Measuring the technical efficiency of public and private hospitals in Australia[1]

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Abstract

This paper presents estimates of the technical efficiency of public and private acute hospitals in Australia — the first study of its kind nationally. Within the private hospital sector, the paper differentiates between for-profit and not-for-profit hospitals, and separately identifies private hospitals that are contracted to provide public services. Applying a stochastic distance function, the analysis uses pooled nation-wide Australian Bureau of Statistics (ABS) and Australian Institute of Health and Welfare (AIHW) establishment and patient data from 2003-04 to 2006-07, weighted to align to the sector's profile. Two types of technical efficiency were estimated, each based on different assumptions about the production decisions of hospitals. Output-oriented efficiency represents the degree to which a hospital could expand its output without changing input use. Input-oriented efficiency represents the degree to which a hospital could economise on its input use without altering its output.

After accounting for factors outside of the control of hospitals (such as patient characteristics), the quality of hospital services (using hospital-standardised mortality ratios as a proxy) and the differing roles and functions of hospitals, Australian acute hospitals were estimated to have scope to improve their efficiency by about 10 per cent in

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the existing policy environment. On average, for-profit and public contract hospitals were estimated to be more efficient than public and not-for-profit private hospitals, 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.

While the method used in this paper offers an improvement on most previous Australian studies, there are still a number of data limitations which, if addressed, could produce more accurate estimation results.

1 Introduction

The Australian health system is under increasing pressure to deliver the same or improved health services using proportionately fewer resources. Many factors contribute to such pressures including the health demands of an ageing population, the development of new and more expensive medical technologies, greater community expectations for access to health services, and limits on the availability of health workers and government funding to support these higher expected levels of service. Quantifying the current level of inefficiency in the hospital system helps provide insight into the degree to which these pressures could be met by a more effective use of resources.

Although a large number of multivariate studies of hospital efficiency have been undertaken worldwide, there are only a few studies of Australian hospitals. 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). These studies vary in the technique used (data envelopment analysis (DEA) or stochastic frontier analysis (SFA)), the type of efficiency measured (cost or technical), the scope of the dataset, and the variables used to control for hospital quality or factors outside of the establishment's control. The findings of these studies indicate that:

- for-profit private hospitals are more technically efficient than not-for-profit private hospitals (Webster, Kennedy and Johnson 1998)
- metropolitan public acute hospitals are more technically efficient than smaller rural hospitals (SCRCSSP 1997; Wang and Mahmood 2000a)
- private hospitals give rise to better health outcomes than public hospitals (Chua, Palangkaraya and Yong 2008).

Some of these studies focused on private hospitals only (Webster, Kennedy and Johnson 1998), while others focused only on public hospitals (for example, Yong and

Harris 1999; Paul 2002). Of the Australian studies available for review, there are none spanning both public and private hospitals nation-wide.

The analysis in this paper extends the current literature by including both public and private hospitals in Australia. It makes the further distinction between for-profit and not-for-profit hospitals in the private sector, and separately identifies private hospitals that are contracted to provide public hospital services. The method used is most similar to that of Paul (2002), who also used a stochastic distance function approach. In addition to spanning a larger sample of hospitals, this analysis extends the work of previous studies with the inclusion of patient variables such as age and comorbidities, and the estimation of hospital-standardised mortality ratios to account for hospital quality. Another key feature of this analysis is the use of sample weights to align the sample dataset more closely to the profile of Australian hospitals.

The paper is structured as follows: section 2 explains the method used to estimate technical efficiency; section 3 details the data used; section 4 presents the results of the efficiency analysis; and section 5 discusses paths for improvement.

2 Method

Estimating technical efficiency

Following Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), inefficiency is measured as a component of the stochastic frontier regression equation. A single output stochastic frontier regression equation can be presented as:

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

where y_i is the dependent variable, x_i is a vector of the independent variables, v_i is the random error term, u_i is the inefficiency component, for hospital i and $f(\cdot)$ is the production function. The term v_i captures random variations across hospitals reflecting random events that might include measurement error or the effects of omitted factors which may not be measurable (Coelli et al. 2005). The same process for estimating technical efficiency can be applied to the multi-output multi-input production function used in this analysis.

Both of the terms v_i and u_i are assumed to be independent and identically distributed. It is assumed that the random error (v_i) adopts a normal distribution with a zero mean and a constant variance. The inefficiency component (u_i) can be assumed to have a half-normal, truncated half-normal, exponential or gamma distribution, with a positive mean. In this analysis 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.

Although the choice of u_i affects the estimated value of the efficiency scores it is not expected to significantly affect the ordinal rankings of individual hospitals (Kumbhakar and Lovell 2000). Robustness checks were performed which verified this expectation.

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

$$Index_i = \exp(-u_i) \quad (2)$$

Types of technical efficiency

In this analysis, hospital efficiency is assessed on the basis of both the output-oriented and input-oriented approaches. The output-oriented approach measures how much additional output a hospital could produce while still employing its current inputs. In this sense, efficiency can be interpreted as a hospital's productivity relative to best practice. This model orientation is appropriate for hospitals that have the flexibility to alter their level of output. This is more likely to be the case for private hospitals, which have greater capacity to raise revenue.

The input-oriented approach to technical efficiency measures how many fewer resources a hospital could employ and still produce the same level of output. In this context, efficiency can be interpreted as a hospital's resource intensity relative to best practice. This approach is appropriate for hospitals which have less flexibility to change their output, but can alter their use of inputs. This is more likely to be the case for public hospitals, which operate under a capped budget.

The output-oriented approach was estimated with an output distance function, while the input-oriented approach was estimated with an input distance function.

Output distance function

For the output distance function, the production technology of the hospital is defined with the output set $P(\mathbf{x})$ which represents the set of all output vectors $y \in R_+^M$ that can be produced using the input vector $x \in R_+^K$, where K and M are the total number of inputs and outputs respectively. An output distance function is defined by how much the output vector can be proportionally expanded by amount θ 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:

$$D_O(\mathbf{x},\mathbf{y}) = \min\left\{\theta : (\mathbf{y}/\theta) \in P(\mathbf{x})\right\} \quad (3)$$

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. Here the output distance for hospital *i* is equal to the random error term minus the inefficiency term:

$$D_{Oi} = \exp(v_i - u_i) \tag{4}$$

The distance D_{Oi} can be considered an estimate of output-oriented technical efficiency because the random error term (v_i) is distributed symmetrically around zero. It is assumed that the output distance function for hospital *i* is of a transcendental logarithmic (translog) form:

$$\ln D_{Oi} = TL(\mathbf{x}_i, \mathbf{y}_i, q_i, \mathbf{z}_i; \boldsymbol{\beta}) \tag{5}$$

where $TL(\cdot)$ refers to the translog function, q_i refers to a measure of hospital quality, $\mathbf{z}_i$ refers to a vector of factors outside the control of hospitals, and $\boldsymbol{\beta}$ refers to the coefficient vector. The homogeneity constraint requires that outputs are homogenous to degree one in outputs (Coelli et al. 2005). These constraints can be met by normalising equation (5) by the K*th* output:

$$\ln\left(\frac{D_{Oi}}{y_{iK}}\right) = TL(\mathbf{x}_i, \mathbf{y}_i^*, q_i, \mathbf{z}_i; \boldsymbol{\beta}) \tag{6}$$

where **y*** is the vector of normalised outputs. Equation (6) can be re-arranged with a random error term to give a variable returns to scale output distance function:

$$-\ln y_{iK} = TL(\mathbf{x}_i, \mathbf{y}_i^*, q_i, \mathbf{z}_i; \boldsymbol{\beta}) - \ln D_{Oi} \tag{7}$$

Hospital quality q_i is interacted with the $\boldsymbol{y}_i$ vector to test whether there is a significant relationship between the quantity of hospital services provided and mortality rates.

Input distance function

The production technology of the hospital is defined with the input set $L(\boldsymbol{y})$ 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 ρ 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:

$$D_I(\mathbf{x}, \mathbf{y}) = \max\left\{\rho : (\mathbf{x}/\rho) \in L(\mathbf{y})\right\} \tag{8}$$

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. Here the input distance for hospital *i* is equal to the random error term minus the inefficiency term:

$$D_{Ii} = \exp(v_i - u_i) \tag{9}$$

The distance D_{Ii} can be considered an estimate of input-oriented technical efficiency because the random error term (v_i) is distributed symmetrically around zero. The translog of the input distance function is given as:

$$\ln D_{Ii} = TL(\mathbf{y}_i, \mathbf{x}_i, q_i, \mathbf{z}_i; \boldsymbol{\beta}) \tag{10}$$

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:

$$\ln\left(\frac{D_{Ii}}{x_{iM}}\right) = TL(\mathbf{y}_i, \mathbf{x}_i^*, q_i, \mathbf{z}_i; \boldsymbol{\beta}) \tag{11}$$

where **x*** is the vector of normalised inputs. By rearranging the left-hand side variables and adding a random error term v_i, the equation to estimate variable returns to scale is obtained:

$$-\ln x_{iM} = TL(\mathbf{y}_i, \mathbf{x}_i^*, q_i, \mathbf{z}_i; \boldsymbol{\beta}) - \ln D_{Ii} \tag{12}$$

Input-oriented technical efficiency is inverted (divided into 1) for ease of interpretation.

Details of all the variables included in the technical efficiency equations are explained in section 3.

Comparing the differences between public and private hospitals

The paper presents the estimated efficiency scores of the different hospital types: public, for-profit private, not-for-profit private, and private hospitals contracted to provide public hospital services. To test whether any differences in their efficiency scores are statistically significant, efficiency scores were regressed as a function of three binary variables:

- *Private / Public or contracted* — to test for a 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 for a difference between for-profit private hospitals (assigned a value of ‘1’) and not-for-profit and all other hospitals (assigned a value of ‘0’)

- *Contract / Other* — to test for a difference between public contract hospitals (assigned a value of '1') and all other hospitals (assigned a value of '0').

These variables were regressed simultaneously with the other parameters and the random error term, in the same likelihood function (Kumbhakar and Lovell 2005).

For a stochastic distance function, the combined regression would be

$$-\ln x_{iM} = TL(\mathbf{x}_i, \mathbf{x}_i^*, q_i, \mathbf{z}_i; \boldsymbol{\beta}) + u_i - v_i \quad (13)$$

$$u_i = \mathbf{a}_i'\boldsymbol{\delta} + \xi_i \quad (14)$$

where $\mathbf{a}_i$ is a vector of ownership group variables for hospital *i*, $\boldsymbol{\delta}$ is the vector of coefficients for those variables and ξ_i is the independently and identically distributed error.

Accounting for quality and effectiveness of care

The quality and effectiveness of hospital care needs to be taken into account when considering hospital efficiency. Ideally this would involve an indicator of the incremental change in a patient's health following an episode of care, but such an indicator is not readily available at the hospital level (PC 2009). Previous studies of hospital efficiency have used adverse events, hospital-acquired infections, unplanned re-admissions or in-hospital mortality as indicators of hospital quality (Herr 2008; Yaisarwang and Burgess 2006; Linna 1998; Zuckerman, Hadley and Iezzoni 1994; SCRCSSP 1997). Some data for each of these variables are included in the National Hospital Morbidity Database (NHMD), although current reporting methods for the first three of these variables suffer from a number of limitations that reduce their usefulness as a measure of quality.

To control for hospital quality, this analysis consequently used a measure of in-hospital mortality adjusted for factors that are beyond the control of a hospital but may still influence the level of in-hospital mortality — referred to as a hospital-standardised mortality ratio (HSMR). While HSMRs are only a partial measure of patient outcomes, there is evidence that in-hospital mortality is correlated with the processes of care for a range of conditions (Jha et al. 2007; Werner and Bradlow 2006). The use of standardised mortality ratios was demonstrated by Paul (2002).

The HSMR is the ratio of the number of observed deaths in a given hospital divided by the number of deaths that would have been expected, after adjusting for factors that affect the likelihood of in-hospital death, multiplied by 100. The number of expected in-hospital deaths for a given hospital were estimated using a negative binomial regression, while controlling for a range of hospital and patient characteristics that are likely to affect in-hospital mortality. This negative binomial approach was used by Korda et al. (2007) to examine the effect of health care on avoidable mortality rates in Australia. This method differs, however, from the common method of producing HSMRs, where the expected mortality rate of a hospital is predicted from a logistic regression using patient-level data (see, for example, Ben-Tovim, Woodman, Harrison et al. 2009; CIHI 2007, 2010; Heijink et al. 2008). This logistic regression approach, however, was not possible in this analysis due to the unavailability of patient-level data.

In the estimation of the HSMRs, the choice of factors to control for was drawn largely from Ben-Tovim, Woodman, Harrison et al. (2009); CIHI (2010); Heijink et al. (2008); Wen et al. (2008). Patient characteristics included: age, gender, Indigenous status, average length of stay, socioeconomic status, major diagnostic category and transfer status. Hospital characteristics included: services offered, teaching status, the ratio of emergency services to total separations, hospital size and the degree of both complexity and specialisation of cases treated.[2]

3 Data

The dataset used in this analysis consisted of 459 acute hospitals, which amounted to a total of 1806 observations for the years 2003-04 to 2006-07. The observations comprised:

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

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). Data on private hospital establishments were drawn from the Private Health Establishments Collection (PHEC) held by the Australian Bureau of Statistics (ABS). Patient-level data on morbidity for both public and private hospitals were drawn from the National Hospital Morbidity Database (NHMD) held by the AIHW.

The dataset captures nearly all public acute hospitals and approximately 42 per cent of all private hospitals in Australia. Psychiatric hospitals, free-standing day hospitals and sub-acute and non-acute facilities were excluded from the analysis because they generally offer a more limited range of services compared to acute overnight hospitals.

Since data on private hospitals were only made available on a voluntary basis, it is acknowledged that the sample of private sector data used in this analysis may not be fully representative of Australia's private hospital sector. In particular, there is a

2 A more detailed explanation of the estimation process of HSMRs is available in PC (2010).

under-representation of not-for-profit hospitals compared to for-profit hospitals: not-for-profit hospitals comprise around 43 per cent of all private hospitals in Australia (AIHW 2009a) but only 15 per cent of the sample of private hospitals in the analysis. This also leads to an under-representation of the smaller-sized private hospitals, as many of these are not-for-profit establishments.

To align the sample to the true profile of the private hospital sector, sampling weights were applied in the estimation process, as detailed in PC (2010). These weights captured the extent to which hospitals of different sizes and different locations were represented in the sample. This means that the mean efficiency scores are a more accurate representation of any hospital in Australia of a given size or location, even if the hospital was not included in the dataset. This weighting technique, however, cannot control for the possibility that hospitals with different levels of efficiencies may have a different likelihood of participating in the study. Attempts to control for this type of non-random sampling would require additional data about the non-participating hospitals. To the extent that non-participating hospitals may be relatively less efficient, the mean efficiency scores of not-for-profit hospitals may be over-estimated. However, given that the estimated position of the best-practice frontier is largely shaped by the best-performing hospitals and should be relatively insensitive to the omission of inefficient observations, the estimated scores of the remaining groups are unlikely to be affected by this sampling issue.

Variables used in the efficiency analysis

The variables used to explain efficiency include:

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

As is common practice in efficiency analysis, all input and output variables were specified in natural logarithms so that the measures represented proportional values rather than absolute levels.[3] All logarithmic variables were mean-centred to improve the ease of interpreting the coefficient values. Mean-centering is the process of subtracting the mean of a variable from every individual observation of that variable. The normalising variable in each of the functions was inverted, which has the effect of reversing the signs of the coefficients for that function.

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 PC (2010).

The summary statistics of these variables disaggregated by hospital ownership are presented in tables 3 and 4 in the appendix.

Outputs

Admitted patient services

The categories for admitted patient services were measured as the number of casemix-adjusted separations based on major diagnostic categories (MDCs):

- acute separations (MDC 2 to 13, 16 to 18, 21 and 22)
- pregnancy and neonate separations (MDC 14 and 15)
- mental and alcohol separations (MDC 19 and 20)
- other separations (MDC 23)
- normalising variable (MDC 1).

MDC 1 served as the normalising output variable in the output-oriented distance function because 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. 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.

Non-admitted patient services

Since there is no national casemix classification for non-admitted patient services, there was a greater need to disaggregate non-admitted patient services at a more detailed level than for admitted patient care. Measured as the number of occasions of service, the output categories were:

- accident and emergency services
- allied health, dental and other outpatient services
- mental, alcohol and psychiatric services
- dialysis and endoscopy[4]

[4] It is recognised that some jurisdictions treat patients who are undergoing dialysis or endoscopy as admitted patients while others treat them as non-admissions.

- diagnostic (pathology and radiology) services
- community services, district nursing and other outreach services.

Other output variables

For the hospital quality regressions, two other variables were used. First, a ratio measure of the number of accident and emergency occasions of services to the number of casemix-adjusted separations was used to capture a hospital's volume of accident and emergency services relative to its total size of operation. This, in part, accounts for differences between hospitals in the overall severity of their cases, allowing for a corresponding difference in mortality risk. Second, the proportion of patients treated with surgical and other procedures was used to reflect the extent to which a hospital specialises in surgical and other diagnosis-related group (DRG) cases, as opposed to medical DRG cases which require a different level of resource intensity. This distinction also affects mortality risk.

Due to the structure of the model, in the output-oriented distance function, the coefficients of output variables should be negatively signed, reflecting that as a hospital's outputs increase for a given set of inputs, so does its productivity. In the input-oriented distance function, outputs should be positively signed, reflecting that as a hospital's outputs increase for a given set of inputs, there is a decline in resource intensity.

Inputs

Staff

Staff variables were measured as the number of full-time-equivalent staff for the following categories:

- nursing staff
- diagnostic (pathology and radiology) and allied staff
- other (domestic, administration and other) staff.

Since there was no available data on the number of doctors who exercise their rights of private practice in public and private hospitals, medical staff had to be excluded as an input in the analysis. This exclusion is equivalent to assuming that hospitals employ their medical staff in fixed proportion to their other inputs. The extent to which this is the case, however, is unknown. Therefore, the estimated efficiency scores should not be interpreted to reflect specifically the performance of a hospital's medical workforce.

Supplies and other inputs

The following variables relating to supplies and other inputs were used:

- medical and surgical supplies (constant price expenditure)
- pharmaceutical supplies (constant price expenditure)
- other inputs (constant price expenditure on other hospital inputs, such as administration and clerical services, housekeeping, and repairs and maintenance)
- number of staffed beds (as a proxy for capital).

All expenditure variables were deflated by their respective components from ABS *Hospital Cost Index* (ABS 2008c). The number of staffed beds was used as the normalising variable. Adjustments were made to this variable to attempt to ensure consistency between the public and private reporting systems.[5]

In the output-oriented distance function, the input variables are expected to be positively signed, indicating that an increase in the use of an input reduces productivity. In the input-oriented distance function, inputs are expected to be negatively signed, indicating that an increase in the use of an input increases resource intensity, for a given level of output.

Patient-risk characteristics

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

- age (1-4 years, 5-19 years, 20-59 years, 60-69 years, 70 years and older)
- socioeconomic status (measured by the Socio-economic Index for Areas — Index of Relative Disadvantage and Advantage (SEIFA index)) (ABS 2008b)
- Charlson index of comorbidity (Charlson et al. 1987).[6]

Although patients' indigenous status would have enhanced the patient profile, this variable could not be used due to unreliability of data (AIHW 2010).

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5 Public hospitals report the *number of staffed beds* (AIHW 2009), while private hospitals report the *number of total available beds* (ABS 2008a). It was inferred that the private hospital variable referred to total beds, which would therefore be higher than staffed *beds*. An estimation of the number of staffed beds in private hospitals was therefore used as a comparable measure to the public hospital variable, as outlined in PC (2010). It was since learnt that the ABS definition of *total available beds* is equivalent to staffed beds. However, the extent to which this adjustment affects the comparative efficiency scores is unclear.

6 The Charlson index is an odds-ratio of the risk of mortality within one year. For example, a Charlson score of 6 indicates a 6:1 (or 86 per cent) chance of the patient dying within one year.

In the output-oriented distance function, a negatively-signed coefficient would indicate that hospitals with proportionally more patients with the respective characteristic are expected to be less productive. In the input-oriented distance function, a positively-signed coefficient would indicate that hospitals with proportionally more patients with this characteristic are expected to be more resource-intensive.

Hospital establishment characteristics

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

- remoteness (defined by the Australian Standard Geographical Classification Remoteness Area (ASGC-RA)) (ABS 2005)
- specialist facilities (palliative care unit, high-level intensive care unit, residential care unit, domiciliary care unit, and rehabilitation unit)
- teaching status
- proportion of patients who are treated as public patients
- network membership
- Evans and Walker index (Evans and Walker 1972).

Hospital remoteness reflects the differences in resource availability, as well as differences in hospitals' service responsibilities within the health system. Data on the presence of specialist units was intended to augment existing data on hospital beds as a measure of a hospital's capital. Teaching status was defined according to whether a hospital was affiliated with a university to provide undergraduate medical education. The proportion of patients with public patient status was used as a proxy measure for the different incentives faced by hospitals when treating public and non-public patients. Network membership reflects the management structures of some hospitals in Victoria. The Evans and Walker index is a measure of the relative complexity of work undertaken by hospitals, adjusted for establishment size.

Hospital quality

The HSMR variable shows the extent to which a hospital's investment in its level of quality affects its level of productivity or resource-intensity. In the output-oriented distance function, a negatively-signed coefficient would indicate that hospitals with higher-than-expected HSMRs are expected to be less productive. In the input-oriented distance function, a positively-signed coefficient would indicate that hospitals with higher-than-expected HSMRs are expected to be more resource intensive.

4 Results

The estimated coefficients of the output-oriented model and the input-oriented model are presented in appendix tables 5 and 6 respectively. The significance of the coefficients are found to differ, to some degree, depending on 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).

Based on preliminary regressions, the output and input variables which generated incorrectly-signed coefficients were omitted from the final models. 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). It is possible that the incorrect signs for these variables could be attributed to inconsistencies or other limitations in their data collection.

To test each model's sensitivity to the choice of the half-normal distribution for the inefficiency error term, the models were also estimated with an exponential distribution. A Spearman's rank test showed that the relativities of the efficiency scores did not significantly differ between the two distributions (PC 2010).

Coefficient results

The results indicate that the most important output to influence both 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 was 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 are found 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 are 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; 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 score 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 that do not have a significant impact on expected resource intensity are: patients' socioeconomic status; 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 differ 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 value of the ownership coefficients could not be published due to confidentiality requirements for private hospital data.[7] 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 signs and magnitude of these terms in 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 large enough to suggest 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.

7 Due to confidentiality restrictions, the coefficients of the terms σ^2_u and σ^2_v 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.

Technical efficiency scores

The technical efficiency scores of the output-oriented and input-oriented models are reported in table 1 according to hospital ownership and establishment size. An averaged measure of the efficiency scores generated by both models (averaged at the individual observation level) is also reported.

Table 1 **Technical efficiency scores by hospital ownership and size**[a]

	Public	*Private*			*Public contract*	*All hospitals*
		Not-for-profit	*For-profit*	*All*		
Very small						
Output-oriented	87.5	88.0	94.2	89.9	np	87.6
Input-oriented	89.0	92.7	92.5	92.9	np	89.1
Averaged	88.2	90.4	93.3	91.4	np	88.3
No. observations	558	20[b]	np	np	np	581
Small						
Output-oriented	89.7	88.0	94.9	94.2	np	90.8
Input-oriented	88.5	92.7	92.9	92.8	np	89.6
Averaged	89.1	90.4	93.9	93.5	np	90.2
No. observations	222	20[b]	np	np	np	295
Medium						
Output-oriented	89.5	77.9	94.8	91.8	np	90.5
Input-oriented	88.5	87.9	91.2	90.6	np	89.5
Averaged	89.0	82.9	93.0	91.2	np	90.0
No. observations	167	22	np	np	np	295
Large						
Output-oriented	90.1	88.1	94.2	93.0	93.1	91.4
Input-oriented	89.6	88.2	90.7	90.2	93.3	90.3
Averaged	89.8	88.2	92.5	91.6	93.2	90.8
No. observations	155	17	68	85	39	279
Very large						
Output-oriented	91.4	87.8	95.7	92.5	90.7	91.6
Input-oriented	90.1	91.2	93.1	92.4	94.6	90.8
Averaged	90.7	89.5	94.4	92.4	92.7	91.2
No. observations	252	35	52	87	17	356
All hospitals						
Output-oriented	89.1	85.6	94.8	92.6	92.4	90.0
Input-oriented	89.1	90.2	91.8	91.4	93.6	89.8
Averaged	89.1	87.9	93.3	92.0	93.0	89.9
No. observations	1354	94	295	389	63	1806

a Additional statistics (median and percentile values) are reported in PC (2010). Hospital size is defined by number of casemix-adjusted separations (cms) per year, where very large is 20 001 or more cms; large is 10 001 to 20 000 cms; medium is 5001 to 10 000 cms; small is 2001 to 5000 cms; and very small is 2000 or fewer cms. **b** Due to ABS confidentiality restrictions, the small and very small categories are aggregated for not-for-profit private hospitals. 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.

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 would 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.

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 would mean that the hospital is using 25 per cent more inputs than necessary to produce its current output level, or equivalently, that it could reduce its input use by 20 per cent and still produce the same volume of output.

Comparisons across all hospitals

Based on the averaged efficiency scores, hospitals in Australia are performing at around 90 per cent of their potential efficiency (table 1). 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 on input use. On average, the most efficient hospitals are for-profit private hospitals, followed closely by public contract hospitals, and then by 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.

Comparisons between the two model orientations highlight further differences by hospital ownership. The greatest gap between the output-oriented and input-oriented model 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.

Due to their different production behaviours, it was expected that the input-oriented approach would favour public hospitals, while the output-oriented approach would favour private hospitals. However, this expectation does not imply that the efficiency scores of public hospitals are expected to be higher under the input-oriented model than under the output-oriented model. It also does not necessarily imply 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 narrows to 2.3 percentage points under the input-oriented model.

Model orientation is also found to affect the gap between for-profit and not-for-profit private hospitals: this gap increases to around 9 percentage points in the output-oriented model, yet falls 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.

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 external limitations potentially placed on their capacity to expand production or reduce resources.

Comparisons by hospital size

In some cases, levels of efficiency, as well as the relativities between types of hospital ownership, are found to vary by hospital size (table 1). For example, the gap between the output-oriented efficiency scores for for-profit private hospitals and public hospitals tends to widen among the smaller size categories. Furthermore, while the output-oriented scores for for-profit private hospitals are fairly stable across hospital sizes, there is greater variation across sizes among public hospitals. Specifically, larger public hospitals are found to be noticeably more efficient than smaller public hospitals. One possible explanation for this is that smaller public hospitals experience lower occupancy rates due the requirement that they operate at a minimum size but typically treat relatively low numbers of patients in remote areas.[8] Among the not-for-profit private hospitals, the output-oriented efficiency of medium hospitals is also noticeably lower than that of all other hospitals. However, given the comparatively few observations in this sample, this result may reflect an outlier observation.

In terms of input-oriented 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.

Correlations between output- and input-orientations

To examine whether or not hospitals which perform well in terms of maximising output also perform well in terms of economising on resource use, correlation tests were conducted between the output- and input-oriented efficiency scores (table 2).

Table 2 **Correlation between output- and input-oriented efficiency scores**

	Public	*Private*			*Public contract*	*All hospitals*
		Not-for-profit	*For-profit*	*All*		
Very small	0.585	0.126[a]	0.304	-0.168	np	0.569
Small	0.322		0.690	0.664	np	0.416
Medium	0.335	0.868	0.557	0.685	np	0.507
Large	0.571	0.638	0.476	0.532	0.397	0.560
Very large	0.337	0.301	0.531	0.382	0.493	0.336
All hospitals	0.486	0.683	0.550	0.539	0.412	0.500

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 table 1.

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

8 Small and very small public hospitals report an occupancy rate of 54.5 per cent, compared to 80 per cent or above for medium, large and very large public hospitals (PC 2010).

Across all sizes, private hospitals show a higher degree of correlation between their scores compared to public hospitals and contracted hospitals. This suggests that private hospitals are relatively more capable of both expanding output while also economising on inputs. With the possible 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 further 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.

5 Scope for improvement in efficiency analysis

There are a number of ways in which more accurate estimates of hospital efficiency could be achieved with improvements in data reporting.

Firstly, the count of beds is not a complete measure of a hospital's capital because, ideally, capital measures should be disaggregated according to categories of activity. Such categories could include the number of ICU beds, non-acute beds, palliative care beds, same-day chairs and operating theatres. While hospital capital was partly captured in the analysis by variables which reflected hospitals' roles and functions, the analysis could be improved by the availability of more detailed data. Furthermore, it would be preferable for total physical beds to be reported, rather than staffed beds, as this would be a more accurate measure of a hospital's total capital.

Secondly, the analysis could be improved with the availability of data on medical staff. Currently, there is no reliable reporting of the number of doctors practising privately in both private and public hospitals.

Thirdly, while the use of HSMRs as a proxy for hospital quality offered a significant improvement on unadjusted in-hospital mortality rates, it is recognised that mortality rates are only one dimension of hospital quality. Improvements in the reporting of other indicators — such as unplanned re-admission rates, infection rates and adverse events — would substantially improve the scope for analysing hospital quality and its relationship with efficiency.

Fourth, there are recognised deficiencies in the reporting of non-admitted patient data. This analysis could be improved with more consistent methods of reporting non-admitted patient services and with adjustments made for differences in the casemix.

Appendix

Table 3 **Profile of sample hospitals, by establishment and patient characteristics**

	Public	*Private*	*Public contract*
Establishment characteristics			
Teaching hospital	17.8	24.2	44.4
Member of network	12.0	0	6.3
Medical DRGs	77.9	42.3	63.8
Surgical and other DRGs	22.1	57.7	36.2
Public patient	83.4	1.0	75.4
Non-public patient	16.6	99.0	24.6
Same-day separations	40.9	52.7	47.0
Emerg. to admissions ratio	3.0	0.1	1.2
Admissions from other hospital (%)	8.6	2.1	5.0
Evans and Walker Index 2 (average score)	0.5	0.5	0.8
Palliative-care unit (%)	14.5	4.9	36.5
High-level ICU (%)	19.9	19.3	44.4
Rehabilitation unit (%)	26.0	21.9	23.8
Patient characteristics (% of patients)			
Female	53.1	54.5	55.5
Aged less than 1 year	2.2	1.1	2.9
Aged 1-4 years	3.2	1.4	3.4
Aged 5-19 years	4.4	2.1	4.3
Aged 20-59 years	44.6	45.9	49.0
Aged 60-69 years	13.3	16.3	13.1
Aged 70+ years	28.8	30.7	24.2
From major city	25.9	67.3	77.8
From inner regional	34.2	24.9	15.5
From outer regional	27.8	7.1	6.3
From remote	5.8	0.5	0.3
From very remote	6.3	0.2	0.1
SEIFA 1 (most disadvantaged)	40.5	15.2	18.4
SEIFA 2	27.5	14.7	18.2
SEIFA 3	16.1	23.3	19.6
SEIFA 4	9.7	23.4	23.4
SEIFA 5 (most advantaged)	6.2	23.4	20.4
Charlson score 0 (fewest comorbidities)	72.0	77.8	70.8
Charlson score 1	10.59	6.36	8.02
Charlson score 2	11.06	9.00	13.57
Charlson score 3	1.86	1.36	1.62
Charlson score 4	1.49	0.47	1.18
Charlson score 5	2.50	4.65	3.90
Charlson score 6 or more (most comorbidities)	0.53	0.34	0.87
Number of observations	**1354**	**389**	**63**

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

Table 4 Profile of sample hospitals, by outputs and inputs

	Public	*Private*	*Public contract*
Outputs — admitted patient separations (number)			
Total separations	11 312.4	12 408.0	18 261.5
Casemix-adjusted separations	11 747.1	13 397.8	19 842.7
MDC 1 separations	896.2	478.2	1 347.2
Acute separations	9 432.3	11 609.1	15 460.9
Pregnancy and neonate separations	1 265.0	844.7	1 824.9
Mental and alcohol separations	577.7	149.3	755.3
Other separations	468.6	650.4	454.3
Outputs — non-admitted patient occasions of service (number)			
Accident and emergency	15 318.7	2 633.2	22 628.9
Allied health and dental	11 529.6	600.0	12 092.6
Mental, alcohol and psychiatric services	5 883.8	12.1	16 960.1
Dialysis and endoscopy	118.1	381.4	101.6
District nursing and outreach	5 271.8	20.5	5 314.4
Pathology and radiology	26 262.3	3 611.3	30 749.6
Other outpatients	25 332.1	289.0	31 635.4
Inputs			
Nursing staff (no.)	233.8	147.5	338.3
Diagnostic & allied health staff (no.)	76.0	8.1	114.5
Other non-medical staff (no.)	161.9	76.8	241.0
Medical & surgical supplies cost ($'000)	5 357.6	3 088.7	8 513.2
Pharmaceutical supplies ($'000)	3 049.0	1 215.5	5 782.9
Other inputs ($'000)	7 781.2	11 68.6	15 222.2
Staffed beds (no.)[a]	122.6	118.1	180.0
Number of observations	**1354**	**389**	**63**

[a] Public hospital beds are reported staffed beds, and private and public contract hospital beds are estimated staffed beds.

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

Table 5 Coefficient estimates — output-oriented distance function[a]

	Coefficient	Standard error	z-value
Frontier equation			
Outputs			
Acute separations	-0.4682 ***	0.0155	-30.21
Acute separations — squared	-0.0174 ***	0.0019	-8.95
Pregnancy & neonate separations	-0.0916 ***	0.0116	-7.90
Pregnancy & neonate separations — squared	-0.0422 ***	0.0060	-7.01
Mental & alcohol separations	-0.0576 ***	0.0076	-7.60
Mental & alcohol separations — squared	-0.0052 **	0.0023	-2.29
Other separations	-0.0841 ***	0.0080	-10.49
Other separations — squared	-0.0359 ***	0.0030	-12.05
Accident & emergency occasions of services	-0.0568 ***	0.0185	-3.08
Accident & emergency occasions of service — squared	-0.0196 **	0.0090	-2.17
Pathology & radiology occasions of service	-0.0229 *	0.0138	-1.66
Pathology & radiology occasions of service — squared	-0.0168 ***	0.0054	-3.09
Dialysis & endoscopy occasions of service	-0.0077	0.0159	-0.49
Dialysis & endoscopy occasions of service — squared	-0.0027 **	0.0013	-2.05
Allied health & dental occasions of service	-0.0187	0.0119	-1.57
Allied health & dental occasions of service — squared	0.0051	0.0046	1.11
Mental, alcohol & psychiatric occasions of services	-0.0168	0.0121	-1.39
Mental, alcohol & psychiatric occasions of services — squared	-0.0012	0.0014	-0.80
Inputs			
Nursing staff	0.1393 ***	0.0227	6.13
Nursing staff — squared	0.0483	0.0580	0.83
Diagnostic & allied health staff	0.0067	0.0104	0.65
Diagnostic & allied health staff — squared	0.0063	0.0075	0.83
Drug costs	0.1404 ***	0.0155	9.06
Drug costs — squared	0.0985 ***	0.0214	4.59
Supplies costs	0.1041 ***	0.0164	6.35
Supplies costs — squared	0.0535	0.0430	1.24
Other costs	0.0533 ***	0.0141	3.79
Other costs — squared	0.0804 ***	0.0249	3.23
Beds	0.2573 ***	0.0168	15.35
Beds — squared	-0.0154	0.0260	-0.59
Quality indicator			
HSMR	-0.0323 ***	0.0123	-2.62
HSMR — squared	0.0047	0.0033	1.45
Outputs — cross terms			
Acute seps × Preg & neo seps	0.0205 *	0.0115	1.78
Acute seps × Mental & alc seps	0.0381 ***	0.0064	5.95
Acute seps × Other seps	0.0731 ***	0.0072	10.21
Acute seps × Acc & emerg sv	0.0151 ***	0.0053	2.86
Acute seps × Path & rad sv	0.0141	0.0098	1.44

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Table 5 (continued)

	Coefficient		*Standard error*	*z-value*
Acute seps × Dial & endo sv	0.0080		0.0073	1.10
Acute seps × Allied & dental sv	0.0049		0.0040	1.21
Acute seps × Mental, alc & psych sv	-0.0412	***	0.0025	-16.48
Preg & neo seps × Mental & alc seps	0.0091	***	0.0029	3.13
Preg & neo seps × Other seps	-0.0033		0.0045	-0.74
Preg & neo seps × Acc & emerg sv	0.0072		0.0060	1.20
Preg & neo seps × Path & rad sv	-0.0280	***	0.0069	-4.07
Preg & neo seps × Dial & endo sv	-0.0055		0.0038	-1.45
Preg & neo seps × Allied health & dent sv	0.0045		0.0062	0.72
Preg & neo seps × Mental, alc & psych sv	0.0039		0.0043	0.90
Mental & alc seps × Other seps	-0.0182	***	0.0035	-5.22
Mental & alc seps × Acc & emerg sv	0.0073	*	0.0038	1.90
Mental & alc seps × Path & rad sv	-0.0013		0.0049	-0.26
Mental & alc seps × Dial & endo sv	-0.0074	**	0.0031	-2.40
Mental & alc seps × Allied health & dent sv	-0.0060		0.0045	-1.34
Mental & alc seps × Mental & alc & psych sv	0.0015		0.0041	0.37
Other seps × Acc & emerg sv	0.0194	***	0.0050	3.88
Other seps × Path & rad sv	-0.0097	*	0.0058	-1.66
Other seps × Dial & endo sv	0.0048		0.0052	0.94
Other seps × Allied health & dent sv	-0.0015		0.0040	-0.38
Other seps × Mental, alc & psych sv	0.0024		0.0048	0.50
Acc & emerg sv × Path & rad sv	0.0126	**	0.0059	2.14
Acc & emerg sv × Dial & endo sv	0.0000		0.0089	0.00
Acc & emerg sv × Allied health & dent sv	-0.0126	**	0.0059	-2.12
Acc & emerg sv × Mental, alc & psych sv	0.0002		0.0066	0.02
Path & rad sv × Dial & endo sv	-0.0012		0.0059	-0.20
Path & rad sv × Allied health & dent sv	0.0046		0.0055	0.85
Path & rad sv × Mental, alc & psych sv	0.0039		0.0055	0.72
Dial & endo sv × Allied health & dent sv	-0.0040		0.0049	-0.81
Dial & endo sv × Mental, alc & psych sv	0.0027		0.0029	0.93
Allied health & dent sv × Mental, alc & psych sv	-0.0003		0.0045	-0.07
Inputs — cross terms				
Nursing staff × Diag & allied health staff	-0.0683	**	0.0341	-2.00
Nursing staff × Drug cost	0.0282		0.0728	0.39
Nursing staff × Supplies cost	0.0235		0.0796	0.29
Nursing staff × Other cost	-0.0420		0.0560	-0.75
Nursing staff × Beds	-0.0031		0.0491	-0.06
Diag & allied health staff × Drug cost	-0.0003		0.0243	-0.01
Diag & allied health staff × Supplies cost	-0.0380		0.0295	-1.28
Diag & allied health staff × Other cost	0.0615	**	0.0257	2.39
Diag & allied health staff × Beds	0.0107		0.0224	0.48
Drug cost × Supplies cost	-0.2191	***	0.0467	-4.69
Drug cost × Other cost	-0.0095		0.0468	-0.20
Drug cost × Beds	-0.0303		0.0595	-0.51
Supplies cost × Other cost	-0.0829		0.0538	-1.54
Supplies cost × Beds	0.1282	**	0.0590	2.17

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Table 5 (continued)

	Coefficient	Standard error	z-value
Other costs × Beds	-0.0847 **	0.0333	-2.55
Outputs & inputs — cross terms			
Acute seps × Nursing staff	-0.0525 ***	0.0197	-2.66
Acute seps × Diag & allied health staff	-0.0107	0.0078	-1.37
Acute seps × Drug costs	-0.0241 *	0.0146	-1.65
Acute seps × Supplies costs	0.0388 ***	0.0082	4.75
Acute seps × Other costs	0.0150	0.0095	1.58
Acute seps × Beds	0.0225	0.0159	1.41
Preg & neo seps × Nursing staff	-0.0029	0.0239	-0.12
Preg & neo seps × Diag & allied health staff	-0.0066	0.0068	-0.97
Preg & neo seps × Drug costs	0.0273	0.0184	1.48
Preg & neo seps × Supplies costs	0.0048	0.0224	0.21
Preg & neo seps × Other costs	-0.0221	0.0135	-1.64
Preg & neo seps × Beds	-0.0170	0.0179	-0.95
Mental & alc seps × Nursing staff	-0.0050	0.0175	-0.29
Mental & alc seps × Diag & allied health staff	0.0133 **	0.0061	2.17
Mental & alc seps × Drug costs	-0.0414 ***	0.0148	-2.80
Mental & alc seps × Supplies costs	0.0385 ***	0.0134	2.87
Mental & alc seps × Other costs	-0.0129	0.0127	-1.01
Mental & alc seps × Beds	-0.0036	0.0151	-0.24
Other seps × Nursing staff	0.0121	0.0208	0.58
Other seps × Diag & allied health staff	0.0099	0.0077	1.28
Other seps × Drug costs	0.0135	0.0166	0.81
Other seps × Supplies costs	-0.0183	0.0148	-1.24
Other seps × Other costs	-0.0420 ***	0.0134	-3.13
Other seps × Beds	0.0262	0.0163	1.61
Acc & emerg sv × Nursing staff	0.0303	0.0258	1.18
Acc & emerg sv × Diag & allied health staff	-0.0099	0.0081	-1.23
Acc & emerg sv × Drug costs	0.0490 ***	0.0169	2.90
Acc & emerg sv × Supplies costs	0.0378 **	0.0164	2.31
Acc & emerg sv × Other costs	0.0005	0.0146	0.03
Acc & emerg sv × Beds	-0.0873 ***	0.0211	-4.14
Path & rad sv × Nursing staff	0.0942 ***	0.0274	3.44
Path & rad sv × Diag & allied health staff	-0.0279 ***	0.0102	-2.73
Path & rad sv × Drug costs	-0.0420 *	0.0217	-1.94
Path & rad sv × Supplies costs	-0.0071	0.0211	-0.34
Path & rad sv × Other costs	-0.0327 **	0.0167	-1.96
Path & rad sv × Beds	0.0189	0.0205	0.92
Dial & endo sv × Nursing staff	-0.0385	0.0382	-1.01
Dial & endo sv × Diag & allied health staff	0.0054	0.0136	0.39
Dial & endo sv × Drug costs	-0.0102	0.0184	-0.56
Dial & endo sv × Supplies costs	0.0106	0.0171	0.62
Dial & endo sv × Other costs	0.0236 **	0.0100	2.36
Dial & endo sv × Beds	0.0268	0.0270	0.99
Allied health & dent sv × Nursing staff	0.0407 *	0.0237	1.71

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Table 5 (continued)

	Coefficient	*Standard error*	*z-value*
Allied health & dent sv × Diag & allied health staff	0.0230 ***	0.0087	2.64
Allied health & dent sv × Drug costs	-0.0459 ***	0.0179	-2.57
Allied health & dent sv × Supplies costs	-0.0154	0.0195	-0.79
Allied health & dent sv × Other costs	0.0459 ***	0.0155	2.95
Allied health & dent sv × Beds	-0.0552 ***	0.0176	-3.14
Mental, alc & psych sv × Nursing staff	-0.0230	0.0258	-0.89
Mental, alc & psych sv × Diag & allied health staff	-0.0103	0.0110	-0.93
Mental, alc & psych sv × Drug costs	0.0112	0.0193	0.58
Mental, alc & psych sv × Supplies costs	0.0258 *	0.0137	1.88
Mental, alc & psych sv × Other costs	0.0205	0.0147	1.39
Mental, alc & psych sv × Beds	-0.0170	0.0197	-0.86
Quality indicator — cross terms			
HSMR × Acute seps	-0.0134 ***	0.0046	-2.94
HSMR × Preg & neo seps	-0.0092	0.0072	-1.28
HSMR × Mental & alc seps	0.0136 ***	0.0051	2.66
HSMR × Other seps	0.0159 **	0.0068	2.34
HSMR × Acc & emerg sv	0.0047	0.0096	0.48
HSMR × Path & rad sv	-0.0218 *	0.0112	-1.95
HSMR × Dial & endo sv	-0.0146	0.0116	-1.26
HSMR × Allied health & dent sv	0.0051	0.0106	0.48
HSMR × Mental & alc sv	0.0075	0.0079	0.95
Patient characteristics[b]			
Share of patients aged <1 year	-0.0056 **	0.0028	-2.00
Share of patients aged 1-4 years	0.0088 ***	0.0033	2.68
Share of patients aged 5-19 years	-0.0045 *	0.0025	-1.79
Share of patients aged 60-69 years	0.0014	0.0010	1.45
Share of patients aged 70+ years	-0.0022 ***	0.0004	-5.79
Share of patients from SEIFA 1	0.0000	0.0002	-0.19
Share of patients from SEIFA 2	-0.0002	0.0002	-0.99
Share of patients from SEIFA 3	0.0003	0.0002	1.55
Share of patients from SEIFA 4	-0.0002	0.0003	-0.71
Share of patients with Charlson score 2	-0.0007 *	0.0004	-1.80
Share of patients with Charlson score 3	-0.0070 ***	0.0024	-2.97
Share of patients with Charlson score 4	-0.0024 ***	0.0009	-2.61
Share of patients with Charlson score 5	-0.0016	0.0010	-1.59
Share of patients with Charlson score 6+	0.0289 ***	0.0082	3.54
Establishment characteristics[c]			
Located in major city	0.0259 **	0.0103	2.52
Located in outer regional area	-0.0494 ***	0.0091	-5.41
Located in remote area	-0.1468 ***	0.0173	-8.48
Located in very remote area	-0.2353 ***	0.0196	-11.98
Surgical & other DRG separations	0.0010 ***	0.0004	2.66
Public patients	0.0006 **	0.0003	2.11

(Continued next page)

Table 5 (continued)

	Coefficient	Standard error	z-value
Teaching hospital	0.0198 **	0.0093	2.13
Member of hospital network	0.0161	0.0138	1.17
High-level intensive care unit	-0.0209 **	0.0095	-2.20
Palliative care unit	0.0223 **	0.0094	2.38
Rehabilitation unit	0.0104	0.0088	1.18
Domiciliary care unit	-0.0051	0.0075	-0.68
Evans and Walker Index 2	0.3532 ***	0.0334	10.56
State or Territory[d]			
New South Wales	-0.0557 ***	0.0121	-4.60
Victoria	-0.0600 ***	0.0127	-4.71
South Australia	-0.0088	0.0201	-0.44
Western Australia	-0.0134	0.0169	-0.80
Tasmania	0.1953 ***	0.0249	7.84
Northern Territory	-0.0707 **	0.0307	-2.30
ACT	-0.0235	0.0262	-0.90
Year[e]			
2004-05	-0.0196 ***	0.0076	-2.57
2005-06	-0.0242 ***	0.0073	-3.33
2006-07	-0.0223 ***	0.0084	-2.65
Constant	0.1901 ***	0.0482	3.94
Inefficiency equation			
Ownership[f]			
Private (vs. Public & Contracted)	np ***	np	3.84
For-profit (vs. Not-for-profit)	np ***	np	-5.64
Contracted (vs. Not contracted)	np ***	np	-3.06
ln σ^2_u	np ***	np	-27.90
ln σ^2_v	np ***	np	-27.05
Model criteria			
Log likelihood (pseudo)	2 319.98		
Akaike Information Criterion (AIC)	-4 237.97		
Bayesian Information Criterion (BIC)	-3 132.70		
Degrees of freedom	1 605		
Number of observations	1 806		

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 σ^2_v and ln σ^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 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 6 **Coefficient estimates — input-oriented distance function[a]**

	Coefficient	*Standard error*	*z-value*
Frontier equation			
Outputs			
Acute separations	0.7880 ***	0.0274	28.77
Acute separations — squared	0.0585 ***	0.0067	8.72
Pregnancy & neonate separations	0.1717 ***	0.0138	12.42
Pregnancy & neonate separations — squared	0.1091 ***	0.0097	11.24
Mental & alcohol separations	0.0772 ***	0.0086	8.99
Mental & alcohol separations — squared	0.0242 ***	0.0055	4.38
Other separations	0.1158 ***	0.0079	14.61
Other separations — squared	0.0856 ***	0.0075	11.47
Accident & emergency occasions of services	0.0245	0.0245	1.00
Accident & emergency occasions of services — squared	0.1232 ***	0.0320	3.85
Pathology & radiology occasions of services	0.0253	0.0217	1.17
Pathology & radiology occasions of services — squared	0.0297 *	0.0180	1.65
Allied health & dental occasions of services	0.0517 ***	0.0185	2.79
Allied health & dental occasions of services — squared	-0.0141	0.0187	-0.76
Mental, alcohol & psychiatric occasions of services	0.0200	0.0243	0.82
Mental, alcohol & psychiatric occasions of services — squared	0.0091	0.0102	0.89
MDC 1 separations	0.0340 *	0.0203	1.68
MDC 1 separations — squared	-0.0255 **	0.0123	-2.08
Inputs			
Nursing staff	-0.0366 ***	0.0111	-3.28
Nursing staff — squared	0.0132 ***	0.0046	2.85
Drug costs	-0.0549 ***	0.0152	-3.61
Drug costs — squared	-0.0280 ***	0.0051	-5.54
Supplies costs	-0.0369 ***	0.0134	-2.75
Supplies costs — squared	0.0078	0.0095	0.82
Other costs	-0.0105	0.0120	-0.88
Other costs — squared	0.0021	0.0035	0.59
Quality indicator			
HSMR	0.0772 ***	0.0139	5.54
HSMR — squared	-0.0139 ***	0.0039	-3.59
Outputs — cross terms			
Acute seps × Preg & neo seps	-0.0816 ***	0.0249	-3.28
Acute seps × Mental & alc seps	0.0346 *	0.0186	1.87
Acute seps × Other seps	-0.0539 **	0.0215	-2.51
Acute seps × Acc & emerg sv	0.0197	0.0122	1.61
Acute seps × Path & rad sv	-0.0341 *	0.0193	-1.77
Acute seps × Allied health & dent sv	-0.0127	0.0148	-0.86
Acute seps × Mental, alc & psych sv	0.0373 ***	0.0106	3.53
Acute seps × MDC 1 seps	-0.0305 ***	0.0073	-4.20
Preg & neo seps × Mental & alc seps	-0.0230 ***	0.0090	-2.57
Preg & neo seps × Other seps	-0.0156 **	0.0066	-2.37
Preg & neo seps × Acc & emerg sv	0.0238 ***	0.0089	2.68

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Table 6 (continued)

	Coefficient		*Standard error*	*z-value*
Preg & neo seps × Dial & endo sv	0.0063		0.0081	0.78
Preg & neo seps × Allied health & dent sv	0.0061		0.0074	0.83
Preg & neo seps × Other outpatient sv	-0.0490	***	0.0127	-3.85
Preg & neo seps × MDC 1 seps	0.0036		0.0108	0.33
Mental & alc seps × Other seps	-0.0140	*	0.0083	-1.69
Mental & alc seps × Acc & emerg sv	0.0032		0.0102	0.32
Mental & alc seps × Dial & endo sv	0.0040		0.0103	0.39
Mental & alc seps × Allied health & dent sv	-0.0028		0.0085	-0.33
Mental & alc seps × Other outpatient sv	0.0149		0.0153	0.97
Mental & alc seps × MDC 1 seps	-0.0061		0.0095	-0.64
Other seps × Acc & emerg sv	0.0633	***	0.0115	5.49
Other seps × Dial & endo sv	-0.0230	*	0.0131	-1.75
Other seps × Allied health & dent sv	-0.0340	***	0.0097	-3.51
Other seps × MDC 1 seps	0.0119		0.0106	1.12
Acc & emerg sv × Dial & endo sv	-0.0304	***	0.0117	-2.61
Acc & emerg sv × Allied health & dent sv	-0.0256		0.0158	-1.62
Acc & emerg sv × Other outpatient sv	0.0303	***	0.0116	2.62
Path & rad sv × Dial & endo sv	0.0023		0.0065	0.36
Path & rad sv × Allied health & dent sv	-0.0009		0.0059	-0.15
Path & rad sv × Other outpatient sv	-0.0801	***	0.0172	-4.66
Allied health & dent sv × Mental, alc & psych sv	0.0101		0.0067	1.51
Allied health & dent sv × MDC 1 seps	-0.0018		0.0162	-0.11
Inputs — cross terms				
Nursing staff × Drug cost	0.0282	***	0.0097	2.89
Nursing staff × Supplies cost	-0.0305	***	0.0100	-3.05
Nursing staff × Other cost	-0.0062		0.0058	-1.07
Drug cost × Supplies cost	-0.0459	***	0.0106	-4.33
Drug cost × Other cost	-0.0043		0.0084	-0.51
Supplies cost × Other cost	0.0388	***	0.0098	3.97
Outputs & inputs — cross terms				
Acute seps × Nursing staff	0.0860	***	0.0128	6.71
Acute seps × Other staff	0.0890	***	0.0157	5.67
Acute seps × Drug costs	0.0189	**	0.0084	2.25
Acute seps × Supplies costs	-0.0547	***	0.0116	-4.71
Preg & neo seps × Nursing staff	-0.0112		0.0090	-1.25
Preg & neo seps × Other staff	0.0304	***	0.0110	2.77
Preg & neo seps × Drug costs	-0.0254	*	0.0138	-1.84
Preg & neo seps × Supplies costs	0.0248	***	0.0081	3.08
Mental & alc seps × Nursing staff	0.0074		0.0092	0.80
Mental & alc seps × Other staff	-0.0180		0.0113	-1.59
Mental & alc seps × Drug costs	0.0019		0.0126	0.15
Mental & alc seps × Supplies costs	-0.0170	**	0.0075	-2.26
Other seps × Nursing staff	0.0207	**	0.0101	2.06
Other seps × Other staff	-0.0512	***	0.0130	-3.95
Other seps × Drug costs	-0.0034		0.0127	-0.27
Other seps × Supplies costs	0.0176	**	0.0077	2.28

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Table 6 (continued)

	Coefficient	Standard error	z-value
Acc & emerg sv × Nursing staff	0.0079	0.0084	0.95
Acc & emerg sv × Other staff	-0.0275 ***	0.0099	-2.78
Acc & emerg sv × Drug costs	-0.0115	0.0101	-1.14
Acc & emerg sv × Supplies costs	0.0157 **	0.0066	2.37
Path & rad sv × Nursing staff	-0.0115	0.0104	-1.11
Path & rad sv × Other staff	0.0024	0.0102	0.24
Path & rad sv × Drug costs	0.0237 **	0.0117	2.04
Path & rad sv × Supplies costs	0.0054	0.0082	0.66
Allied health & dent sv × Nursing staff	0.0098	0.0106	0.92
Allied health & dent sv × Other staff	0.0302 **	0.0119	2.53
Allied health & dent sv × Drug costs	0.0101	0.0102	0.99
Allied health & dent sv × Supplies costs	-0.0248 ***	0.0078	-3.18
Mental, alc & psych sv × Nursing staff	-0.0283 ***	0.0110	-2.58
Mental, alc & psych sv × Other staff	0.0134	0.0086	1.55
Mental, alc & psych sv × Drug costs	-0.0188 **	0.0082	-2.29
Mental, alc & psych sv × Supplies costs	0.0077	0.0070	1.10
MDC 1 seps × Nursing staff	-0.0511 ***	0.0136	-3.74
MDC 1 seps × Drug costs	0.0311	0.0239	1.30
MDC 1 seps × Supplies costs	0.0496 **	0.0235	2.11
MDC 1 seps × Other costs	-0.0180	0.0128	-1.40
Quality indicator — cross terms			
HSMR × Nursing staff	0.0147 *	0.0080	1.84
HSMR × Drug costs	0.0236 *	0.0129	1.83
HSMR × Supplies costs	-0.0046	0.0103	-0.44
HSMR × Other costs	0.0078	0.0082	0.95
Patient characteristics[b]			
Share of patients aged <1 year	0.0050 **	0.0024	2.08
Share of patients aged 1-4 years	-0.0088 **	0.0038	-2.33
Share of patients aged 5-19 years	0.0023	0.0031	0.75
Share of patients aged 60-69 years	-0.0009	0.0011	-0.80
Share of patients aged 70+ years	0.0028 ***	0.0004	6.23
Share of patients from SEIFA 1	0.0002	0.0003	0.66
Share of patients from SEIFA 2	0.0001	0.0003	0.27
Share of patients from SEIFA 3	-0.0003	0.0003	-1.14
Share of patients from SEIFA 4	-0.0001	0.0003	-0.30
Share of patients with Charlson score 2	0.0012 ***	0.0003	3.43
Share of patients with Charlson score 3	0.0000	0.0024	0.00
Share of patients with Charlson score 4	0.0005	0.0013	0.41
Share of patients with Charlson score 5	0.0005	0.0010	0.52
Share of patients with Charlson score 6+	-0.0291 ***	0.0076	-3.82
Establishment characteristics[c]			
Located in major city	0.0713 ***	0.0130	5.49
Located in outer regional area	-0.0082	0.0108	-0.75
Located in remote area	0.0075	0.0212	0.35

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Table 6 (continued)

	Coefficient		Standard error	z-value
Located in very remote area	0.0309		0.0269	1.15
Surgical & other DRG separations	-0.0023	***	0.0005	-5.00
Public patients	-0.0009	**	0.0004	-2.05
Teaching hospital	0.0042		0.0106	0.40
Member of hospital network	-0.0431	***	0.0150	-2.87
High-level intensive care unit	-0.0046		0.0124	-0.38
Palliative care unit	-0.0095		0.0082	-1.16
Rehabilitation unit	0.0044		0.0092	0.47
Domiciliary care unit	0.0032		0.0083	0.39
Evans and Walker Index 2	0.1441	***	0.0400	3.61
State or Territory[d]				
New South Wales	0.0636	***	0.0147	4.33
Victoria	0.0761	***	0.0161	4.73
South Australia	0.0048		0.0173	0.28
Western Australia	-0.0078		0.0172	-0.46
Tasmania	0.0913	***	0.0260	3.51
Northern Territory	0.0090		0.0297	0.30
ACT	0.1521	***	0.0251	6.06
Year[e]				
2004-05	-0.0186	**	0.0084	-2.21
2005-06	-0.0226	***	0.0084	-2.71
2006-07	-0.0212	**	0.0090	-2.37
Constant	-0.5567	***	0.0765	-7.27
Inefficiency equation				
Ownership[f]				
Private (vs. Public & Contracted)	np		np	-0.24
For-profit (vs. Not-for-profit)	np		np	-0.62
Contracted (vs. Not contracted)	np	***	np	-4.85
ln σ^2_u	np	***	np	-22.67
ln σ^2_v	np	***	np	-22.67
Model criteria				
Log likelihood (pseudo)	2 156.08			
Akaike Information Criterion (AIC)	-3 984.16			
Bayesian Information Criterion (BIC)	-3 082.34			
Degrees of freedom	1 642			
Number of observations	1 806			

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 σ^2_v and ln σ^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 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.

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