 separations per year. C Large hospitals are report between 10 001 and 20 000 separations per year.<br>d Medium hospitals are those reporting 5001 and 10 000 separations per year. C Very small and small *hospitals* reporting less than 5000 separations per year. **np** Not published due to ABS confidentiality concerns. **..** Not applicable.

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

The gap between public and private HSMRs appears to widen as hospitals get smaller — with the exception of medium-sized hospitals. The difference in means for small and very small hospitals is around 23 percentage points. However, the dispersion of HSMRs for smaller private hospitals is significantly larger than that for public hospitals, suggesting that the difference in means may be substantially

influenced by very low outliers — the HSMR score at the  $5<sup>th</sup>$  percentile is just under 10 for private hospitals, compared to around 44 for public hospitals.

Even though the Commission sought to measure the effect of size and specialisation, it is unlikely that this is fully taken into account, given the wide dispersion of HSMRs for smaller hospitals and the number of smaller private hospitals with very low HSMRs. Given the larger proportion of smaller public hospitals that are located in remote and regional areas, smaller public hospitals are unlikely to be able to specialise to the same extent as private hospitals of a similar size.

Furthermore, it is possible that the if the availability of primary care is an important determinant of in-hospital mortality (Heijink et al. 2008; Jarman et al. 1999), then the HSMRs of smaller public hospitals may also reflect the relative absence of primary care in more remote communities.

## **Variation in HSMRs across time**

The Commission also examined the relative position of each hospital over time by undertaking Spearman rank correlation test of hospital HSMRs for each year (table 4.4). Large changes in mortality ratios could either indicate large shifts in the quality of care provided or indicate random variation. The correlations for 2004 gradually declined from 0.688 to 0.564, suggesting a decline in consistency over time. However, the correlations between 2004 and 2005 (0.688), 2005 and 2006 (0.718) and 2006 and 2007 (0.743) have increased, suggesting that that possible random variation has been declining over time.

### Table 4.4 **HSMR rank correlation over timea**



**a** Spearman's rank correlation coefficients. **\*** p<0.01

*Source*: Productivity Commission estimates.

More broadly, variation in HSMRs can be examined by classifying hospitals into high, intermediate and low mortality groups, as per CIHI (2007). Hospitals classed as being high mortality refers to those with HSMRs and confidence intervals in excess of 100, while low mortality hospitals were estimated to have HSMRs and confidence intervals below 100. Hospitals with HSMRs and confidence intervals that intersected 100 were classed as intermediate.

Of the 163 large and very large hospitals included in the sample for all four years, around 15 per cent were low for all four years, 11.7 per cent were high for all four years and 11 per cent were intermediate. Around 35 per cent moved between having intermediate and low HSMRs, and the remaining 28 per cent moved between having intermediate and high HSMRs. Variation was much larger for the medium, small and very small hospitals, with only around 4.5 per cent classed as low for all four years, and 3.8 per cent remaining as high over this time. This is in part attributable to the increasing impact of individual deaths on mortality rates as the number of separations decrease.

# **Caterpillar plots**

 $\overline{a}$ 

Ben-Tovim, Woodman, Harrison et al. (2009) present HSMRs graphically, with hospitals ranked by HSMRs on the *x*-axis and HSMRs on the *y*-axis. These plots provide a readily accessible means of displaying the distribution of HSMRs across a hospital sub-sample, along with confidence intervals that provide an indication of the reliability of the estimates (see appendix C).

The HSMRs for very large, large and medium-sized public and private hospitals across Australia in 2006-07 are presented in figures 4.1, 4.2, and 4.3. As is evident across these figures, the size of the confidence intervals increases as the size of hospitals diminish.<sup>3</sup> It is for this reason that plots for the numerous small and very small hospitals have not been presented.

The confidence intervals are calculated using an approximation method that is contingent on the number of deaths observed in each hospital. Given that, within each hospital size grouping, public hospitals are generally larger than privately-run hospitals, the confidence intervals are often wider for private hospitals. This means that it is more likely that the private hospital confidence intervals will cross an HSMR score of 100.

<sup>&</sup>lt;sup>3</sup> Technically, the size of the confidence intervals increase as the number of deaths observed in a hospital decreases.



#### **Figure 4.1 Hospital-standardised mortality ratios for very large hospitals, 2007a,b,c,d**

*Source*: Productivity Commission estimates.

Taking into account the confidence intervals, this demonstrates the broad similarity of HSMR outcomes for the very large public and private hospitals. Around 23 per cent of very large public hospitals have HSMRs above 100, taking into account the confidence interval. For private hospitals of the same size, around 21 per cent have HSMRs in excess of 100. Around 41 per cent of very large public hospitals have HSMRs below 100, while this figure is around 43 per cent for very large private hospitals.

**a** Very large hospitals are those reporting more than 20 000 separations per year. **b** Confidence intervals indicate precision of the HSMR estimates, and are contingent on the size of hospital and the number of observed deaths. They are calculated using Byar's approximation, as set out in CIHI (2007) and appendix C. **c** Private hospitals awarded public contracts are not identified separately due to confidentiality requirements. They are classified as private hospitals in this figure. **d** The 5 per cent lowest and highest HSMR estimates for very large hospitals are not published due to ABS confidentially concerns.



Figure 4.2 **Hospital-standardised mortality ratios for large hospitals, 2007a,b,c,d** 

*Source*: Productivity Commission estimates.

Around 39 per cent of large public hospitals have HSMRs are below 100, in comparison to around 37 per cent of large private hospitals. For medium-sized hospitals, the difference is reversed with around 24 per cent of public hospitals and 29 per cent of private hospitals are shown with HSMRs below 100.

The difference between public and private hospitals becomes more pronounced for the smaller hospitals. Around 10 per cent of very small, small and medium public hospitals have HSMRs above 100, while this is about 25 per cent for comparable private hospitals. About 45 per cent of these private hospitals have an adjusted mortality ratio that is below 100, but for comparable public hospitals, the number is notably lower, at around 10 per cent.

**a** Large hospitals are those reporting between 10 000 and 20 000 separations per year. **b** Confidence intervals indicate precision of the HSMR estimates, and are contingent on the size of hospital and the number of observed deaths. They are calculated using Byar's approximation, as set out in CIHI (2008) and appendix C. **c** Private hospitals awarded public contracts are not identified separately due to confidentiality requirements. They are classified as private hospitals in this figure. **d** The 5 per cent lowest and highest HSMR estimates for large hospitals are not published due to ABS confidentially concerns.



### Figure 4.3 **Hospital-standardised mortality ratios for medium hospitals, 2007a,b,c,d**

**a** Medium hospitals are those reporting 5000 and 10 000 separations per year. **b** Confidence intervals indicate precision of the HSMR estimates, and are contingent on the size of hospital and the number of observed deaths. They are calculated using Byar's approximation, as set out in CIHI (2007) in appendix C. **c** Private hospitals awarded public contracts are not identified separately due to confidentiality requirements. They are classified as private hospitals in this figure. **d** The 5 per cent lowest and highest HSMR estimates for medium hospitals are not published due to ABS confidentially concerns.

*Source*: Productivity Commission estimates.

# **4.5 Improving HSMRs as a measure of hospital quality**

There are opportunities to improve the modelling of HSMRs in the future. First, estimating mortality rates at the hospital level with a negative binomial regression does not take into account the wide range of variation in mortality risks associated with individual patients. While the negative binomial is an acceptable approach for modelling mortality at a hospital level, adjusting mortality risk at the patient level requires logistic regression and patient-level data — as demonstrated by Ben-Tovim, Woodman, Harrison et al. (2009) and Heijink et al. (2008). This is a preferred approach because risk is taken into account at the patient level, rather than on the basis of hospital-wide averages.
Second, information about the context of a hospital within the health system is likely to improve the validity of HSMRs as an indicator of in-hospital quality of care. This is due to the fact that access to health services — in addition to those provided by hospitals — is likely to have a notable impact on hospital mortality. Heijink et al. (2008) show that the number of general practitioners in the surrounding areas has a significant effect on in-hospital mortality, something that was not able to be taken into account in this study. Jarman et al. (1999) point out that access to other health services is also likely to affect mortality levels in a more direct manner. Hospitals faced with a greater availability of aged care services are more able to discharge patients to these services, and any subsequent deaths are not in a hospital.

Related to this, is that the time taken to travel to a hospital may be a useful measure of the accessibility of hospital services.

Third, HSMRs could be improved by access to more detailed information about the nature and severity of patient diagnoses. Risk adjustment in the HSMRs presented in this chapter involves taking into account the primary diagnosis of patients, as well as the emergency ratio and average length of stay. However, as noted by Shojania and Forster (2008), in some instances administrative data may be inadequate to account for influential differences in casemix.

While Ben-Tovim, Woodman, Harrison et al. (2009) use the same approach, this is a broad categorisation of diagnosis, and encompasses a broad range of acuity, severity and complexity of cases. Systematic differences between public and private hospitals in the mortality risk associated with patients within a primary diagnosis group will not be accounted for in the risk-adjustment process as it has been implemented. More detailed diagnostic information would substantially improve the risk-adjustment process.

# 5 Technical efficiency

## **Key points**

- The Commission measured hospital technical efficiency in terms of:
	- output orientation how well a hospital maximises output from its given resources
	- input orientation how well a hospital economises on resources to produce a given output level.
- Subject to data limitations outlined in chapter 3, hospitals are estimated to have the potential to increase their output by almost 10 per cent based on their current level of input use, under the output-orientation approach.
	- Public contract hospitals are the most efficient, followed, in order, by for-profit private hospitals, public hospitals and not-for-profit private hospitals.
	- These relative rankings are statistically significant and generally stable across different hospital sizes.
- The efficiency of public hospital tends to be higher among the larger hospitals. The efficiency of private hospitals shows not discernibly change with hospital size.
- Hospitals have the potential to reduce their input use by just over 10 per cent, based on their current level of output, under the input-orientation method.
	- Public contract hospitals are the most efficient. Differences between the other hospitals are not statistically significant.
- Hospitals with higher than expected hospital-standardised mortality ratios (HSMRs) (that is, poorer quality) are estimated to be less productive and more resource intensive than hospitals with lower than expected HSMRs (that is, higher quality).

Building on the explanation of modelling methods given in chapter 2 and the description of the dataset presented in chapter 3, this chapter presents the results of the estimated distance functions and technical efficiency scores of hospitals in Australia. A summary of the Commission's approach is outlined in section 5.1. The coefficient results of the models are presented in section 5.2. The technical efficiency scores are reported and discussed in section 5.3.

# **5.1 Summary of Commission's approach**

The Commission used stochastic frontier analysis (SFA) to estimate the output-oriented and input-oriented technical efficiency of hospitals in Australia.

The variables used to explain efficiency include:

- hospital outputs
- hospital inputs
- quality of outputs
- patient risk characteristics
- hospital characteristics.

The rationale for the inclusion of these variables is described in chapter 2 and appendix C. A description of the available data, summary statistics, and expected signs of the coefficients is given in chapter 3. To recap the Commission's approach, the estimated models are based on the following specifications:

- data for the years 2003-04 to 2006-07 pooled into a single cross section
- weighted dataset to represent the true population
- translog functional form
- variable returns-to-scale
- a half-normal distribution for the efficiency term.

### **Data limitations**

As noted in chapter 3, data are available for the number of medical staff in public hospitals, but not for medical staff in private hospitals and doctors exercising their private practice rights in public hospitals. To ensure comparability between public and private hospitals, the analysis therefore excludes all medical staff. There are also limitations to the availability of data for hospital capital. In the analysis, capital is measured by the number of staffed beds and a set of binary variables which indicate the presence of particular facilities in a hospital. Future analysis would benefit from attempts to include the effects of medical staff on hospital efficiency, as well as more detailed estimates of capital usage in hospitals.

# **5.2 Estimation results**

The first step in the analysis is to determine the best-practice frontier for each hospital. The 'frontier' can be interpreted as the optimal level of productivity or the level of resource intensity that is *expected* of a hospital, given its characteristics. The coefficients, therefore, show how a particular characteristic influences a hospital's expected productivity (in the output-oriented model) or expected resource-intensity (in the input-oriented model). In effect, the coefficients show by how much and in what direction a variable shifts a hospital's best-practice frontier (see box 5.1).

## Box 5.1 **Coefficients in the distance function**

The sign and magnitude of the coefficients of a distance function indicate how each variable affects a hospital's distance to the frontier (chapter 2; appendix C).

While distance can be considered synonymous with inefficiency, there is not a simple linear relationship between distance and efficiency, because efficiency is also determined by the relative distances of other hospitals and the assumed distribution of efficiency term.

Since, as a computational convention, distance functions are estimated using either an output or an input as a dependent variable, it is sometimes easier to conceptualise the coefficients of variables as representing *shifts* of the frontier relative to a hospital's position.

Additionally, the dependent variables for the output and input-distance functions are inverted, as is common practice in this field of analysis (chapter 3). The effect of this is to change the interpretation of the respective signs of the coefficients, as explained in this section.

The expected signs of the coefficients were discussed in chapter 3. In brief, the sign of:

- each output is expected to be negative (positive) in the output (input) oriented distance function
- each input is expected to be positive (negative) in the output (input) oriented distance function
- hospital quality is expected to be negative (positive) in the output (input) oriented distance function
- each patient and hospital characteristic is expected to be negative (positive) in the output (input) oriented distance function, where these characteristics are associated with a reduction in a hospital's expected productivity (an increase in a hospital's expected input use).<sup>1</sup>

For both model orientations, the squared terms show the rate at which the impact of a particular variable can vary over its range. The second-order terms (the output and

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<sup>1</sup> Assuming the dependent variable has been inverted.

input cross-terms) are more complex to interpret but are included to refine the fit of the overall model.

With respect to the quality variables, it should be noted that these coefficients do not necessarily reflect any causal link between hospital quality and efficiency. Rather, they are used to capture any systematic correlation between these two indicators of performance.

#### *Ownership variables*

The ownership variables are not included in the frontier equation, because the analysis is not intended to control for differences by ownership when determining the best-practice frontiers. Rather, the ownership variables are regressed against the inefficiency error term, in order to identify which hospitals are further away from their respective benchmarking frontier, where this distance represents the extent of their technical inefficiency. A positively-signed ownership coefficient would indicate that a hospital with that ownership status is further away from its frontier. That is, the hospital is further from its maximum level of output capacity (in the output-oriented model) or minimum level of resource use (in the input-oriented model). The significance level of the coefficients verifies whether any differences in efficiency between hospitals, according to their ownership type, are statistically significant or not (appendix C).

### **Reported results**

The following tables present the estimated coefficient results of the output-oriented model (table 5.1) and the input-oriented model (table 5.2). The significance of the coefficients are found to differ, to some degree, according to the model orientation. This reveals that an analysis of hospitals' technical efficiency needs to acknowledge whether hospitals can — in practice — gain efficiency by expanding their output (as per the output-oriented model) or by economising on inputs (as per the input-oriented model).



# Table 5.1 **Coefficient estimates — output-oriented distance functiona**



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**a** Data for 2003-04 to 2006-07, weighted by sample representation. Output and input variables are logged, mean-centred and normalised. Dummy variables for zero values included in regression but not reported. The model applies a half-normal distribution to the efficiency equation. **b** Base categories are: share of patients aged 20-59 years; share of patients from SEIFA 5 (least disadvantaged); share of patients with Charlson score 1 or below (fewest comorbidities). **c** Base category is inner regional area. **d** Base jurisdiction is Queensland. **e** Base year is 2003-04. **f** Due to their confidentiality restrictions, the coefficient terms for ln *2 v* and  $\ln \sigma_u^2$  were suppressed by the ABS because these values would enable the calculation of efficiency scores for individual hospitals or hospital groups. The ABS also deemed it necessary to suppress the coefficient terms and standard errors of the ownership dummy variables. Significance levels denoted as: \* 10%; \*\* 5%; \*\*\* 1%. Standard errors are robust due to the sample weighting. **seps**: number of separations. **sv**: number of occasions of service. **np** Not available for publication due to ABS confidentiality concerns.

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



# Table 5.2 **Coefficient estimates — input-oriented distance functiona**

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**88** PUBLIC AND PRIVATE HOSPITALS: MULTIVARIATE ANALYSIS



**a** Data for 2003-04 to 2006-07, weighted by sample representation. Output and input variables are logged, mean-centred and normalised. Dummy variables for zero values included in regression but not reported. The model applies a half-normal distribution to the efficiency equation. **b** Base categories are: share of patients aged 20-59 years; share of patients from SEIFA 5 (least disadvantaged); share of patients with Charlson score 1 or below (fewest comorbidities). **c** Base category is inner regional area. **d** Base jurisdiction is Queensland. **e** Base year is 2003-04. **f** Due to their confidentiality restrictions, the coefficient terms for ln *2 v* and  $\ln \sigma_u^2$  were suppressed by the ABS because these values would enable the calculation of efficiency scores for individual hospitals or hospital groups. The ABS also deemed it necessary to suppress the coefficient terms and standard errors of the ownership dummy variables. Significance levels denoted as: \* 10%; \*\* 5%; \*\*\* 1%. Standard errors are robust due to the sample weighting. **seps**: number of separations. **sv**: number of occasions of service. **np** Not available for publication due to ABS confidentiality concerns.

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

Based on preliminary regressions, output and input variables that generated incorrectly-signed coefficients were omitted from the final models reported in the tables. These variables were: district nursing and outreach services, other outpatient services and other staff (in both the output- and input-oriented models), and dialysis and endoscopy services, and diagnostic and allied health staff (in the input-oriented model only).

To test the model's sensitivity to the choice of the half-normal distribution for the inefficiency error term, the model is also estimated with an exponential distribution. The results are presented and briefly discussed in appendix D.

### **Factors affecting technical efficiency**

The most important output that influences a hospital's productivity and resource intensity is the volume of acute separations provided, followed by pregnancy and neonate, mental and alcohol, and other separations. Services to non-admitted patients are found to have less impact. Of these, accident and emergency services are the most important in the output-oriented model, while allied health and dental services are of most importance in the input-oriented model.

The inputs that have the greatest impact on a hospital's productivity include the number of staffed beds, the number of nursing staff and expenditure on drugs. Resource intensity is most greatly affected by expenditure on other items, although the overall importance of the input variables is less profound in the input-oriented model.

Hospitals' mortality ratios prove to be significant in both model orientations, particularly the output-oriented model. This confirms that hospitals which have higher than expected mortality rates are estimated to be relatively less productive for their given input level, and also more resource intensive for their given output level.

### *Patient and hospital characteristics*

When it is assumed that hospitals aim to maximise output from their given resources (as per the output-oriented model), hospitals are expected to be more productive if they:

• treat proportionally fewer patients who are very old (aged over 70) or very young (neonate age or aged 5 to 19), but more patients aged 1 to 4 years

- treat proportionally fewer patients of slightly higher comorbidity (Charlson score 2 to 4, compared to Charlson score 1 or below) but only up to a threshold: hospitals that treat proportionally more patients of highest comorbidity (Charlson score 6) are also expected to be relatively more productive.
- are located in or relatively closer to a major city
- undertake proportionally more surgical or other DRG separations and fewer medical separations
- treat proportionally more public patients
- have university-affiliated teaching status
- have a palliative care unit
- do not have a high-level intensive care unit
- treat relatively more complicated cases for their establishment size (as measured by the Evans and Walker index).

Factors which have no significant impact on expected productivity are: patients' socio-economic status (as represented by SEIFA); the presence of a rehabilitation unit or domiciliary care unit; and whether or not the hospital belongs to a network.

When it is assumed that hospitals aim to minimise their input use to produce a given level of output (as per the input-oriented model), hospitals are expected to be less resource intensive if they:

- treat proportionally fewer patients who are very old (aged over 70) or very young (neonate age), and more patients aged 1 to 4
- treat proportionally fewer patients of slightly higher comorbidity (Charlson score 2 to 4, compared to Charlson 1 or below) but only up to a threshold: hospitals which treat more patients of highest comorbidity (Charlson score 6) are also found to be relatively less resource intense.
- are located outside of a major city
- undertake proportionally more surgical or other DRG separations and fewer medical separations
- treat proportionally more public patients
- belong to a hospital network
- treat relatively more complicated cases for their establishment size (as measured by the Evans and Walker index).

Factors which do not have a significant impact on expected resource intensity are: patients' socioeconomic status (as represented by SEIFA); teaching status; and specialist units (high-level intensive care, palliative care, rehabilitation and domiciliary care).

Note that state and territory dummy variables are used to control for jurisdiction-specific factors, such as differences in data reporting methods or regulatory settings, and should not be interpreted as indicators of the relative efficiency between the jurisdictions. Similarly, the year dummy variables are included to control for time-specific variations in the data that cannot be captured by the observed variables, and should not necessarily be interpreted as a time-dependent trend in hospital efficiency.

#### *Hospital ownership*

The significance of the ownership dummy variables differed depending on the model orientation. All ownership variables were found to be statistically significant in the output-oriented model, whereas only the dummy variable for public contract hospitals was significant in the input-oriented model. The interpretation of these variables and their significance is discussed in the next section.

The value of the ownership coefficients could not be published due to confidentiality requirements for private hospital data.2 However, the signs of the coefficients, and the magnitude of the significance levels, can still be used to explain the respective rankings of the different hospital groups. For example, the terms of the output-oriented model show that private hospitals are collectively less efficient than public and contracted hospitals. However, they also show that the difference between for-profit and not-for-profit private hospitals is sufficiently large that for-profit private hospitals are more efficient than public hospitals, while not-for-profit hospitals are less so. The relativities between the four hospital groups are illustrated more precisely by the value of the efficiency scores themselves, as discussed in the next section.

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<sup>&</sup>lt;sup>2</sup> Due to confidentiality restrictions, the coefficients of the terms  $\sigma_u^2$  and  $\sigma_v^2$  were suppressed by the ABS because it was reasoned that these terms would enable the efficiency scores of individual hospitals or hospital groups in the private sector to be calculated. The ABS also deemed it necessary to suppress the coefficient values and standard errors of the ownership dummy variables.

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# **5.3 Technical efficiency scores**

The technical efficiency scores of the output-oriented and input-oriented models are reported in table 5.3 according to hospital ownership, and further disaggregated by hospital size in table 5.4. An averaged measure of efficiency scores generated by both models (averaged at the individual observation level) is also reported.



### Table 5.3 **Technical efficiency scores by hospital ownership**

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

#### **How to interpret the efficiency scores**

Computationally, the technical efficiency scores relate to the distance of a hospital's current production point from its respective benchmarking frontier. The exact interpretation is specific to the model orientation. For the output-oriented model, the efficiency scores measure the volume of output that a hospital is currently producing, relative to the maximum volume it could potentially produce from its current inputs. For example, an output-oriented efficiency score of 90 per cent would mean that a hospital is producing 90 per cent of its full output potential. This could be interpreted to mean that the hospital is producing at 10 per cent below its

maximum capacity, or that it has the potential to increase its current output level by 11 per cent without needing to increase its resources.3

For the input-oriented model, the efficiency scores represent the percentage by which a hospital exceeds the minimum volume of inputs required to produce its current output level. As is standard practice in stochastic frontier analysis, the reported scores for the input-oriented model are inverted for comparability with the output-oriented scores and also for the calculation of the averaged scores. For example, an estimated input-oriented efficiency score of 125 per cent is inverted to give a score of 80 per cent. This means that the hospital can reduce its input use by 20 per cent and still produce the same volume of output.<sup>4</sup>

### **Comparisons across all hospitals**

Based on the averaged efficiency scores, hospitals in Australia are performing at around 90 per cent of maximum efficiency (table 5.3). The similarity of the output-oriented and input-oriented scores across all hospitals suggests that Australian hospitals are generally equally as efficient at maximising production from their given inputs, as they are at economising in input use. On average, the most efficient hospitals are for-profit private hospitals, followed closely by public contract hospitals, and then public and not-for-profit private hospitals.

When hospitals are assessed according to how well they maximise production from their inputs, the most efficient hospitals are for-profit private hospitals (94.8 per cent), followed by public contract hospitals (92.4 per cent), public hospitals (89.1 per cent) and not-for-profit private hospitals (85.6 per cent). The differences between all of these hospital groups are found to be statistically significant.

When hospitals are assessed according to how well they economise on inputs to produce their output, the most efficient hospitals are found to be public contract hospitals (93.6 per cent), followed by for-profit private hospitals (91.8 per cent), not-for-profit private hospitals (90.2 per cent) and public hospitals (89.1 per cent). However, only the difference between public contract hospitals above all other hospitals is deemed statistically significant. This means that public, for-profit private and not-for-profit private hospitals perform equally well as each other in terms of economising on input use. As can be seen, the gap between their efficiency

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<sup>3</sup> Computed as  $(100 - 90) / 90 = 11$ .

<sup>4</sup> Computed as  $(125 - 100) / 125 = 20$ .

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scores narrows substantially under this model orientation compared to the output-oriented results.

Comparisons of the output-oriented and input-oriented efficiency scores highlight further differences by hospital ownership. The greatest gap in efficiency scores is observed among not-for-profit hospitals, which are found to be more efficient at economising on inputs rather than expanding production. By a smaller margin, the same can be said for public contract hospitals. In contrast, for-profit private hospitals are found to be better, on average, at expanding production rather than economising on inputs, while public hospitals are found to be equally as efficient according to these two performance measures.

As noted in chapter 2, it was expected that the input-oriented model would favour public hospitals, while the output-oriented model would favour private hospitals. This does not mean that the efficiency scores of public hospitals should be higher under the input-oriented model rather than under the output-oriented model. It also does not necessarily mean that public hospitals should be ranked higher than private hospitals under the input-oriented model, while the rankings should reverse under the output-oriented model. Rather, the effect of the model orientation is shown in the margin of difference between the public and private efficiency scores: under the output-oriented model, private hospitals are more efficient than public hospitals by 3.5 percentage points, yet this difference closes to 2.3 percentage points under the input-oriented model.

The gap between for-profit and not-for-profit private hospitals is also found to depend greatly on the model orientation, increasing to around 9 percentage points in the output-oriented model, while falling to less than 2 percentage points in the input-oriented model. These observations highlight the need to consider both forms of model orientation in order to avoid biasing the results based on the assumption made about hospitals' production behaviour.

Of course, when making these assessments about hospital performance within the bounds of the models' assumptions, it is acknowledged that a hospital's efficiency score is not only reflective of their own production decisions, but also the environment in which they are operating and any external limitations potentially placed on their capacity to expand production or reduce resources.

### **Comparisons by hospital size**

Levels of efficiency, as well as the relativities between types of hospital ownership, are found to vary by hospital size (table 5.4).



# Table 5.4 **Technical efficiency scores by hospital ownership and size**









**a** The small and very small size categories are aggregated for not-for-profit private hospitals due to ABS confidentiality restrictions. Therefore, the same aggregated figures are tabulated for these two categories. **np** Not available for publication due to ABS confidentiality restrictions.

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

In terms of output-oriented technical efficiency, across all size categories, for-profit hospitals (94.8 per cent) perform better than all other hospitals, while not-for-profit hospitals (85.6 per cent) have the greatest scope for improvement. However, the extent of these differences varies, to some degree, according to hospital size. For instance, the gap between for-profit private hospitals and public hospitals is 4.1 percentage points among large hospitals, but widens to 6.6 percentage points among very small hospitals.

Although the output-oriented efficiency scores are fairly stable across hospital sizes among the for-profit hospitals, the efficiency of smaller public hospitals is noticeably lower than that of larger public hospitals. One possible explanation is that smaller public hospitals are operating at lower levels of occupancy rates arising from the combination of the minimum sizes with which hospitals operate and the relatively low numbers of patients treated in more remote communities.

The output-oriented technical efficiency of medium not-for-profit private hospitals (77.9 per cent) is also noticeably lower than that of all hospitals (90.5 per cent).

Given that there are comparatively few observations in this sample, this result is likely to reflect an outlier observation.

In terms of input-oriented technical efficiency, not-for-profit hospitals are found to outperform both for-profit and public hospitals in the small and very small size categories, as well as public hospitals in the very large size category. While these differences cannot be deemed statistically significant, these comparisons suggest that it is at these sizes of operation that not-for-profit private hospitals can demonstrate their relatively greater input resourcefulness.

The degree of dispersion in efficiency scores — as measured by the 5th and 95th percentiles — also varies by hospital size. In particular, the efficiency scores of the smaller public and not-for-profit hospitals are more dispersed than those of larger hospitals. For example, the efficiency scores of very small public hospitals range from 71.5 to 97.3 per cent, while those of very large public hospitals range from 84.1 to 96.7 per cent. These differences may suggest that smaller public hospitals are more heterogeneous than larger hospitals.5 That is to say, it is less likely that any two public hospitals of very small size are alike, so their comparative performances are more likely to differ than those of two larger hospitals. This type of variation may have not been captured adequately in the model.

The Commission sought to test whether the observed patterns in efficiency scores were related to the extent to which a hospital can specialise in its services. For example, the finding that small for-profit hospitals are more efficient than small public hospitals may be due to the opportunity for smaller private hospitals to specialise in a narrower range of services. The Commission ran correlation tests between hospitals' efficiency scores and their degree of specialisation. (Specialisation was measured by the share of a hospital's total volume of admitted patient separations that was concentrated in the five most frequent types of services, as defined by major diagnostic categories). There were no consistent findings to support a trend between specialisation and efficiency, although it is possible that this result may reflect this measure of specialisation itself. Results are reported in appendix D.

### *Correlation between output-oriented and input-oriented efficiency scores*

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The Commission undertook correlation tests of output and input-oriented technical efficiency scores to examine whether or not hospitals that perform well in terms of maximising output also perform well in terms of economising on resource use

<sup>5</sup> Medium-sized not-for-profit hospitals also stand out for having highly dispersed efficiency scores, but this may be due to outlier effects, as noted earlier.

(table 5.5). A correlation value closer to positive one indicates a greater degree of similarity between a hospital's output- and input-oriented efficiency scores, while a value closer to negative one indicates greater divergence. Values closer to zero indicate that there is little similarity between a hospital's two efficiency scores.





**a** Small and very small size categories are aggregated for not-for-profit private hospitals due to ABS confidentiality requirements. **np** Not published due to ABS confidentiality restrictions. Number of observations corresponds to the preceding data reported in tables 5.3 and 5.4.

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

Across all sizes, private hospitals show a higher degree of correlation between their output and input-oriented efficiency scores compared to public hospitals and contracted hospitals. This suggests that private hospitals are more capable of both expanding output while also economising on inputs, compared to other hospital groups. There is, however, wide variation by hospital size. In particular, not-for-profit private hospitals show the greatest degree of correlation in the medium size category (0.868), yet also the weakest degree of correlation in the small and very small size category  $(0.126)$ .

The negative correlation value for very small private hospitals suggests that, on average, those small private hospitals which are generally better at maximising output are worse at economising on inputs (and vice versa). This link, however, is relatively weak and may be distorted by the pooling of the not-for-profit and for-profit categories.

With the exception of medium-sized not-for-profit private hospitals, no hospital group demonstrates a strong correlation score (very close to one). This suggests that hospitals which perform the best in terms of maximising output are generally unlikely to be the best at economising on inputs too (and vice versa). This lack of correlation highlights the need to independently consider both forms of model orientation when assessing hospital performance, as well as the limitations of relying on averaged scores.

# 6 A preliminary analysis of hospital costs

#### **Key points**

- Hospitals are commonly compared in terms of their costs, so measuring how well hospitals minimise their costs is attractive for policy.
- There are significant limitations to the quality and availability of financial data available for this analysis. These include a lack of:
	- consistent data on capital costs, particularly for public hospitals
	- medical costs of doctors exercising their rights of private practice in public and private hospitals
	- consistent data on staffed beds between public and private hospitals.
- On the basis of available data, Australian hospitals have the potential to reduce some operating expenditures by about 7 per cent in the short run, without any change to their external policy environment.
- For the various components of hospital costs included in this analysis, there was no significant difference in the cost efficiencies between public, public contract, for-profit private, and not-for-profit hospitals.
- The analysis and results illustrate the current limits to comparing hospital costs.
- More robust and consistent cost data would enable estimates of the factors that influence costs and cost efficiency to be produced in the future.

This chapter presents the results of the Commission's attempt to estimate the determinants of hospital costs of Australian hospitals. A summary of the Commission's approach is given in section 6.1. The factors that affect costs are summarised in section 6.2. The efficiency scores derived from this estimation are presented in section 6.3. The scope for future improvement in measuring the determinants of costs is given in section 6.4.

# **6.1 Summary of the Commission's approach**

The Commission used stochastic frontier analysis (SFA) to estimate the determinants of hospital costs in Australia. A brief introduction to SFA is given in chapter 2, and a more detailed discussion is in appendix C.

The cost variable used for this analysis is operating expenditure (excluding interest payments, depreciation and medical practitioner costs). The variables used to explain cost include:

- hospital outputs
- quality of outputs
- input prices
- patient-risk characteristics
- hospital characteristics.

The rationale for the inclusion of these variables is described in chapter 2 and appendix C. A description of the available data, summary statistics, and expected signs of the coefficients is given in chapter 3.

As detailed in chapters 2 and 3, the estimated cost models are based on the following specifications:

- translog function form
- weighted dataset to represent the true population
- an exponential distribution for the efficiency term
- all four years of data are pooled into a single cross section.

### **Data limitations**

Unfortunately there were a number of major data issues that significantly limit the usefulness of the analysis and any results. These are summarised in chapter 3, and include the following:

• A lack of capital costs — there are no consistent data available on capital costs, such as interest and depreciation for land, buildings and equipment, particularly for public hospitals. Capital costs were consequently not included in the dependent variable nor was a price of capital calculated. This is a problem experienced in other similar studies involving Australian hospitals (Wang, Zhao and Mahmood 2006; Yong and Harris 1999).

- A lack of medical costs medical costs are not collected for doctors exercising their rights of private practice in public and private hospitals. Medical costs were accordingly excluded from the dependent variable data. The lack of medical costs also precluded the calculation of an average wage and salary for medical staff.
- Collinear price indexes the prices of hospital pharmaceutical supplies, medical and surgical supplies, and other hospital supplies were only available at a national level in the form of price deflators. These proved to be highly collinear and were subsequently excluded from the analysis.

Apart from under-reporting the dependent variable, the absence of capital costs also meant that it was not possible to calculate an average cost per unit of capital — that is, a price of capital.

The effect of excluding medical costs and staff and practitioners from the study implies that hospitals do not substitute between other hospital inputs and their medical workforce.

To account for the lack of capital data, the number of staffed beds in a hospital was included as a proxy for hospital capital. Apart from concerns regarding the suitability of beds as a measure of capital (chapter 3), including a variable for capital is akin to assuming that capital is fixed and that the estimated cost function is a short-run function. While using a short-run cost function circumvents the problem of a lack of capital price data, the estimated results necessarily mean that they are only relevant for the short run.

# **6.2 Estimation results**

The coefficients of explanatory variables indicate how that variable influences the data-constrained measure of operating expenditure.

For each of the first-order input price and output variables, a positive coefficient indicates that costs increase with an increase in that variable. Conversely, a negative coefficient suggests that costs decrease with an increase in that variable. The expected signs for each of the explanatory variables is explained in chapter 3.

For each of the variables that are squared, the coefficient describes the rate at which a variable increases or decreases costs. For example, if the coefficient of a first-order variable has a positive sign and its squared term is negative, it suggests that the variable increases costs at a decreasing rate. In the case of the second-order output variables, if the coefficient is positive it suggests the presence of diseconomies of scale, and a negative coefficient suggests the presence of economies of scale.

#### *Ownership variables*

The ownership variables are not included in the frontier equation, but are regressed against the inefficiency error term (appendix C). The coefficients of the various binary variables in the inefficiency equation identify which hospitals are further away from their respective benchmarking frontier. While, the coefficients of these binary variables are not reported due to commercial-in-confidence concerns, their sign and statistical significance are reported. Specifically, a positively-signed coefficient indicates that a hospital characterised by that variable is further away from its frontier. That is, the hospital is further from its minimum level of cost for its current output level. This distance represents the extent of their inefficiency. The associated significance level of the coefficients verifies whether any differences in efficiency scores between hospitals are significant or not.

### **Coefficient results**

Table 6.1 presents the results for the preferred model using the translog function with operating expenditure as the dependent variable.

There are significantly fewer significant variables explaining operating expenditure, than there were variables explaining hospital output (chapter 5). The most likely reason for this is the poor quality of data. As noted, there are concerns over the measurement of costs, especially the prices of non-labour hospital inputs.

Cost per allied and diagnostic staff is significant in both its original and squared form. The coefficient on the original variable suggests a significant negative relationship between the cost per allied and diagnostic staff and hospitals costs and is the opposite to the expected sign of the coefficient. This result could possibly suggest that there are issues with the quality of the labour expenditure data. It presents a further reason to be careful with the interpretation of the efficiency results.



# Table 6.1 **Results of short-run cost function, 2003-04 to 2006-07a**





(Continued next page)

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**a** Data for 2003-04 to 2006-07, weighted by sample representation. All output and input variables are logged, mean-centred and normalised. Dummy variables for zero values included in regression but not reported. **b** Base categories are: share of patients aged 20-59 years; share of patients from SEIFA 5 (least disadvantaged); share of patients with Charlson score 1 or below (fewest comorbidities). **c** Base category is: located in inner regional area. **d** Base jurisdiction is Queensland. **e** Base year is 2003-04. Significance levels denoted as: \* 10%; \*\* 5%; \*\*\* 1%. Standard errors are robust. Due to confidentiality restrictions, coefficient terms for ln  $\sigma^2_{~\nu}$  and ln  $\sigma^2_{~u}$  were suppressed by the ABS, because these values would enable the calculation of efficiency scores for individual hospitals or hospital groups. The ABS also deemed it necessary to suppress the coefficient terms of the ownership dummy variables. **seps**: number of separations. **sv**: number of occasions of service. **np** Not available for publication due to ABS confidentiality concerns.

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

The total number of staffed beds, as expected, has a significantly positive relationship with a hospital's costs.

The number of acute casemix-adjusted separations and emergency department visits had a significant positive relationship with hospital costs for both the first-order and squared variables. The number of mental and alcohol separations, other separations, allied and dental services and outreach and district nursing services, all had a significant positive relationship with costs for the squared variable.

The first-order HSMR variable has a significant negative relationship with total costs, while the squared HSMR variable has a significant positive relationship with costs, suggesting that costs are eventually influenced by poor quality output. Increasing a hospital's HSMR (that is, worsening hospital quality) will on average lead to an increase in the marginal cost of producing acute, pregnant and neonate separations and diagnostic services. In contrast, decreasing a hospital's HSMR will on average lead to a decrease in the marginal cost of MDC 1 separations, emergency department visits and outreach and district nursing services.

The coefficient results show that hospital costs are *higher* if they:

- are located in a major city or remote or very remote area (compared to an inner regional hospital)
- have university-affiliated teaching status
- have a level III intensive care unit
- treat relatively more complex cases as measured by the Evans and Walker 2 index.

The coefficient results, drawing upon the constrained data noted earlier, suggests that the socioeconomic profile of a hospital's patients do not have a significant relationship with the hospital's costs.

There seems to be a significant positive relationship between the percentage of patients between 60 and 69 years old (compared to the percentage of patients between 20 and 59 years old) with hospital costs.

The results also suggest that there is a significant positive relationship between the percentage of patients with a Charlson score of 4 and 6 and above (compared to the percentage of patients with a Charlson score of 1) with hospital costs. Interestingly there is a significant negative relationship between the percentage of patients with a Charlson score of 5 (compared to the percentage of patients with a Charlson score of 1) and hospital costs.

The coefficient results imply that there is a significant negative relationship between having a palliative care unit and hospital costs.

Note that state and territory binary variables are used to control for jurisdiction-specific factors (such as differences in data reporting methods or regulatory settings) and should not be interpreted as an indicator of relative efficiency between the jurisdictions. Similarly, the year dummy variables are included to control for time-specific variations in the data that cannot be captured by the observed variables, and should not be interpreted as a time-dependent trend in hospital efficiency.

## **6.3 Preliminary cost efficiency scores**

The efficiency score measures the distance of a hospital's current cost point from its respective benchmarking frontier (chapter 2). Under the specific assumptions of this model, and recognising the limits of the data, efficiency scores measure the extent to which a hospital could reduce its costs while still producing the same level of output. Specifically, a hospital with an efficiency score of 90 per cent could lower its short-run costs by 10 per cent to the best-practice amount while producing the same amount of output. This can also be interpreted to mean that this hospital is operating at about 11 per cent (or 100 divided by 90 per cent) above the minimum possible cost it could produce the same amount of output in the short run.

The preliminary efficiency scores suggest that on the basis of available data and its limitations, Australian hospitals are on average approximately 93 per cent cost efficient for those factors within scope of the analysis in the short run (table 6.2). This would imply that a hospital could on average reduce its costs by approximately 7 per cent in the short run while still producing the same level of output.

The available data seem to suggest that private hospitals are at their most efficient when they are small (94.4 per cent) or very small (94.2 per cent) compared to large (92.7 per cent) or medium (93.1 per cent) in size. Differences in the efficiency scores of public hospitals are less marked.

The second stage regression (inefficiency equation) suggests that on the basis of the available data, there is no significant difference between the short-run efficiency of different hospital types (public, for-profit, not-for-profit and public contract).

These scores compare favourably with other Australian studies using SFA to analyse hospital costs, though these studies use slightly different methods. Wang, Zhao and Mahmood (2006) found the mean cost inefficiency of NSW public hospitals in 1997-98 to be approximately 10 per cent, while Yong and Harris (1999) found the mean cost inefficiency of large Victorian public hospitals in 1994-95 to be approximately 3 per cent. Wang, Zhao and Mahmood include total beds in their analysis, however they use a cost function with more aggregated output groupings. Yong and Harris include total beds in a second stage equation as a proxy for size rather than in the primary regression as a proxy for capital, instead assuming that variation in the cost of capital is unlikely to explain differences in recurrent expenditure between hospitals.





**a** Small and very small size categories are aggregated for not-for-profit private hospitals due to ABS confidentiality requirements. **np** Not available for publication due to ABS confidentiality restrictions.

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

### **6.4 Scope to improve future efficiency measurement**

As previously mentioned, there are a number of data items that are not reported or reported inconsistently which in turn limit the usefulness of the hospital cost analysis in this chapter. An improvement in the quality of such data would lead to a more robust measurement of cost efficiency.

Some of the data improvements necessary to improve technical efficiency are also relevant for the cost analysis (chapter 5). These include consistent reporting of total number of beds by public and private hospitals and a more detailed reporting of hospital facilities. Data improvements especially relevant to measuring the determinants of hospital costs include the reporting of capital costs, medical costs and pharmaceutical prices.

Capital costs include depreciation costs and the user cost of capital. The Commission has previously noted (PC 2009) that depreciation costs, interest payments (a component of the user cost of capital) and asset values (required for the calculation of the user cost of capital) are not currently reported consistently between jurisdictions or between public and private hospitals. An improvement in this area of reporting would remove the need to use total beds to estimate a short-run cost function. Depreciation and interest expenses could also be reported as a ratio per bed, to approximate the price of capital (Rosko and Proenca 2005).

There were no data on medical costs of doctors exercising their rights of private practice in public hospitals (in the National Public Hospital Establishment Database) and in private hospitals (in the Private Hospital Establishment Collection). The Commission chose to therefore exclude medical costs from the analysis. Medical charge data are available from the Hospital Casemix Protocol (HCP) collected by the Department of Health. Given difficulties faced in accessing other aspects of hospital data, the Commission chose not to access these data in the time available for this study. If these data were obtained, it would still be difficult to calculate a comparable price of medical labour for public and private hospitals, given the nature of the HCP data.

# A Workshop participants

The Commission discussed its preliminary method and findings with a number of interested parties at a teleconference workshop on 12 March 2010, and through subsequent correspondence. The interested parties are presented in the following table (table A.1).

Person	Position and organisation	
Wayne Adams	Chief Information Officer, Australian Health Insurance Association	
Katrina Ball	Director Policy Analysis, SA Dept of Treasury and Finance	
<b>Paul Geeves</b>	Principal Consultant, Government Relations, Tasmanian Department of <b>Health and Human Services</b>	
Dr Brian Hanning	Medical Director, Australian Health Service Alliance	
Elizabeth Hay	Policy Manager, NSW Health	
Mark Johnson	Acting Manager Information, Tasmanian Department of Health and Human <b>Services</b>	
<b>Kylie Keats</b>	<b>Catholic Negotiating Alliance</b>	
<b>Paul McGuire</b>	Senior Director, Queensland Health	
Kevin Ratcliffe	Principal Consultant, Tasmanian Department of Health and Human Services	
<b>Christine Stone</b>	Manager, Department of Health, Victoria	
Dr Peter Thomas	Policy Manager, Australian Private Hospitals Association	
<b>Patrick Tobin</b>	Director Policy, Catholic Health Australia	

Table A.1 **Interested parties consulted by the Commission** 

# B Literature review

### **B.1 Previous multivariate studies of hospital efficiency**

A summary of the methods and data used in previous overseas and Australian multivariate studies of hospital efficiency is given in table B.1. The table is organised according to the type of function (cost or production) and modelling techniques used (data envelopment analysis (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 B.1 **Selected literature review — benchmarking studies**







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#### *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 No. acute inpatient seps, hospitals in 1995-96. non- and sub-acute beddays, occasions of service, 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-forprofit 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 casemixadjusted 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 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 None. None.

metre floor space.

#### Table B.1 (continued)

1995-96.



### **B.2 Previous studies on the relationship between hospital efficiency and quality**

### Table B.2 **Selected literature review — hospital volume and mortality**









### Table B.4 **Other relevant studies — hospital volume and mortality**







# C Theoretical framework

The mathematical formulation of the Commission's approach is outlined in this appendix.

### **C.1 Modelling hospital mortality with negative binomial regressions**

Modelling in-hospital mortality using hospital-level data requires a statistical model that takes into account the fact that the number of in-hospital mortalities is a non-negative integer.

The Poisson model is the simplest count model, and describes the number of occurrences of an event, *mi* (such as the number of mortalities occurring in hospital *i*) as:

$$
m_i = \frac{e^{-\lambda} \lambda^{m_i}}{m_i!}
$$
 (1)

where the mean and variance of *m* are both equal to  $\lambda$ , where:

$$
\lambda = e^{x_i \beta} \tag{2}
$$

where **x**i is a vector of explanatory variables of hospital *i*.

This model, however, holds only if the mean and variance are equal. This is not the case with hospital mortality data, which include a large number of hospitals with relatively few deaths and a smaller number of large and very large hospitals with comparatively more deaths. This is a case of over-dispersion, where the variance is significantly greater than the mean.

If the variance of the dependent variable is greater than the mean,  $\lambda$  can be specified as:

$$
\lambda = e^{\mathbf{x}_i \boldsymbol{\beta} + \varepsilon_i} \tag{3}
$$

where error term  $\varepsilon_i$  has a gamma distribution. This in turn leads to a negative binomial distribution for the number of deaths with mean  $\lambda$  and variance:

$$
\sigma^2 = \lambda + \alpha \lambda^2 \tag{4}
$$

where  $\alpha$  represents the level of over-dispersion.

The test of whether a Poisson or negative binomial model would be appropriate would depend upon the statistical significance of  $\alpha$ . If  $\alpha$  is significant, as it is in this study, the negative binomial would be the appropriate model. Otherwise, the Poisson model would be appropriate (Cameron and Trivedi 2005; Winkleman and Boes 2006).

Under such a model, it is assumed that:

- there is a mortality rate the rate at which deaths occur
- the mortality rate can be multiplied by an 'exposure' to determine the expected number of deaths. In this case, the exposure is the number of casemix-adjusted separations
- over very small exposures, the probability of observing more than one death is small compared to the size of the exposure (Cameron and Trivedi 2005; Kennedy 2003; Winkleman and Boes 2006).

### **C.2 Approximating confidence intervals for hospital-standardised mortality ratios**

In presenting hospital-standardised mortality ratios (HSMRs) for individual hospitals, as in the 'caterpillar' plots in chapter 4, it is important to acknowledge the uncertainty that is inherent in estimated values. As noted by Ben-Tovim, Woodman, Harrison et al. (2009), the conventional method of incorporating a measure of uncertainty is by calculating the confidence intervals around each HSMR. This is usually done using 95 percent confidence limits (Ben-Tovim, Woodman, Harrison et al. 2009; CIHI 2007; Lakhani, Olearnik and Eayres 2005). It is expected that the HSMR will be within this range 95 per cent of the time on repeat testing of a population. The size of the confidence interval indicates the precision of the HSMR.

The confidence intervals shown in the caterpillar plots are calculated in the same manner as CIHI (2007) and Ben-Tovim, Woodman, Harrison et al. (2009), using what is referred to as Byar's approximation. Given that:

$$
HSMR_i = \frac{deaths_i}{E(deaths_i \mid \mathbf{X}_i)} \times 100
$$
\n<sup>(5)</sup>

where **X***i* represents a vector of patient and hospital characteristics, the lower confidence limit for hospital *i* is given by the equation:

$$
HSMR_{iLL} = \frac{deaths_i}{E(deaths_i \mid \mathbf{X}_i)} \times \left(1 - \frac{1}{9(deaths_i)} - \frac{1.96}{3\sqrt{deaths_i}}\right)^3 \times 100
$$
 (6)

Similarly, the upper confidence limit is given by:

$$
HSMR_{iUL} = \frac{(deaths_i + 1)}{E(deaths_i | \mathbf{X}_i)} \times \left(1 - \frac{1}{9(deaths_i + 1)} - \frac{1.96}{3\sqrt{(deaths_i + 1)}}\right)^3 \times 100 \tag{7}
$$

This is explained in more detail in the Compendium of Clinical and Health Indicators user Guide (Lakhani, Olearnik and Eayres 2005).

### **C.3 Estimating hospital efficiency**

#### **Estimating distance functions**

The distance function is the stochastic frontier analysis analogue of multi-output multi-input production. The function can be specified as an:

- output distance function which measures the maximum amount by which outputs can be expanded and still be producible with the given set of inputs
- input distance function which measures the maximum amount by which inputs can be reduced and still remain feasible for the outputs they produce (Kumbhakar and Lovell 2000).

The output distance function is more appropriate for hospitals that can influence their level of outputs, such as private hospitals. The input distance function is more appropriate for measuring the technical efficiency for hospitals that find it difficult to reduce their output but which are able to alter their use of inputs, such as public hospitals. These two approaches also allow the relationship between hospital quality and changes to input use and hospital outputs to be explored.

#### *Output distance function*

For the output distance function, the production technology of the hospital is defined with the output set  $P(x)$  which represents the set of all output vectors *y*∈  $R_+^M$  that can be produced using the input vector  $x \in R_+^K$ . An output distance function is defined by how much the output vector can be proportionally expanded by amount  $\theta$  with the input vector held fixed (Coelli and Perelman 1999; Lovell et al. 1994). The output distance function may be defined on the output set as:

$$
D_{\phi}(\mathbf{x}, \mathbf{y}) = \min \{ \theta : (\mathbf{y}/\theta) \in P(\mathbf{x}) \}
$$
 (8)

The output distance function will take a value of one or less if the output vector **y** is an element of the feasible output set. If **y** is on the outer boundary of the input set, the distance function will take a value of one.

The translog output distance function for hospital *i* is given as:

$$
\ln D_{oi} = TL(\mathbf{x}_i, \mathbf{y}_i, q_i, \mathbf{z}_i; \mathbf{\beta})
$$
\n(9)

The homogeneity constraints are that outputs are homogenous to degree one in outputs, given by (Coelli et al. 2005; PC 2009). These constraints can be met by normalising equation (9) by the K*th* output:

$$
\ln\left(\frac{D_{oi}}{y_{ik}}\right) = TL(\mathbf{x}_i, \mathbf{y}_i^*, q_i, \mathbf{z}_i; \boldsymbol{\beta})
$$
\n(10)

where  $y^*$  is the vector of normalised outputs. Equation (10) can be re-arranged with a random error term to give a variable returns to scale output distance function:

$$
-\ln y_{ik} = TL(\mathbf{x}_i, \mathbf{y}_i^*, \mathbf{z}_i; \boldsymbol{\beta}) - \ln D_{0i} + v_i
$$
\n(11)

where *TL*(.) refers to the transcendental logarithmic (translog) function. In the output distance function, hospital quality  $q_i$  is interacted with the  $y_i$  vector to test whether there are economies of scope between hospital activity and mortality rates. Again, the dependent variable is multiplied by  $-1$  to ensure that the coefficients on the right-hand side reverse their signs.

#### *Input distance function*

The production technology of the hospital is defined with the input set  $L(\mathbf{v})$  which represents the set of all input vectors  $x \in R_+^K$  that can produce the output vectors

 $y \in R_+^M$ . An input distance function is defined by how much the input vector can be proportionally contracted by amount  $\rho$  with the output vector held fixed (Coelli and Perelman 1999; Lovell et al. 1994). The input distance function may be defined on the input set as:

$$
D_{I}(\mathbf{x}, \mathbf{y}) = \max \{ \rho : (\mathbf{x} / \rho) \in L(\mathbf{y}) \}
$$
(12)

The input distance function will take a value of one or more if the input vector **x** is an element of the feasible input set. If **x** is on the inner boundary of the input set, the input distance function will take a value of one.

The translog of the input distance function is given as:

$$
\ln D_{I_i} = TL(\mathbf{y}_i, \mathbf{x}_i, q_i, \mathbf{z}_i; \boldsymbol{\beta})
$$
\n(13)

The input distance function must be homogeneous of degree one in inputs (Coelli and Perelman 1999). These conditions can be met by normalising the inputs by the M*th* input:

$$
\ln\left(\frac{D_{li}}{x_{iM}}\right) = TL(\mathbf{y}_i, \mathbf{x}_i^*, q_i, \mathbf{z}_i; \boldsymbol{\beta})
$$
\n(14)

where **x\*** is the vector of normalised inputs. Rearranging the left-hand side variables and adding a random error term  $v_i$ , we obtain the equation to estimate variable returns to scale:

$$
-\ln x_{iM} = TL(\mathbf{y}_i, \mathbf{x}_i^*, q_i, \mathbf{z}_i; \boldsymbol{\beta}) - \ln D_{I_i} + v_i
$$
\n(15)

where  $D_{ij}$  is equal to the input-oriented distance and technical efficiency. In the translog functional form, the hospital quality  $q_i$  is interacted with vector  $\mathbf{x}_i$ , to test the extent to which there are economies of scope between input use and (standardised) mortality rates. In chapter 5, the input-oriented technical efficiency is inverted (divided into 1) for ease of interpretation.

### **Estimating cost functions**

The estimation of hospital cost efficiency begins with a model of hospital costs which takes the general form of:

$$
c_i = f(\mathbf{w}, \mathbf{y}_i, q_i, \mathbf{z}_i) \exp(v_i - ce_i)
$$
 (16)

**135**

where hospital *i*'s total cost  $c_i$  is a function of **w** (the vector of input prices),  $y_i$  (the vector of outputs),  $q_i$  (the hospital-standardised mortality ratio),  $z_i$  (a vector of factors outside the control of hospitals),  $ce_i$  (the measure of cost efficiency) and  $v_i$ (the random error term).

The translog variable returns to scale equation takes the form:

$$
\ln c_i = \alpha_0 + \sum_{m=1}^{M} \alpha_m \ln w_m + \sum_{k=1}^{K} \beta_k \ln y_{ki} \n+ 0.5 \sum_{m=1}^{M} \sum_{n=1}^{M} \alpha_{mn} \ln w_m \ln w_n + 0.5 \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln y_{ki} \ln y_{li} \n+ \sum_{k=1}^{K} \sum_{m=1}^{M} \gamma_{km} \ln w_m \ln y_{ki} + \delta q_i + \sum_{k=1}^{K} \varepsilon_k q_i \ln y_{ki} \n+ \sum_{p=1}^{P} \zeta_p z_{pi} - ce_i + v_i
$$
\n(17)

for *M* number of inputs, and *K* number of outputs. Equation (17) is not a fully specified translog function. This equation is a restricted translog function, since quality variables are assumed to interact with outputs only. Since the vector **z** represents control variables, these are assumed not to interact with other variables.

As the cost frontier needs to be linearly homogenous in input prices, *ci* and input prices  $w_1, \ldots, w_{M-1}$  are normalised by the input price of the Mth factor  $w_M$ , so that:

$$
\ln\left(\frac{c_i}{w_M}\right) = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln\left(\frac{w_m}{w_M}\right) + \sum_{k=1}^{K} \beta_k \ln y_k
$$
  
+0.5
$$
\sum_{m=1}^{M-1} \sum_{n=1}^{M-1} \alpha_{mn} \ln\left(\frac{w_m}{w_M}\right) \ln\left(\frac{w_n}{w_M}\right) + 0.5 \sum_{k=1}^{K} \sum_{l=1}^{K} \beta_{kl} \ln y_k \ln y_l
$$
  
+
$$
\sum_{k=1}^{K} \sum_{m=1}^{M-1} \delta_{km} \ln y_{ki} \ln\left(\frac{w_m}{w_M}\right) + \delta q_i + \sum_{k=1}^{K} \varepsilon_k q_i \ln y_{ki}
$$
  
+
$$
\sum_{p=1}^{P} \zeta_p z_{pi} - ce_i + v_i
$$
 (18)

It is worth noting that **w** is assumed not to vary across individual hospitals, but reflects the market price of inputs faced by each private and public hospital sector in each jurisdiction. A more compact notation for the translog is:

$$
\ln\left(\frac{c_i}{w_M}\right) = TL(\mathbf{w}^*, \mathbf{y}_i, q_i, \mathbf{z}_i; \boldsymbol{\beta}) - ce_i + v_i
$$
\n(19)

where *TL*(*.*) indicates that the function has a translog form and **w**\* indicates that the input price variables are normalised.

A challenge for measuring public costs is the absence of reliable estimates of capital costs. Public hospital accounting systems rarely account for depreciation and the opportunity cost of capital given the historical pattern of hospital funding. In the absence of adequate capital costs and capital prices, a short-run cost function is used, which is given as:

$$
\ln\left(\frac{c_i}{w_M}\right) = TL(\mathbf{w}^*, \mathbf{y}_i, q_i, k_i, \mathbf{z}_i; \boldsymbol{\beta}) - ce_i + v_i
$$
\n(20)

where  $k_i$  is the number of hospital beds and is a proxy for the capital stock in the hospital. In chapter 6, the cost efficiency is inverted (divided into 1) to assist comparisons with the technical efficiency scores.

### **Testing for statistical differences between hospitals**

Whereas the distance and cost functions describe the determinants of what constitutes hospital best practice, many authors have long sought to identify the factors that could possibly explain their reported efficiency. In the case of this study, this includes identifying if there is a statistical difference between different hospital ownership groups.

There are two commonly used ways in which additional variables have been be used to explain variations in efficiency. One approach is to regress the explanatory variables on the efficiency scores themselves. This is possible with stochastic frontier analysis of the Aigner–Lovell–Schmidt type because unlike traditional ordinary least squares, the residuals are not orthogonal to the regressors. This approach can be presented as:

$$
u_i = f(\mathbf{Z}_i) + \varepsilon_i \tag{21}
$$

This approach is frequently used in techniques such as data envelopment analysis, where the data envelopment analysis (DEA) scores (*ui*) are regressed on a number of other variables (*zi*) to derive *conditional* DEA scores.

A problem with this two-stage approach is a lack of consistency in the assumptions about the distribution of the efficiency scores. In the first stage, the scores were assumed to be independently and identically distributed in order to estimate their values. However, in the second stage they were assumed to be a function of a number of firm-specific factors and are therefore not identically distributed (Coelli et. al 2005).

In the case of stochastic frontier analysis, it is possible to estimate all of the parameters, including those that might affect the inefficiency score and the random error term, in the same likelihood function.

For a simple production function, the combined regression would be:

$$
\ln y_i = \beta_0 + \sum_{m=1}^{M} \beta_{mi} x_{mi} - u_i + v_i
$$
 (22)

$$
\mu_i^u = \delta_0 + \sum_{j=1}^J \delta_{ji} z_{ji} + \xi_i
$$
 (23)

where  $\mu_i^u$  are the conditional means of *u* for hospital *i*, *j* is the covariate subscript for hospital *i*, and  $\xi$  is the independently and identically distributed error.

### **Other issues**

As is common practice, all terms are specified in natural logarithms, except shares and binary variables, so that the measures represent proportional values rather than absolute levels. All variables to be logged that have a natural value of zero are assigned a value of zero in the transformed dataset. Battese's (1996) method is used to correct for the bias this approach introduces. All logarithmic variables are mean corrected.

The first line of equation (18), which comprises 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 (Nguyen and Coelli 2009; Siciliani 2006).

### *Reporting efficiencies*

The preceding equations produce a variety of ways to view and measure hospital efficiency. The following table (table C.1) summarises some of the more important efficiency dimensions used in this study and in which chapters they are reported.

Description	Summary of equation	Chapter reported in
Output-oriented technical efficiency	$D_{\alpha i}$ from equation (11)	5
Input-oriented technical efficiency	$D_{\scriptscriptstyle{li}}$ from equation (15)	5
Average technical efficiency	$(D_{ii} + D_{0i})/2$	5
Cost efficiency	$ce_i$ from equation (19)	6

Table C.1 **Summary of efficiency scores used in this study** 

#### *Interpreting the distance function coefficients*

How are the coefficients of the estimable equations (13) and (15) to be interpreted? These are used to determine the parameters of the distance functions described in equations (9) and (13).

Following Perelman and Santin (2005), the elasticities of outputs and inputs with respect to distance (*D*) are given as:

$$
r_{D,x_k} = \frac{\partial D}{\partial x_k} = \frac{\partial \ln D(x, y)}{\partial \ln x_k} \frac{D(x, y)}{x_k}
$$
 (24)

$$
r_{D,y_m} = \frac{\partial D}{\partial y_m} = \frac{\partial \ln D(x, y)}{\partial \ln y_m} \frac{D(x, y)}{y_m}
$$
(25)

A positive coefficient in the output distance function is associated with an increase in efficiency (distance), and a negative value is associated with a decrease in efficiency. In this study, since the dependent variable  $y_m$  has been pre-multiplied by –1, the interpretation of the coefficients is reversed.

At the same time, a positive coefficient in the input distance function is associated with a decrease in efficiency and a negative value is associated with an increase in efficiency. Again, since the dependent variable  $x_k$  has been pre-multiplied by  $-1$ , the interpretation of the coefficients is reversed.

The effect of a small change of an input on an output can be assessed in terms of the partial derivatives:

$$
s_{y_m, x_k} = \frac{\partial y_m}{\partial x_k} = \frac{r_{D, x_k}}{r_{D, y_m}}
$$
(26)

The effect of a small change of an output on another output (through the marginal rate of transformation of outputs) is given by:

$$
s_{y_m, y_n} = \frac{\partial y_n}{\partial y_m} = -\frac{r_{D, y_m}}{r_{D, y_n}}
$$
(27)

And the effect of a small change of an input on another output (through the marginal rate of substitution) is given by:

$$
s_{x_k, x_j} = \frac{\partial x_k}{\partial x_j} = -\frac{r_{D, x_j}}{r_{D, x_k}}
$$
(28)

### **C.4 Evans and Walker indexes**

The Evans and Walker information indexes 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 indexes. 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:

$$
X_i^1 = \sum_j \overline{H}_j^1 p_{ij} \tag{29}
$$

which is a weighted average of the standardised complexity indexes  $\overline{H}_{j}^{1}$  of each Australian refined diagnostic-related group (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  $\overline{H}^1$ , the index of complexity for the *jth* AR-DRG is used:

$$
H_j^i = \sum_i q_{ij} \ln\left(\frac{I}{q_{ij}}\right) \tag{30}
$$

Equation (30) describes the information gain arising from the probability of the j*th* AR-DRG being treated by the i*th* hospital. Since *I* is the number of hospitals, the lower the probability  $q_{ij}$ , the larger will be their combined natural logarithm, and the information gain. Pre-multiplying gives the probability of that information gain occurring.

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

$$
\bar{H}_{j}^{1} = \frac{H_{j}^{1}}{\sum_{j} H_{j}^{1} q_{j}}
$$
\n(31)

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). Rather than being a total measure of complexity as in the first index, the second measure is divided by the expected complexity faced by a hospital .

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  $\overline{H}_{i}^{2}$ :

$$
X_i^2 = \sum_j \overline{H}_j^2 p_{ij} \tag{32}
$$

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 *ith* hospital:

$$
H_j^2 = \sum_i q_{ij} \ln\left(\frac{q_{ij}}{p_i}\right) \tag{33}
$$

As with the first index, equation (33) is standardised to ensure that the index has a mean of one:

$$
\bar{H}_{j}^{2} = \frac{H_{j}^{2}}{\sum_{j} H_{j}^{2} q_{j}}
$$
 (34)

### **C.5 Hospital beds**

Differences in the definitions used by public and private hospital sectors on the reported number of beds have the potential to distort the measured relative efficiencies of public and private hospitals. Public hospitals report the number of beds that are staffed (AIHW 2009), whereas private hospitals are asked to report the number of beds that are available (ABS 2008a). Since the number of beds that are physically available is at least as great and usually more than the number of beds that are staffed at any point, on the basis of publicly available data, there is likely to be inconsistent reporting of public and private hospital beds.

There do not appear to be any data at the national level on the number of physically available beds in public hospitals or the number of staffed beds in private hospitals. Instead, the Commission sought to estimate the number of private hospital beds that are staffed, to develop a measure consistent with the method of counting public hospital beds

Following Anson-Dwamena and Studer (2009), the average number of patients on any given day in a private hospital is given by:

$$
Patients per day = \frac{Patient days}{365}
$$
 (35)

Since each patient requires a bed, equation (35) gives the average number of beds the hospital needs staffed per day. However, since the demand for beds varies day-to-day, hospitals need additional beds to be staffed.

Assuming that the variation in the demand for beds follows a normal or Poisson distribution, the standard deviation is given as:

$$
SD = \sqrt{\frac{Pattern \; days}{365}}\tag{36}
$$

If the hospital administrators wish to ensure that beds are available 95 per cent of the time in a hospital, then the additional number of beds required will be 1.96 times the standard deviation of beds, so that in total:

No. of staffed beds = 
$$
\frac{Patient \; days}{365} + 1.96 \sqrt{\frac{Patient \; days}{365}}
$$
 (37)

This rather simplistic approach does not take into account the effect of sameday separations and the different mix of beds in hospitals (ICU, acute, sub-acute and non-acute, for example). It does, however, reasonably predict the number of staff beds in public hospitals (table C.2).



### Table C.2 **Estimated number of staffed beds in public and private hospitals**

**..** Not available. **na** Not applicable.

*Source*: Productivity Commission calculations based on AIHW and ABS data.

It is not clear to the Commission how public contract hospitals report the number of beds, as to whether these are ounts of the staffed or physically available beds. The Commission has assumed that, across the group of public contract hospitals as a whole, they are reporting physically available beds because they are privately owned or managed.

It is apparent that the predicted number of staffed beds in public hospitals is close to the reported number of staffed beds (table C.2). To ensure comparability in the measure of beds between the three groups of hospitals, the Commission used estimates of the number of staffed beds for private and public contract hospitals. On average, the number of physically available beds is between 4 and 5 per cent greater than the predicted number of staffed beds for private hospitals, and between 3 and 4 per cent greater for public contract hospitals.

# D Additional results

### **D.1 Hospital mortality — negative binomial results**

The negative binomial model presented in chapter 4 was also run with the inclusion of hospital ownership variables so as to assess whether hospital ownership has a statistically significant effect on expected mortality rates. Incidence rate ratios from this model specification are presented below in table D.1.

Given the wide variation in mortality observed in very small, small and medium-sized hospitals, the negative binomial regression was also conducted with a sample restricted to large and very large hospitals. Incidence rate ratios for both model specifications are also included in table D.1.



#### Table D.1 **Alternative hospital mortality modelsa**

Incidence rate ratios




**a** Standard errors in parentheses.

*Source*: Productivity Commission estimates.

# **D.2 Technical efficiency — modelling sensitivity tests**

In stochastic frontier analysis, the distribution of the error term can be specified as half normal, truncated normal or exponential. The choice of distribution does not affect the ranking of individual hospitals by efficiency score, although it can affect the magnitude of the efficiency scores themselves. The Commission's analysis (presented in chapters 5 and 6) applied a half normal distribution because it reflected the actual dispersion of the data more precisely than the alternative options. The exponential distribution was found to have the effect of unduly dispersing the efficiency scores too widely, while the truncated normal distribution could not produce a model that solved.

For comparison, the results of the output oriented and input oriented distance functions with the exponential error term are reported in tables D.2 and D.3 respectively. Correlation and rank tests were conducted to verify that the stability of the ordinal ranking of hospitals remained stable between the two different models.



### Table D.2 **Coefficient estimates — output-oriented distance function with normal–exponential error terma**

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ADDITIONAL RESULTS



**a** Data for 2003-04 to 2006-07, weighted by sample representation. Output and input variables are logged, mean-centred and normalised. Dummy variables for zero values included in regression but not reported. The<br>model applies an exponential distribution to the efficiency term. <sup>b</sup> Base categories are: share of patients aged 20-59 years; share of patients from SEIFA 5 (least disadvantaged); share of patients with Charlson score 1 or<br>below (fewest comorbidities). <sup>C</sup> Base category is inner regional area. <sup>d</sup> Base jurisdiction is Qu **e** Base year is 2003-04.  $f$  Due to their confidentiality restrictions, the coefficient terms for In  $\sigma^2{}_{\nu}$  and In  $\sigma^2{}_{u}$  were suppressed by the ABS, because these values would enable the calculation of efficiency scores for individual hospitals or hospital groups. The ABS also deemed it necessary to suppress the coefficient terms of the ownership dummy variables. Significance levels denoted as: \* 10%; \*\* 5%; \*\*\* 1%. Standard errors are robust due to the sample weighting. **seps**: number of separations. **sv**: number of occasions of service. **np** not available for publication due to ABS confidentiality concerns.

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



### Table D.3 **Coefficient estimates — input-oriented distance function with normal–exponential error terma**





(Continued next page)

ADDITIONAL RESULTS



**a** Data for 2003-04 to 2006-07, weighted by sample representation. Output and input variables are logged, mean-centred and normalised. Dummy variables for zero values included in regression but not reported. The<br>model applies an exponential distribution to the efficiency term. <sup>b</sup> Base categories are: share of patients aged 20-59 years; share of patients from SEIFA 5 (least disadvantaged); share of patients with Charlson score 1 or below (fewest comorbidities). **c** Base category is inner regional area. **d** Base jurisdiction is Queensland. **e** Base year is 2003-04.  $f$  Due to their confidentiality restrictions, the coefficient terms for In  $\sigma^2{}_{\nu}$  and In  $\sigma^2{}_{u}$  were suppressed by the ABS, because these values would enable the calculation of efficiency scores for individual hospitals or hospital groups. The ABS also deemed it necessary to suppress the coefficient terms of the ownership dummy variables. Significance levels denoted as: \* 10%; \*\* 5%; \*\*\* 1%. Standard errors are robust due to the sample weighting. **seps**: number of separations. **sv**: number of occasions of service. **np** not available for publication due to ABS confidentiality concerns.

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

To test the consistency of efficiency scores between the half-normal distribution and the exponential distribution, a Pearson's correlation test was used to measure the strength of similarity between the estimates of the two models, while a Spearman's rank test was used to test whether the ordinal ranking of the efficiency scores remained stable between the two models (table D.4). The results show that the relativities of the efficiency scores do not significantly differ between the two models.



### Table D.4 **Results of sensitivity tests between half-normal and exponential error distributionsa**

**a** Correlation tests based on unweighted estimates. **b** Test statistic means that the null hypothesis — that the efficiency scores of the two models are independent of each other — can be rejected. This means that the scores of the two model follow a sufficiently similar ordinal ranking.

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

# **D.3 Technical efficiency — selected correlation results**

The Commission undertook correlation tests to test whether there was an observable pattern between the output-oriented efficiency scores and hospital occupancy rates and the degree of hospital specialise in particular activities (table D.5). A hospital's occupancy rate is defined as the number of patient days divided by the number of beds multiplied by 365. A hospital's degree of specialisation was defined by the share of a hospital's total volume of admitted patient separations that was concentrated in the five most frequent types of services, as defined by major diagnostic categories.

A correlation value closer to positive one indicates a greater similarity between a hospital's efficiency score and their degree of specialisation, while a value closer to negative one would indicates the opposite. A value close to zero signals little similarity either way.

The correlation values suggest a variety of trends across hospital ownership groups and sizes. Occupancy rates are generally positively, and significantly correlated, with output oriented efficiency for public hospitals and some groups of not-forprofit hospitals. This suggests that these groups of hospitals, increases in occupancy rates are associated with increases with efficiency.





**a** Small and very small size categories are aggregated for not-for-profit private hospitals due to ABS confidentiality requirements. Number of observations corresponds to the preceding data reported in tables 5.3 and 5.4. **np** Not available for publication due to ABS confidentiality concerns. **\*** Significant at the five per cent level.

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

In contrast, a hospital's degree of specialisation is not highly correlated with its output-oriented technical efficiency. This finding, however, may reflect the limited nature of the variable used to reflect hospital specialisation. Other variables that might have proven more effective in measuring specialisation would include the Evans and Walker (1972) index of specialisation, and the Gini coefficient (Daidone and D'Amico 2009).

# E Referees' reports

# **E.1 Referee report of Adjunct Professor Tim Coelli (University of Queensland)**

This Productivity Commission (PC) study of hospital performance in Australia sets a new benchmark in terms of the sample coverage and the range of input, output and control variables included in the econometric analysis. The PC team has faced a number of data access challenges, and are to be commended for the quality and breadth of their analysis.

### **Data sample**

The sample data involves 459 hospitals observed over a four-year period from 2003-04 to 2006-/07. Of these hospitals, 343 are public, 99 are private and 17 are contract hospitals. A total of 1806 observations are used to estimate the econometric models. In my assessment, this sample size is more than sufficient to allow the Productivity Commission (PC) to reliably estimate an econometric model that involves a flexible functional form and a number of important input, output and control variables.

One area of concern with the data is the low response rate among not-for-profit hospitals. The PC uses weighted econometric methods to address this issue. They also note that some sample selection bias could remain. For example, if the non-respondents tend to be relatively inefficient. If this was the case, the mean efficiency of the not-for-profit group could be overestimated to some extent. However, the position of the estimated best-practice frontier is unlikely to be notably affected by the omission of inefficient observations, and hence the results for the remaining groups are unlikely to be affected by this sampling issue.

### **Frontier methodology**

There are two frontier estimation methods that are commonly used in the literature: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). DEA is a linear programming method that has the advantage that no particular functional form needs to be specified. However, SFA is an econometric method that is less susceptible to the effects of data noise and outliers and which also allows one to easily incorporate control variables that involve categorical and ratio data. Hence, in my assessment the choice of SFA is appropriate for this study.

The translog function form has been used. It is a flexible second-order functional form that can accommodate a range of scale and substitution possibilities. This functional form should generally be used in preference to a first-order functional form (such as the Cobb-Douglas) when sufficient sample data is available, as it is in this case.

The PC has chosen to estimate three different types of frontier models: an input-oriented distance function, an output-oriented distance function and a cost function. One can make a case for the use of each of these models on the basis of the management/ownership characteristics of a particular hospital. Given that the PC study pools data from various hospital types (including public, private for-profit and private not-for-profit) the use of the three different models provides a form of a sensitivity analysis, to ensure that no one type of hospital is disadvantaged by the model type that is chosen.

### **Output measures**

The output measures involve a number of categories of admitted and non-admitted separations, with the former casemix-adjusted. The level of detail is substantially better than many past studies of hospital efficiency. The authors emphasize the point that these are measures of intermediate outputs rather than incremental health benefits derived from the services. However, this is standard practice in this literature, given the very substantial challenges that would be involved in attempting to derive these latter output measures.

### **Input measures**

The input measures include three categories of staff members (nursing, diagnostic and other), three monetary measures of non-staff variable inputs (drugs, medical and surgical supplies and other) along with the number of beds. This group of input measures is better than that used in the majority of past studies, but can still be improved upon (given access to better data). In particular, the beds measure treats an intensive care bed no differently to a standard bed, and the staff measures exclude doctors. These issues could introduce some biases in efficiency estimates if the casemix weights (used to define the output measures) include allowances for the extra capital costs associated with complex cases, and if there are differences among hospitals in the degree to which doctors versus nurses undertake certain "grey area" tasks.

### **Quality measures**

Quality issues have been often overlooked in past studies of health sector efficiency. The PC is to be commended for their efforts in this regard. The inclusion of a mortality rate measure that is adjusted for patient risk characteristics is not a perfect measure, but should go a long way to capturing any notable variations in the effects of service quality upon efficiency potentials.

### **Control measures**

The PC has considered a wide range of exogenous control measures that could potentially be affecting efficiency potentials, including network membership, accident and emergency rates, and so on. These measures help the analyst to avoid labelling a hospital as being 'inefficient' when they may be using more resources per unit output because they face different operating conditions relative to other members of the sample.

## **Additional comments**

In the future, the analysis could be extended to include some estimates of scale economies or scale efficiencies. This information could be particularly valuable to the current public discussion of the effects of casemix funding on small regional hospitals.

The PC has identified two important areas where data is lacking, namely, data on capital costs and medical practitioners. The hospitals sector should be strongly encouraged to collect and then make this type of data available to future studies of this nature.

Finally, I note that the PC have expressed some frustration with the degree to which privacy requirements have constrained what can reported in this document. I would like to add my support here, and also observe that privacy requirements unduly constrain access to data in many regulated sectors in Australia. I find this difficult to comprehend in those situations where public funds and/or monopoly regulation is involved. Even in the USA (where private enterprise is king) there is much more public transparency with regards to data reporting in these situations. As an

example, I encourage the reader to access the Federal Energy Regulatory Commission website (http://www.ferc.gov/) and look at the large amount of detailed firm-level data that is publicly reported there. I am not as familiar with the health sector in the USA, but I understand that similar public data reporting requirements apply there as well.

# **E.2 Referee report of Professor Jim Butler (Australian National University)**

The analyses contained in this report use a large dataset on Australian public and private hospitals covering a period of four financial years (2003-04 to 2006-07). A total of 459 hospitals are included with 1806 observations available for analysis. The compilation of this dataset itself is an impressive achievement, particularly involving as it did the merging of information from ABS collections on private hospitals with data from the AIHW on hospital morbidity and other aspects of public and private hospitals. It is unfortunate that the resulting dataset appears unlikely to be available in the public domain for use by other analysts. Researchers will undoubtedly share the Commission's laments in this regard.

Econometric modelling invariably involves choices of the phenomena to be modelled, the functional form to be estimated, the estimation methods and statistical assumptions to be imposed on the data (to name a few). The report is generally very clear about the choices that have been made. One aspect that could perhaps have been elaborated upon more fully was the decision to treat the data as a pooled cross-section dataset with time trend dummies included rather than as a panel dataset. The data appear to be suitable for analysis using panel methods.

The approaches to estimating hospital quality and hospital efficiency are well documented and have been widely used in the literature. The measure of hospital quality is the hospital-standardised mortality ratio (HSMR), a ratio of actual to expected numbers of in-hospital deaths. Expected numbers of deaths are obtained from an estimated relationship between the number of in-hospital deaths and vectors of patient and hospital characteristics. In principle, these vectors should include factors related to hospital mortality that are beyond the control of the hospital, implying that any remaining unexplained variation in hospital mortality is attributable to factors that are within the control of the hospital. In practice, the distinction between the determinants of mortality that are exogenous and endogenous to the hospital is not always clear cut. The choice of hospital characteristics included in the Commission's analysis is defensible and, as alluded to in the report, may usefully serve as proxies for attributes of patients not captured in the vector of patient characteristics. The use of a negative binomial model to estimate the relationship is entirely appropriate given that the data are hospital-level and the dependent variable is a non-negative integer (counts of deaths).

The use of stochastic frontier analysis (SFA) with a one-sided error component to measure inefficiency as opposed to deterministic data envelopment analysis (DEA) is a defensible choice. Three sets of efficiency scores are estimated, two relating to technical efficiency and one relating to cost efficiency. The sensitivity of the technical efficiency scores to the assumed distribution of the one-sided error term (but not the cost efficiency scores) is investigated. High correlations (both Pearson's and Spearman's rho) between the technical efficiency scores under two different distributional assumptions are found.

The analyses of hospital quality show private hospitals having significantly lower HSMRs than either public hospitals or public contract hospitals, with variations in this difference occurring across hospital size groupings. This is a very interesting result, but its veracity depends upon the extent to which the vectors of patient and hospital characteristics fully capture differences in the severity of disease between patients. This caveat is recognised in the report.

Two sets of technical efficiency scores are provided based on the estimation of output-oriented and input-oriented distance functions. As both of these are based on the production function, one might expect there to be a high correlation between them. The report investigates this issue (see table 5.5) and, while it indicates that the correlation coefficients are certainly positive, they are not perhaps as high as one would expect. For all public hospitals, the correlation coefficient is 0.486 and for all private hospitals it is 0.539. The two sets of results also show differing effects of hospital ownership on efficiency although the materiality of any differences in efficiency by hospital ownership type is, for pragmatic purposes, debatable. The output-oriented scores show statistically significant differences in efficiency by ownership type with for-profit private hospitals being the most efficient and not-for-profit private hospitals the least, but the difference in average efficiency scores between the most and least efficient groups is less than 10.0 percentage points (94.8 versus 85.6). The input-oriented scores place public contract hospitals as being the most efficient and public hospitals the least, with the difference between the average scores for the most and least efficient being 4.5 percentage points (93.6 versus 89.1).

Regarding cost efficiency, no statistically significant differences in cost efficiency scores by ownership type are found. With the exception of public contract hospitals which have an average cost efficiency score of 90.4, the other three ownership types all have average scores in the range 93.0 - 94.0. Given the duality between cost and production functions, and the statistical significance of ownership type in the

analysis of technical efficiency scores, this result is surprising. Data limitations may be part of the explanation.

Overall, this is a rich report which makes a substantial contribution to the empirical Australian literature on hospital efficiency. The quality of the econometric modelling suggests that the results will be of substantive interest to a range of parties. Nevertheless, given the limitations of the data and the econometric/measurement problems that are inevitable in work of this kind, a robotic interpretation of the results should be resisted.

# References

- ABS (Australian Bureau of Statistics) 2005, *Australian Standard Geographical Classification (ASGC)*, Cat. no. 1216.0, Canberra.
- —— 2008a (and previous issues), *Private Hospitals*, Cat. no. 4390.0, Canberra.
- —— 2008b, *Socio*-*Economic Indexes for Areas (SEIFA): Technical Paper 2006*, Cat. no. 2039.0.55.001, Canberra.
- —— 2008c, *Hospital Cost Index*, Prepared for the Commonwealth/State Technical Working Party for the Australian Health Care Agreements by the Australian Bureau of Statistics, September Quarter, Canberra.
- ACHS (Australian Council on Healthcare Standards) 2008, *Australasian Clinical Indicator Report 2001–2007: Determining the Potential to Improve Quality of Care*, 9th edn, Sydney.
- ACSQHC (Australian Commission on Safety and Quality in Health Care) 2009, *Windows into Safety and Quality in Health Care 2009*, ACSQHC, Sydney.
- AHRQ (Agency for Healthcare Research and Quality) 2009, *AHRQ Quality Indicators*, Rockville. http://qualityindicators.ahrq.gov/index.htm (accessed 15 December 2009).
- —— 2005, *AHRQ releases standardized hospital bed definitions*, Rockville. http://www.ahrg.gov/research/havbed/definitions.htm (accessed 15 December 2009).
- Aigner, D.J., Lovell, C.A. K. and Schmidt, P. 1977, 'Formulation and estimation of stochastic frontier production function models', *Journal of Econometrics*, vol. 6, no. 1, pp. 21–37.
- AIHW (Australian Institute of Health and Welfare) 2009a, *Australian Hospital Statistics 2007-08*, Health Services Series no. 33, Cat. no. HSE 71, Canberra.
	- —— 2009b, *Towards National Indicators of Safety and Quality in Health Care*, Cat. no. HSE 75, Canberra.
- —— 2010. *Indigenous identification in hospital separations data—quality report*. Health Services Series no. 35. Cat. no. HSE 85, AIHW, Canberra.
- Aiken, L.H., Clarke, S.P., Sloane, D.M., Sochalski, J. and Silber, J.H. 2002, 'Hospital Nurse Staffing and Patient Mortality, Nurse Burnout, and Job

Dissatisfaction', *Journal of the American Medical Association*, vol. 288, no. 6, pp. 1987-1993.

- Al Shammari, M. 1999, 'A multi-criteria data envelopment analysis model for measuring the productive efficiency of hospitals', *International Journal of Operations and Production Management*, vol. 19, no. 9, pp. 879–90.
- Anson-Dwamena, R. and Studer, K. 2009, 'Hospital 'staffed beds': a concept in need of clarification, Office of Minority health and Public Policy, Virginia Department of Health, accessed 17 March 2009,  $\langle$ www.vdh.virginia.gov/ healthpolicy/.../method-for-assessing-staffed-beds.pdf>
- Arocena, P. and Garcia-Prado, A. 2007, 'Accounting for quality in the measurement of hospital performance: evidence from Costa Rica', *Health Economics*, vol. 16, pp. 667-85.
- Aujesky, D., Mor, M.K., Geng, M., Fine, M.J., Renaud, B. and Ibrahim, S.A. 2008, 'Hospital volume and patient outcomes in pulmonary embolism', *Canadian Medical Journal*, vol. 178, no. 1, pp. 58-60.
- Aylin, P., Bottle, A. and Majeed, A. 2007 'Use of administrative data or clinical databases as predictors of risk of death in hospital: comparison of models' *British Medical Journal*, vol. 334, pp. 1044–1047.
- Banker, R.D., Conrad, R.F. and Strauss, R.P. 1986, 'A comparative application of data envelopment analysis and translog methods: an illustrative study of hospital production', *Management Science*, vol. 39, no. 10, pp. 1265–73.
- Balk, B.M. 2001, 'Scale efficiency and productivity change', *Journal of Productivity Analysis*, 15:159–183.
- Battese, G. 1996, 'On the estimation of production functions involving explanatory variables which have zero values', Working Paper in Econometrics and Applied Statistics, Department of Econometrics, University of New England, Armidale.
- Bedard, J.C. and Wen, K.W. 1990, 'A comparison of the efficiency effects of prospectiv*e* Reimbursement System', *Research in Governmental and Non-profit Accounting*, vol. 6, pp. 63–82.
- Ben-Tovim, D., Woodman, R.J., Harrison, J.E., Pointer, S., Hakendorf, P. and Henley, G. 2009, *Measuring and Reporting Mortality in Hospital Patients*, AIHW, Cat. no. HSE 69, Canberra.

 $-$ ,  $-$ , Hakendorf, P. and Harrison, J.E., 2009 'Standardised mortality ratios: neither constant nor a fallacy', *British Medical Journal*, vol. 338, pp. 1748.

Bilodeau, D., Crémieux, P-Y, Jaumard, B., Ouellette, P., and T. Vovor, 2004, 'Measuring hospital performance in the presence of quasi-fixed inputs: an analysis of Québec hospitals', *Journal of Productivity Analysis*, vol. 21, pp. 183– 199.

- Biørn, E., Hagen, T.P, Iversen, T., and Magnussen, J. 2003, 'The effect of activity based financing on hospital efficiency: a panel data analysis of DEA efficiency scores 1992-2000', *Health Care Management Science*, vol. 6, pp. 271-83.
- Birkmeyer, J.D., Siewers, A.E., Finlayson, E.V., Stukel, T.A., Lucas, F.L., Batista, I., Welch, H.G., Wennberg, D.E., 2002, 'Hospital volume and surgical mortality in the United States', *New England Journal of Medicine*, vol. 346, no. 15, pp. 1128-37.
- Birkmeyer, J.D., Dimick, J.B. and Staiger, D.O. 2006, 'Operative Mortality and Procedure Volume as Predictors of Subsequent Hospital Performance', *Annals of Surgery*, vol. 243, pp. 411–417.
- Borden, J.P. 1988, 'An assessment of the impact of diagnosis-related group (DRG) based reimbursement on the technical efficiency of New Jersey hospitals using data envelopment analysis', *Journal of Accounting and Public Policy*, vol. 7, pp. 77–96.
- Breyer, F. 1987, 'The specification of a hospital cost function a comment on the recent literature', *Journal of Health Economics*, vol. 6, pp. 147–57.
- Bridges, J., Haas, M. and Mazevska, D. 1999, *A Qualitative Insight into Rural Casemix Education,* Centre for Health Economics Research and Evaluation Project Report 10, Melbourne.
- Brien, S.E. and Ghali, W.A. 2008 'CIHI's hospital standardized mortality ratio: friend or foe?', *Healthcare Papers*, vol. 8(4) pp.57–61.
- Brook, C. n.d., *Casemix funding for acute hospital care in Victoria, Australia*. www.health.vic.gov.au/\_\_data/assets/pdf\_file/0005/403169/casemix\_funding .pdf (accessed 11 February 2009).
- Brown, H.S. 2003, 'Managed care and technical efficiency', *Health Economics*, vol. 12, pp. 149–58.
- Burgess, J.F. and Wilson, P.W. 1995, 'Decomposing hospital productivity changes, 1985–1988: a nonparametric Malmquist approach', *Journal of Productivity Analysis*, vol. 6, pp. 343–63.
- —— 1998, 'Variation of inefficiency in US hospitals', *Canadian Journal of Operational Research and Information*, vol. 36, pp. 84–102.
- Butler, 1988a, 'Hospital costs and information theory case mix indexes: results for Queensland', *Prometheus*, vol. 6, no. 2, pp. 327–50.
- —— 1988b, 'Issues in hospital funding', in CEDA (Committee for Economic Development of Australia), *The Economics of Health Care*, APAIS, Canberra, pp. 87–116.
- —— 1995, *Hospital Cost Analysis*, Kluwer Academic, Dordrecht.
- Cameron, A.C. and Trivedi, P.K 2005 *Microeconometrics using Stata*, Stata Press, Texas.
- Campbell, D., Green, S., Gruen, R., Jolley, D., Pitt, V. and Zavarsek, S. 2006, *Hospital and Clinician Volume or Specialisation in Cancer Care*, Monash Institute for Health Services Research, Melbourne.
- Campbell, S.M., Roland, M.O. and Buetow, S.A. 2000, 'Defining quality of care', *Social Science and Medicine*, vol. 51, pp. 1611–1625.
- Carson, P.J. 2009, 'Providing Specialist Services in Australia Across Barriers of Distance and Culture', *World Journal of Surgery*, vol. 33, pp. 1562–1567.
- Charlson, M.E., Pompei, P., Ales K.L. and MacKenzie, C.R. 1987, 'A new method of classifying prognostic comorbidity in longitudinal studies: development and validation', *Journal of Chronic Diseases*, vol. 40, no. 5, pp. 373–83.
- Charnes, A., Cooper, WW, and Rhodes, E. 1978, 'Measuring the efficiency of decision-making units', *European Journal of Operational Research*, vol. 2, pp. 429–44.
- Chen, S. N. 2006, 'Productivity changes in Taiwanese hospitals and the national health insurance', *Service Industries Journal*, vol. 26 no. 4, pp. 459–77.
- Chirikos, T. 1998, 'Identifying efficiently and economically operated hospitals: the prospects and pitfalls of applying frontier regression techniques', *Journal of Health Politics Policy and Law*, no. 23, vol. 6, pp. 879–904.
- Chirikos, T.N., French, D.D. and Luther, S.L. 2004, 'Potential Economic Effects of Volume-Outcome Relationships in the Treatment of Three Common Cancers', *Cancer Control*, vol. 11, no. 4, pp.258–264.
- Chowdhury, M.M., Dagash, H. and Peirro, A.. 2007, 'A systematic review of the impact of volume of surgery and specialization on patient outcome', *British Journal of Surgery*, vol. 94, no. 2. pp. 145–161.
- Christian, C.K., Gustafson, M.L., Betensky, R.A, Daley, J. and Zinner, M.J. 2005, 'The Volume–Outcome Relationship: Don't Believe Everything You See', *World Journal of Surgery*, vol. 29, pp. 1241–1244.
- Chua, C.L., Palangkaraya, A. and Yong, J. 2008, *A Two-Stage Estimation of Hospital Performance Using Mortality Outcome Measures: An Application*

*Using Victorian Hospital Data*, Melbourne Institute Working paper no. 10/08, The University of Melbourne.

- —— 2009, *Hospital Competition, Technical Efficiency and Quality*, Melbourne Institute Working paper no. 16/09, The University of Melbourne.
- CIHI (Canadian Institute of Health Intelligence) 2007 *HSMR: A New Approach for Measuring Hospital Mortality Trends in Canada*, Ottawa.
- —— 2009 *Hospital Standardised Mortality Ratio Public Release,* http://www.cihi.ca/cihiweb/dispPage.jsp?cw\_page=hsmr\_results\_home\_e Accessed 24 March 2010.
- —— 2010 *Hospital Standardised Mortality Ratio Technical notes*, http://www.cihi.ca/cihiweb/en/downloads/hsmr\_tech\_notes\_201002\_e.pdf Accessed 21 April 2010.
- Clement, J.P, Valdmanis, V.G., Bazzoli, G.J., Zhao, M., and Chukmaitov, A. 2008, 'Is more better? An analysis of hospital outcomes and efficiency with a DEA model of output congestion', *Health Care Management Science*, vol. 11, pp. 67–77.
- Coelli, T. and Perelman, S. 1999 'A comparison of parametric and non-parametric distance functions: with application to European railways', *European Journal of Operational Research*, vol. 117, pp. 326-39.
- Coelli, T., Rao, D.S.R, and G.E. Battese, 1998, *An Introduction to Efficiency and Productivity Analys*is, Kluwer Academic.
- Coelli, T., Rao, D.S.R, O'Donnell, C.J. and G.E. Battese, 2005, *An introduction to efficiency and productivity analysis*, Springer, New York.
- Daidone, S. and D'Amico, F. 2009, 'Technical efficiency, specialisation and ownership form: evidence from a pooling of Italian hospitals', *Journal of Productivity Analysis*, vol. 32, pp. 203–16.
- Deeble, J. 1965, 'An economic analysis of hospital costs', *Medical Care*, vol. 3, no. 3, pp. 138–46.
- Deily ME, McKay NL: Cost inefficiency and mortality rates in Florida hospitals. Health Econ 2006, 15(4):419-431.
- Department of Health (Victoria) 2009, *Patient Safety Indicators*, Melbourne, www.health.vic.gov.au/psi (accessed 15 December 2009).
- DHS (Department of Human Services Victoria), nd *Casemix Funding in Victoria*, www.health.vic.gov.au/casemix/definitions, accessed 28 January 2010.
- DOHA (Department of Health and Ageing) 2004, *Australian Refined Diagnosis Related Groups Version 5.1: Definitions Manual*, Canberra.
- Devereaux, P.J., Choi, P.T.L, Lacchetti, C., Weaver, B., Schünemann, H.J., Haines, T., Lavis, J.N., Grant, B.J.B., Haslam, D.R.S., Bhandari, M., Sullivan, T., Cook, D.J., Walter, S.D., Meade, M., Khan, H., Bhatnager, N. and Guyatt, G.H. 2002, 'A systematic review and meta-analysis of studies comparing mortality rates of private for-profit and private not-for-profit hospitals', *Canadian Medical Association Journal,* vol. 166, no. 11, pp. 1399–406.
- Devereaux, P.J., Schünemann, H.J., Ravindran, N., Bhandari, M., Garg, A.X., Choi, P.T.L., Grant, B.J.B., Haines, T., Lacchetti, C., Weaver, B., Lavis, J.N., Cook, D.J., Haslam, D.R.S., Sullivan and T., Guyatt, G.H. 2002, 'Comparison of mortality between private for-profit and private not-for-profit hemodialysis centers: a systematic review and meta-analysis', *Journal of the American Medical Association,* vol. 288, no. 19, pp. 2449–57.
- Dor, A. and Farley, D.E. 1996, 'Payment source and the cost of hospital care*:* evidence from a multiproduct cost function with multiple payers', *Journal of Health Economics*, vol. 15, pp. 1–21.
- Dormont, B. and Milcent, C. 2004, 'The sources of hospital cost variability'*, Health Economics*, vol. 13, pp. 927–39.
- Dr. Foster 2010 *Hospital Guide*, http://www.drfosterhealth.co.uk/hospital-guide/ Accessed 24 March 2010.
- Eckermann, S. and Coelli, T. 2008, 'Including Quality Attributes in a Model of Health Care Efficiency: A Net Benefits Approach', Centre for Efficiency and Productivity Analysis, Working paper no. WP03/2008 University of Queensland.
- Evans, R.G. and Walker, H. 1972, 'Information theory and the analysis of hospital cost structure', *Canadian Journal of Economics*, vol. 5, no. 3, pp. 398–418.
- Färe, R., Grosskopf, S., Lovell, C.A.K. and Pasurka, C. 1989, 'Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach', *Review of Economics and Statistics*, vol. 71, no. 1, pp. 90–98.
- Färe, R., Grosskopf, S., and Valdmanis, V. 1989, 'Capacity, competition and efficiency in hospitals: a non-parametric approach', *Journal of Productivity Analysis*, vol. 1, pp. 123–39.
- Färe, R., and Primont, D. 1990, 'A distance function approach to multi-output technologies', *Southern Economic Journal*, vol. 56, pp. 879–91.
- —— 1995*, Multi-Output Production and Duality: Theory and Applications,* Kluwer Academic, Boston.
- Färe, R., Grosskopf, S., Lindgren, B. and Poullier, J. P. 1997, 'Productivity growth in health care delivery', *Medical Care*, vol. 35, no. 4, pp. 354–66.
- Farrell, M.J. 1957, 'The measurement of productive efficiency', *Journal of the Royal Statistical Society,* vol. 120, no. 3, pp. 253–90.
- Feldstein, M.S. 1967, *Economic Analysis for Health Service Efficiency*, North Holland, Amsterdam.
- Ferrari, A. 2006, 'The internal market and hospital efficiency: a stochastic distance function approach', *Applied Economics*, vol. 38, pp. 2121–30.
- Ferrier, G. and Valdmanis, V. 1996, 'Rural hospital performance and its correlates', *Journal of Productivity Analysis*, vol. 7, pp. 63–80.
- Finlayson E.V.A., Goodney P.P. and Birkmeyer J.D. 2003, 'Hospital volume and operative mortality in cancer surgery: a national study'. *Archives of Surgery*, vol. 138, no. 7, pp. 721–25.
- Folland, S.T. and Hofler, R.A. 2001, 'How reliable are hospital efficiency estimates? Exploiting the dual to homothetic production', *Health Economics*, vol. 10, pp. 682–98.
- Fuiji, A. 2001, ''Determinants and probability distribution of inefficiency in the stochastic cost frontier of Japanese hospitals', Applied Economic Letters, vol. 8, pp. 807–812.
- Gabbitas, O. and Jeffs, C. 2008, *'Assessing productivity in the delivery of public hospital services*: *some experimental estimates',* Paper presented to the Australian Health Economics Conference, Adelaide, 2–3 October 2008.
- Gandjour, A., Bannenberg, A. and Lauterbach, K.W. 2003, 'Threshold Volumes Associated with Higher Survival in Health Care: A Systematic Review', *Medical Care,* vol. 41, no. 10,pp. 1129–41.
- Gerdtham, U.G., Löthgren, M., Tambour, M. and Rehnberg, C. 1999, 'Internal markets and health care efficiency: a multiple-output stochastic frontier analysis', *Health Economics*, vol. 8, pp. 151–64.
- Glance, L.G., Osler, T.M., Mukamel, D.B. and Dick, A.W. 2007, 'Estimating the potential impact of regionalizing health care delivery based on volume standards versus risk-adjusted mortality rate', *International Journal for Quality in Health Care*, vol. 19, no. 4, pp. 195–202.
- Granneman, T.W., Brown, R.S. and Pauly, M.V. 1986, 'Estimating hospital costs: a multiple-output analysis', *Journal of Health Economics*, vol. 5, no. 2, pp. 107-27.
- Greene, W.H. 1997, 'Frontier Production Functions', in Pesaran, H.M and Schmidt, P. (eds), *Handbook of Applied Econometrics, Volume II, Microeconomics,* Blackwell, Oxford, pp. 81–166.
- Grosskopf, S., Margaritis, D., Valdmanis, V., 1995, 'Estimating output substitutability of hospital services: a distance function approach', *European Journal of Operational Research*, vol. 80, pp. 575–87.
- Grosskopf, S., Hayes, K., Taylor, L. and Weber, W. 1997, 'Budget constrained frontier estimation of fiscal equality and efficiency in schooling', *Review of Economics and Statistics*, vol. 79, pp. 116–24.
- Gruen, R.L., Pitt, V., Green, S., Parkhill, A. Campbell, D. and Jolley, D. 2009, 'The Effect of Provider Case Volume on Cancer Mortality Systematic Review and Meta-Analysis', *CA: A Cancer Journal for Clinicians*, vol. 59, no. 3, pp. 192– 211.
- Haines T, Lavis JN, Grant BJ, Haslam DR, Bhandari M, et al.: A systematic review and meta-analysis of studies comparing mortality rates of private for-profit and private not-for-profit hospitals. Cmaj 2002, 166(11):1399-1406.
- Halm, E.A., Lee, C. and Chassin, M.R. 2002, 'Is Volume Related to Outcome in Health Care? A Systematic Review and Methodologic Critique of the Literature', *Annals of Internal Medicine*, vol. 137, pp. 511–520.
- Harrison, J.P, Coppola, M.N. and Wakefield, M. 2004, 'Efficiency of federal hospitals in the United States', *Journal of Medical Systems*, vol. 28, no. 5, pp. 411–22.
- Harrison, J.P. and Sexton, C. 2006, 'The improving efficiency frontier of not-forprofit religious hospitals', *Hospital Topics*, vol. 84, no. 1, pp. 2–10.
- Hasan, M. 2001, 'Readmission of patients to hospital: still ill defined and poorly understood: counterpoint', *International Journal for Quality in Health Care*, vol. 13, no. 3, pp. 177–79.
- Heckman, J. 1976, 'The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models,' *Annals of Economic and Social Measurement*, vol. 5, no. 4, pp. 475–92.
- Heijink R., Koolman X., Pieter, D., van der Veen, A., Jarman, B. and Westert, G. 2008 'Measuring and explaining mortality in Dutch hospitals: the Hospital Standardised Mortality Rate between 2003 and 2005', *BMC Health Services Research*, vol. 8, no. 1, pp. 73–80.
- Herr, A., 2008, 'Cost and technical efficiency of German hospitals: does ownership matter?', *Health Economics*, vol. 17, pp. 1057–71.
- Hewitt, M. 2000, *Interpreting the Volume-Outcome Relationship in the Context of Health Care Quality: Workshop Summary*, Institute of Medicine, Washington D.C.
- Hilbe, J.M. 2007 *Negative binomial regression*, Cambridge University Press, Cambridge.
- Hofmarcher, M.M., Paterson, I. and Riedel, M. 2002, 'Measuring hospital efficiency in Austria – A DEA Approach', *Health Care Management Science*, vol. 5, pp. 7–14.
- Hogan, A.M. and Winter, D.C. 2008, 'Does Practice Make Perfect?', *Annals of Surgical Oncology*, vol. 15, no. 5. pp. 1267–1270.
- Hollingsworth, B. 2008, 'The measurement of efficiency and productivity of health care delivery', *Health Economics*, vol. 17, pp. 1107–28.
- Hollingsworth, B. and Peacock, S. 2008, *Efficiency Measurement in Health and Health Care*, Routledge, London.
- Hurley, E., McRae, I., Bigg, I., Stackhouse, L., Boxall, A. and Broadhead, P. 2009, *The Australian Health Care System: The Potential for Efficiency Gains* — *A Review of the Literature*, Background paper prepared for the National Health and Hospitals Reform Commission, Canberra, www.nhhrc.org.au /internet/nhhrc/publishing.nsf/Content/A5665B8B9EAB34B2CA2575CB00184 FB9/\$File/Potential%20Efficiency%20Gains%20-%20NHHRC%20Background %20Paper.pdf (accessed 27 July 2009).
- Jackson, T. 2008, *'Hospital Acquired Diagnoses: At What Cost?'* Presentation to the National Forum on Safety and Quality in Health Care, Adelaide, 30 October, www.achs.org.au/pdf/thur.plen4.jackson.pdf (accessed 14 September 2009).
- Jacobs, R. 2001, 'Alternative methods to examine hospital efficiency: data envelopment analysis and stochastic frontier analysis', *Health Care Management Science*, vol. 4, no. 2, pp. 103–15.
- Jarman, B., Gault, S., Alves, B., Hider, A., Dolan, S., Cook, A., Hurwitz, B., and Iezzoni, L.I., 1999 'Explaining differences in English hospital death rates using routinely collected data' *British Medical Journal*, vol. 318, pp. 1515–1520.
- Jensen, P.H, Webster, E. and Witt, J. 2007, 'Hospital Type and Patient Outcomes: An Empirical Examination Using AMI Re-admission and Mortality Records', Melbourne Institute Working paper no. 31/07, Melbourne.
- Jha, A.K., Orav, E.J., Li, Z. and Epstein, A.M. 2007 'The inverse relationship between mortality rates and performance in the hospital quality alliance measures', *Health Affairs*, vol. 26, no. 4, pp. 1104–1110.
- Kahn J.M., Goss, C.H., Heagerty, P.J., Kramer, A.A., O'Brien, C.R. and Rubenfield G.D. 2006, 'Hospital Volume and the Outcomes of Mechanical Ventilation', *New England Journal of Medicine*, vol. 355, no. 1, pp. 41–50.
- Kane, R.L., Shamliyan, T., Mueller, C., Duval, S. and Wilt, T. 2007, *Nursing Staffing and Quality of Patient Care. Evidence Report/Technology Assessment No. 151*, AHRQ Publication No. 07-E005. Agency for Healthcare Research and Quality. Rockville, MD.
- Kelley, E. and Hurst, J. 2006, *Health Care Quality Indicators Project Conceptual Framework* Paper, OECD Health Working Papers No. 23, DELSA/HEA/WD/HWP(2006)3, Organisation for Economic Cooperation and Development, Paris.
- Kennedy, P. 2004 *A Guide to Econometrics (5th ed.)* Blackwell Publishing, Malden.
- Khuri, S.F., Daley, J., Henderson, W., Hur, K., Hossain, M., Soybel, D., Kizer, K.W., Aust, J.B., Bell, R.H., Chong, V., Demakis, J., Fabri, P.J., Gibbs, J.O., Grover, F., Hammermeister, K., McDonald, D., Passaro Jnr, E., Phillips, L., Scamman, F., Spencer, J., and Stremple, J.F. 1999, 'Relation of Surgical Volume to Outcome in EightCommon Operations', *Annals of Surgery*, vol. 230, no. 3, pp. 414–432.
- Korda, R.J., Butler, J.G., Clements, M.S., and Kunitz, S.J. 2007 'Differential impacts of health care in Australia: trend analysis of socioeconomic inequalities in avoidable mortality' *International Journal of Epidemiology* vol. 34, pp. 157-165.
- Kumbhakar, S.C. and Lovell, C.A. Knox 2000, *Stochastic Frontier Analysis*, Cambridge University Press, Cambridge.
- Lakhani, A., Olearnik, H., Eayres, D. (eds). 2005, *Compendium of Clinical and Health Indicators*, The Information Centre for Health and Social Care, National Centre for Health Outcomes Development, London.
- Lave, J.R. 1966, 'A Review of the Methods Used to Study Hospital Costs', *Inquiry*, vol. 3, pp. 57–81.
- Linna, M. 1998, 'Measuring hospital cost efficiency with panel data models'*, Health Economics*, vol. 7, no. 5, pp. 415–27.
- Löthgren, M. 2000, 'Specification and estimation of stochastic multiple-output production and technical inefficiency', *Applied Economics*, vol. 32 pp. 1533–40.
- Lovell et al. (Lovell, C.A.K. Richardson, S., Travers, P. and Wood, L.) 1994, 'Resources and functionings: a new view of inequality in Australia', in Eichhorn, W. (ed) *Models and Measurement of Welfare and Inequality*, Springer-Verlag, Berlin, pp. 787-807.
- Luft, H.S., Bunker, J.P. and Enthoven, A.C. 1979 *Should operations be regionalized? The empirical relation between surgical volume and mortality*. New England Journal of Medicine, vol. 301, pp. 1364–9.
- Mangano, M. 2003, *A Stochastic Frontier Examination of Victorian Public Hospitals*, Paper presented at 2003 PhD Conference in Economics and Business, Perth, November.
- —— 2006, *Frontier Methods for Comparing Public Hospital Efficiency: The Effect of Casemix Funding in Victoria*, PhD Thesis, School of Economics and Finance, Curtin University of Technology, Western Australia.
- Maniadakis, N. and Thanassoulis, E. 2000, 'Assessing productivity changes in UK hospitals reflecting technology and input prices', *Applied Economics*, vol. 32, pp. 1575-89.
- McCue, M., Mark, B.A. and Harless, D.W. 2003, 'Nurse staffing, quality and financial performance', *Journal of Health Care Finance*, vol. 29, no. 4, pp. 54– 76.
- Meeusen, W. and van den Broeck, J. 1977, 'Efficiency estimation from Cobb– Douglas production functions with composed error', *International Economic Review*, vol. 18, no. 2, pp. 435–44.
- Miyata, H., Hashimoto, H., Horiguchi, H., Matsuda, S., Motomura, N. and Takamoto, S. 2008 'Performance of in-hospital mortality prediction models for acute hospitalization: Hospital Standardized Mortality Ratio in Japan' *BMC Health Services Research*, vol.8, pp. 229–238.
- Mohammed, M.A. Deeks, J.J., Girling, A., Rudge, G., Carmalt,. M., Andrew J Stevens, A.J., and Lilford, R.J. 2009 'Evidence of methodological bias in hospital standardised mortality ratios: retrospective database study of English hospitals' *British Medical Journal*, vol. 338, pp. 817–821.
- Morey, R.C. and Dittman, D.A. 1996, 'Cost pass-through reimbursement to hospitals and their impact on operating efficiencies', *Annals of Operations Research*, vol. 67, pp. 117–39.
- Mortimer, D. 2002, *Competing Methods for Efficiency Measurement: A Systematic Review of Direct DEA vs SFA/DFA Comparisons*, Centre for Health Program Evaluation, Working paper no. 136, Monash University, Melbourne.
- Mukamel DB, Zwanziger J, Tomaszewski KJ, 2001. 'HMO penetration, competition, and risk-adjusted hospital mortality', *Health Services Research*, 36(6 Pt 1):1019-1035.
- Nayar, P. and Ozcan, Y. 2008, 'Data envelopment analysis comparison of hospital efficiency and quality', *Journal of Medical Systems*, vol. 32, pp. 198–9.
- NHPC (National Health Performance Committee) 2004, *National Report on Health Sector Performance Indicators 2003*, Australian Institute of Health and Welfare, Cat. No. HWI 78, Canberra.
- Needleman, J. Buerhaus, P. Mattke, S., Stewart, M. and Zelevinsky, K. 2002, 'Nurse-staffing levels and the quality of care in hospitals', *New England Journal of Medicine*, vol. 346, No. 22, pp. 1715–22.
- Newhouse, J. 1970, 'Toward a theory of nonprofit institutions: an economic model of a hospital,' *American Economic Review*, vol. 60, pp. 64–74.
- —— 1994, 'Frontier estimation: how useful a tool for health economics?', *Journal of Health Economics*, vol. 13, pp. 317–22.
- Nguyen, K. and Coelli, T. 2009, *Quantifying the effects of modelling choices on hospital efficiency measures: A meta-regression analysis,* Centre for Efficiency and Productivity Analysis, WP07/2009, University of Queensland, www.uq.edu.au/economics/cepa/docs/WP/WP072009.pdf (accessed 12 November 2009).
- Nicholl, J., West, J., Goodacre, S. and Turner,J. 2007 'The relationship between distance to hospital and patient mortality in emergencies: an observational study', *Emergency Medicine Journal*, vol. 24, pp. 665–668.
- NSW Health 2008, *Episode Funding Policy 2008/2009 NSW*, PD2008\_063, North Sydney.
- O'Neill, L. 1998, 'Multifactor efficiency in data envelopment analysis with an application to urban hospitals', *Health Care Management Science*, vol. no. 1, pp. 19–27.
- O'Neill, L., Rauner, M., Heidenberger, K., and Kraus, M. 2008, 'A cross-national comparison and taxonomy of DEA-Based hospital efficiency studies', *Socio-Economic Planning Sciences*, vol. 42, pp. 158–89.
- Paul, C.J.M. 2002, 'Productive structure and efficiency of public hospitals', in Fox*,* K. J. (ed), *Efficiency in the Public Sector*, Kluwer Academic Publishers, Boston.
- Peacock, S., Chan, C., Mangolini, M. and Johansen, D. 2001, 'Techniques for Measuring Efficiency in Health Services', Staff Working paper, Productivity Commission, July.
- Penfold, R.B., Dean, S., Flemons, W. and Moffatt, M. 2008 'Do Hospital Standardized Mortality Ratios Measure Patient Safety? HSMRs in the Winnipeg Regional Health Authority' *Healthcare Papers*, vol. 8 (4), pp. 8–24.
- Perelman, S. and Santin, D. 2005, 'Measuring educational efficiency at student level with parametric stochastic distance functions: An application to Spanish

PISA results', Working Paper No. 200511/02, Ecole de Gestion de l'Université de Liège, Belgium.

- Preen D.B., Holman C.D.J., Semmens J.B., Spilsbury K., Brameld K.J. 2006, 'Length of comorbidity lookback period affected regression model performance of administrative health data', *Journal of Clinical Epidemiology,* vol. 59, no. 9, pp. 940–6.
- PC (Productivity Commission) 1999a, *An Assessment of the Performance of Australian Railways: 1990 to 1998*, Supplement to Inquiry Report on Progress in Rail Reform, AusInfo, Canberra.
- —— 1999b, *Private Hospitals in Australia*, Commission Research paper, AusInfo, Canberra.
	- —— 2009, *Public and Private Hospitals*, Research Report, Canberra.
- Prior, D. 2006, 'Efficiency and total quality management in health care organizations: a dynamic frontier approach', *Annals of Operations Research*, vol. 145, pp. 281–299.
- Quan, H., Sundarajan, V., Halfon, P., Fong, A., Burnand, B., Luthi, J-C, Saunder, L.D., Beck, C.A., Feasby, T.E. and W.A. Ghali 2005, 'Coding algorithms for defining comorbidities in ICD-9-CM and ICD-10 administrative data', *Medical Care*, vol. 43 no. 1, pp. 1130-9.
- Queensland Department of Health 2004, *Measured Quality Service*, Report to Board of Management, Brisbane.
- Richardson, J. (2005), Priorities of health policy: cost shifting or population health, *Australia and New Zealand Health Policy*, vol. 2, issue 1.
- Rosko, M.D. and Chilingerian, J.A. 1999, 'Estimating hospital inefficiency: does casemix matter?', *Journal of Medical Systems*, vol. 23, no. 1, pp. 57–71.
- Rosko, M. and J. Proenca, 2005, 'Impact of network and system use on hospital X-inefficiency', *Health Care Management Review*, no. 30, vol. 1, pp. 69–79.
- Sammut, J. 2009, *Why Public Hospitals are Overcrowded: Ten Points for Policymakers*, Policy Monograph no. 99, Centre for Independent Studies, Sydney.
- Schmidt, P. and Sickles, R.C. 1984, 'Production frontiers and panel data', *Journal of Business and Economic Statistics*, vol. 2, pp. 367–74.
- Scott, A. and Parkin, D. 1995, 'Investigating hospital efficiency in the new NHS: the role of the translog cost function', *Health Economics*, vol. 4, pp. 467–78.
- SCRCSSP (Steering Committee for the Review of Commonwealth/State Service Provision) 1997, *Data Envelopment Analysis, A Technique for Measuring the Efficiency of Government Service Delivery*, AGPS, Canberra.
- SCRGSP (Steering Committee for the Review of Government Service Provision) 2009, *Report on Government Services 2009*, Productivity Commission, Canberra.
- Shahian, D.M. and Normand, S.L. 2008 'Comparison of 'risk-adjusted' hospital outcomes', *Circulation*, vol. 117, pp. 1955–1963.
- Sherman, H.D. 1984, 'Hospital efficiency measurement and evaluation: empirical test of a new technique', *Medical Care*, vol. 22, no. 10, pp. 922–38.
- Shojania, K.G. and Forster, A.J. 2008 'Hospital mortality: when failure is not a good measure of success', *Canadian Medical Association Journal*, vol. 179, pp.153–157.
- Siciliani, L. 2006, 'Estimating technical efficiency in the hospital sector with panel data: a comparison of parametric and non-parametric techniques', *Applied Health Economics and Health Policy*, vol. 5, no. 2, pp. 99–116.
- Skinner, J. 1994, 'What do stochastic frontier functions tell us about inefficiency?', *Journal of Health Economics*, vol 13, pp. 317–22.
- Solà, M. and Prior, D. 2001, 'Measuring productivity and quality changes using data envelopment analysis: an application to Catalan hospitals', *Financial Accountability and Management*, vol. 17, no. 3, pp. 219–45.
- Spiegelhalter, D. 2004, 'Funnel plots for comparing institutional performance', *Statistics in Medicine*, vol. 24, no. 8, pp. 1185–202.
- Street, A. 2003, 'How much confidence should we place in efficiency estimates?' *Health Economics*, vol. 12, pp. 895–907.
- Sundarajan, V., Henderson, T, Perry, C., Muggivan, A., Quan, H. and Ghali, W.A. 2004, New ICD version of the Charlson Index predicted in-hospital mortality, *Journal of Clinical Epidemiology*, vol. 57, pp. 1288-94.
- Taylor DH Jr, Whellan DJ, Sloan FA: Effects of admission to a teaching hospital on the cost and quality of care for Medicare beneficiaries. N Engl J Med 1999, 340(4):293-299.
- Thiel, H. 1967, *Economics and Information Theory*, North-Holland, Amsterdam.
- Vitikainen, K., Street, A. and Linna, M. 2009, 'Estimation of hospital efficiency-Do different definitions and casemix measures for hospital outputs affect the results?', *Health Policy*, vol. 89, pp. 149–59.
- Vitiliano D.F., and Toren, M., 1994, 'Cost and efficiency in nursing homes: a stochastic frontier approach', *Journal of Health Economics*, vol. 13, pp. 218– 300.
- Urbach, D.R. and Baxter N.N. 2004, 'Does it matter what a hospital is "high volume" for? Specificity of hospital volume-outcome associations for surgical procedures: analysis of administrative data' *Quality and Safety in Health Care*, vol. 13, no. 5, pp. 379-383.
- Wang, J. and Mahmood, A. 2000a, 'Efficiency of the NSW Public Acute Hospitals: An Application of the Data Envelopment Analysis*'*, in Bridges, J. (ed), *Economics and Health: 2000 – Proceedings of the Twenty-second Australian Conference of Health Economists*, University of New South Wales School of Health Services Management, Sydney.
- —— 2000b, 'Relative Efficiency of NSW Public Acute Hospitals: A Stochastic Frontier Cost Function Analysis', in Bridges*,* J. (ed), *Economics and Health:*  2000 *– Proceedings of the Twenty-second Australian Conference of Health Economists*, School of Health Services Management, University of New South Wales, Sydney.
- Wang, J., Zhao, Z. and Mahmood, A. 2006, 'Relative Efficiency, Scale Effect, and Scope Effect of Public Hospitals: Evidence from Australia', The Institute for the Study of Labor (IZA) Discussion paper No. 2520, Bonn
- Webster, R., Kennedy, S. and Johnson, L. 1998, *Comparing Techniques for Measuring the Efficiency and Productivity of Australian Private Hospitals*, Working paper no. 98/3, Australian Bureau of Statistics, Cat. no. 1351.0, Canberra.
- Wen, E., Sandoval, C., Zelmer, J., and Webster, G. 2008 'Understanding and using the hospital standardized mortality ratio in Canada' *Healthcare Papers*, vol. 8, no. 4, pp. 26–36.
- Weng, S-J., Wu, T., Blackhurst, J. and Mackulak, G. 2009, 'An extended DEA model for hospital performance evaluation and improvement', *Health Services and Outcomes Research Methodology*, vol. 9, no. 1, pp. 39–53.
- Werner, R.M and Bradlow, E.T. 2006 'Relationship between Medicare's hospital compare performance measures and mortality rates', *Journal of the American Medical Association*, vol. 296, pp. 2694–2702.
- Wilson, R.M., Runciman, W.B., Gibberd, R.W., Harrison, B.T., Newby, L. and Hamilton, J.D. 1995, 'The quality in Australian health care study', *Medical Journal of Australia*, vol. 163, no. 9, pp. 458–71.
- Winkleman, R. and Boes S., 2006 *Analysis of Microdata*, Springer, Berlin.
- Worthington, A. 2004, 'Frontier efficiency measurement in health care: a review of empirical techniques and selected applications', *Medical Care Research Review*, vol. 61, pp. 135–70.
- Yaisarwang, S. and Burgess, J.F. 2006, 'Performance-based budgeting in the public sector: an illustration from the VA health care system', *Health Economics,* vol. 15, pp. 295–310.
- Yong, K. and Harris, A. 1999, *Efficiency of Hospitals in Victoria Under Casemix Funding: A Stochastic Frontier Approach*, Centre for Health Program Evaluation, Working paper no. 92, Monash University, Melbourne.
- Yuan Z, Cooper GS, Einstadter D, Cebul RD, Rimm AA. 2000, 'The association between hospital type and mortality and length of stay: a study of 16.9 million hospitalized Medicare beneficiaries', *Medical Care*, 38(2):231-245.
- Zahn C., Baker M., MacNaughton J., Flemming C., and Bell R. 2008 'Hospital standardized mortality ratio is a useful burning platform', *Healthcare Papers*, vol. 8, no. 4, pp. 50–53.
- Zuckerman, S., Hadley, J. and Iezzoni, L. 1994, 'Measuring hospital efficiency with frontier cost functions', *Journal of Health Economics*, vol. 13, pp. 255–80.