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Hospital Competition, Technical Efficiency, and Quality

C. L. Chua, A. Palangkaraya and J. Yong

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C. L. Chua, A. Palangkaraya and J. Yong
Melbourne Institute of Applied Economic and Social Research,
The University of Melbourne

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Melbourne Institute of Applied Economic and Social Research
The University of Melbourne
Victoria 3010 Australia
***Telephone* (03) 8344 2100**
***Fax* (03) 8344 2111**
***Email* melb-inst@unimelb.edu.au**
***WWW Address* http://www.melbourneinstitute.com**

Abstract

This paper studies the link between competition and technical efficiency of public hospitals in the State of Victoria, Australia by accounting both quantity and quality of hospital output using a two-stage semi-parametric model of hospital production and Data Envelopment Analysis. On the one hand, it finds a positive relationship between efficiency and competition measured by the Hirschman-Herfindahl Index (HHI). On the other, it finds that efficiency and the number of competing hospitals, in particular the number of competing private hospitals, to be negatively correlated. More importantly, it finds that whether or not quality is treated as an endogenous output variable, as opposed to as an exogenous control variable, may impact on the statistical estimates of the link between efficiency and competition. Also, how the effect of competition on efficiency is modelled empirically may matter, though the impact of the treatment of quality as described above appears to be more important. Overall, the results highlight the importance of quality consideration in assessing the effects of competition on efficiency and points to possibly undesirable resource allocation effects when public hospitals are made to compete with a large number of private hospitals.

Keyword(s): hospital competition; technical efficiency; Hirschman-Herfindahl Index; data envelopment analysis; hospital quality

JEL Code(s): I11, D24, D40

1. Introduction

This paper examines the link between market competition and technical efficiency of public hospitals. As far as we are aware, this paper is one of the first studies applying a two-stage semi-parametric model of hospital production to understand the link between hospital competition and efficiency. The advantage of this econometric methodology, developed by Simar and Wilson (2007), is that it takes into account the underlying data generating process often ignored in earlier studies of hospital efficiency and competition based on regression analyses of non-parametric estimates of productive efficiency on hospital characteristics in a two-stage procedure. In particular, Simar and Wilson (2007) claimed and showed using Monte Carlo simulations that "conventional approaches to inference employed in these papers are invalid due to complicated, unknown serial correlation among the estimated efficiencies."[1] As a side benefit, this paper also addresses an important criticism of existing DEA-based studies, namely their failure to provide any statistical confidence intervals for their findings, by employing Simar and Wilson (2007)'s bootstrap estimators. In addition, this paper contributes to the literature by incorporating a measure of quality as another endogenous dimension of output in the estimation of efficiency. Thus, unlike earlier studies such as Dalmau-Matarrodona and Puig-Junoy (1998), which typically incorporated a proxy of quality only in the second stage regression, effectively treating quality as an exogenous variable, this paper treats quality as another dimension of hospital output in measuring efficiency.[2]

The question of whether hospital competition improves or hinders efficiency is a long-standing issue in health economics. The existing evidence shows that the relationship varies and depends on specific institutional and market setting. Lindrooth et al., (2003) found a positive link for urban hospitals in the United States while Preyra and Pink (2006) found a negative link for hospitals in the Province of Ontario, Canada; and yet Bates et al. (2006) did not find any statistically significant relationship for hospitals in various metropolitan areas of the United States. This lack of conclusive evidence makes it difficult to draw any inference for policymaking purposes.

As in most previous studies, we use the Hirschman-Herfindahl Index (HHI) to measure hospital competition. Specifically, we follow the approach of Zwanziger and Melnick (1988) by deriving the HHI from the ground up starting from the three-digit

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[1] See page 31.

[2] This treatment of quality is consistent with the literature that examines the relationship between hospital competition and quality but ignore the efficiency aspects. See, for examples, Kessler and Geppert (2005) and Gaynor (2006) for a recent review.

Diagnosis Related Groups (DRG) level. In effect, we define a hospital market for each three-digit DRG by using patients' location information (defined at the level of Statistical Local Area (SLA))[3] and the significance of that SLA as a supplier of patients to the hospital.[4]

The data used in this study are patient-level admission data from the state of Victoria, Australia. We make use of two data sources: the Victorian Admitted Episodes Dataset (VAED) and the Hospital Annual Report Database. The first provides hospital admission records of public and private hospitals in every fiscal year starting from 1996/97. The second data source provides financial information such as income, expenditure and employment data (in full-time equivalent units).

The rest of this paper is structured as follows. Section 2 briefly summarizes the findings of related earlier studies. A discussion of the empirical framework follows in Section 3. Section 4 explains the data while Section 5 reports and discusses the empirical findings. Some concluding remarks are given in Section 6.

2. The link between competition and efficiency

Microeconomic theory predicts that in most industries, productive efficiency—technical and allocative—is positively correlated with competition. A large volume of empirical studies exists to support such a relationship. However, the healthcare industry, unlike other industries where competition and efficiency are often positively linked, seems to provides mixed evidence for this relationship. Sometimes an inverse relationship is found and the literature offers an explanation in the form of non-price competition, also known as the 'medical arms race,' which states that more competition among hospitals may lead to higher costs of care, hence lower efficiency.

Empirical studies supporting an inverse relationship between hospital competition and efficiency include Hersch (1984) and Robinson and Luft (1985). In contrast, Zwanziger and Melnick (1988), Fournier and Mitchell (1992), Dranove and White (1994), Vitness (1995), and Lindrooth et al. (2003) produce evidence supporting a positive relationship. A third group of studies provide evidence that there was no significant link, a recent example is Bates et al. (2006). Similar mixed results were found using data from other countries. Using UK

[3] Depending on the region, an SLA can contain one or multiple suburbs or one or multiple post codes. The Australian Bureau of Statistics (ABS, 1996) defines a statistical local area (SLA) "based on the boundaries of incorporated bodies of local government where these exist. These bodies are the Local Government Councils and the geographical areas which the administer are known as Local Government Areas (LGAs)."

[4] This approach is adopted instead of the usual approach of Elzinga and Hogarty (1973) or other geographical based approaches (e.g, Dalmau-Matarrodona and Puig-Junoy, 1998) because for confidentiality reason we were not able to identify the geographical location of private hospitals in the data.

data, Maniadakis *et al.* (1999) found a positive link while Ferrari (2006) found no relationship. Other studies using data from Canada, Spain and Italy also produce contrasting evidence (Preyra and Pink, 2006; Dalmau-Matarrodona and Puig-Junoy, 1998; Celiini et al. 2000).

This inconclusive and sometimes contradictory evidence makes evidence-based public policy recommendations difficult. It is not clear, for example, whether a public authority interested in improving the efficiency of the hospital sector should promote or restrict hospital competition. In the case of Australia, such policy decisions are even more difficult since the Australian hospital sector has a mixed of private and public hospitals and there does not appear to be any study of the relationship that uses Australian data. For example, a policy initiative providing greater levels of public subsidy to private patients may intensify competition between public and private hospitals, yet its effects on efficiency and quality are largely unknown. Previous Australian studies tend to focus on the efficiency aspects of Victorian hospitals, but do not attempt to link measures of efficiency to hospital competition (e.g., Webster *et al.*, 1998; Yong and Harris, 1999; Wang *et al.*, 2006).

3. Analytical Framework

We test the relationship between hospital competition and technical efficiency while taking into account both quantity and quality of hospital care services. For this purpose, we apply a four-step procedure built around the main estimating equation below:

$$E_{ht}^{*} = x_{ht}\beta + z_{ht}\gamma + \varepsilon_{ht} \le 1, \;\; h = 1,\ldots,H \quad t = 1,\ldots T, \tag{1}$$

where E_{ht}^{*} denotes the unobserved (input-oriented) technical efficiency level of a hospital *h* in period *t*, x_{ht} denotes the level of competition faced by *h*, z_{ht} denotes relevant hospital characteristics and ε_{ht} denotes random noises which are assumed to be independently and identically distributed.[5]

The (unobserved) input-oriented technical efficiency (E_{ht}^{*}) measures the proportional reduction in all inputs that are technologically feasible without reducing the level of outputs. Simar and Wilson (2007) argued that the substitution of technical efficiency estimates ($\hat{E}_{ht}$) obtained from data envelopment analysis (DEA) for E_{ht}^{*} in the estimation of (1) poses two problems for existing studies. First, the inference on β and γ is problematic, since $\hat{E}_{ht}$ is

[5] As explained later, because we only have two financial years ($T = 2$), this model will be estimated by pooling the data. Time effect is allowed to appears as a shifter in the intercept.

subject to complex and unknown serially correlation and systematic bias. Second, the use of censored regression models such as the Tobit model in the estimation of (1) is inappropriate, since the Tobit imposes the restrictive assumption that the data generating processes determining the probability of censoring and uncensored relationship are identical. Their argument is based on the reasoning that "[t]he process that determines whether $[\hat{E}_{ht}]=1$ is primarily an artefact of finite samples." For this reason, truncated regression models are more appropriate since they do not impose the constraining assumption.

We adopt Simar and Wilson's (2007) bootstrap approach but with a some modifications to address the two criticisms posed by Simar and Wilson.[6] Unlike Simar and Wilson (2007), who propose the use of parametric bootstrap, we use a nonparametric bootstrap approach introduced in Simar and Wilson (1998). After obtaining the biased corrected estimates of efficiency ($\hat{E}_{ht}^{b}$), we proceed to estimate (1) using truncated regression model, and then apply Simar and Wilson's (2007) bootstrap approach to derive confidence intervals around the parameters of interest (β and γ). This approach has the advantage of retaining 'efficient' hospitals in the sample. This is not possible if we correct the bias in $\hat{E}_{ht}$ by bootstrapping the DEA estimates parametrically.

We implement the approach in four steps. First, we use the separation-level hospital data to construct an index of competition using the Hirschman-Herfindahl Index (HHI). The index is constructed for each three-digit DRG in which a hospital has recorded a patient separation. Then, using the total number of separations of each DRG we construct a separation-weighted average of HHI to provide a measure of the overall degree of competition faced by each hospital. As an auxiliary measure of competition, we also construct the variable 'number of competing hospitals,' which can be further broken down into the number of competing private and public hospitals.

Second, using the same separation-level data, we estimate regression models with short-term unplanned readmission as the dependent variable. The independent variables include hospital dummy variables and variables that control for the risk of unplanned readmission, such as comorbidity (defined as the number of diagnoses beside the primary diagnosis), patient demographics, and three-digit DRG dummy variables. The estimates of risk-adjusted unplanned readmission rates are taken as the estimated coefficients of the hospital dummy

[6] Pilyavsky *et al.* (2006) used the bootstrap approach to correct the bias but deviated from Simar and Wilson's (2007) approach by using Tobit regression instead of truncated regression.

variables. Subtracting these estimated unplanned readmission rates from one gives us a proxy variable for the quality of the hospital care as measured by unplanned readmission.

Third, using annual hospital-level data and the estimated hospital quality, we measure the relative technical efficiency levels of the hospitals via DEA. This method is chosen because we believe there is more uncertainty regarding the underlying hospital production technology than uncertainty on hospital input and output data. On the one hand, since it is a nonparametric method, DEA does not require any specific assumption on hospital production function. In addition, DEA allows estimation involving multiple outputs in a relatively more straightforward manner than regression based approach. On the other hand, unlike manufacturing establishments for example, hospitals maintain high quality data regarding their patient episodes and their use of production inputs, reducing the potential data sensitivity problems with the use of DEA. Furthermore, we can apply the usual bootstrap analysis to examine the sensitivity of DEA estimates to outliers or other data issues.

Finally, we estimate the link between competition and hospital efficiency by running truncated regression models using hospital efficiency levels as the dependent variables and hospital characteristics such as teaching status, proportions of older patients and in-hospital death as control variables. We explain each of these steps in details below.

Hospital Competition

There are various ways of measuring hospital competition, depending on how one defines what constitutes the market of the competing hospitals and, once the market is defined, which competition indicators are used. A popular way of defining markets is by using patient flow data (Elzinga and Hogarty, 1973). Other alternatives tend to be more geographically based, such as using geographic boundaries or a certain radius from the location a hospital.

Common indicators of competition include the Herfindahl-Hirschman Index (HHI), number of hospitals and concentration ratio. Despite their differences, a recent study by Wong *et al.* (2005) found that most measures of hospital competition are highly correlated. Furthermore, when included as explanatory variables in models of hospital costs, they yielded relatively the same inferences. Following studies such as Dalmau-Matarrodona and Puig-Junoy (1998), we use both HHI and the number of competing hospitals in the regression model in (1), since HHI may not adequately capture inequality in hospital market shares. In fact, it is possible that two markets can have the same HHI but totally different market share distributions.[7]

Our definition of hospital market and measures of hospital competition follow those of Zwanziger and Melnick (1988). The main advantage of this methodology is it requires only the location of patients. Due to confidentiality restrictions, we are not able to identify the location of private hospitals. This data limitation precludes us from constructing hospital market based on the Elzinga-Hogarty method or other methods based on the geographic location of hospitals.

The Zwanziger-Melnick method postulates that hospital markets can be inferred from the location of patients. If two hospitals serve a significant proportion of patients coming from the same location, we say that these hospitals are operating in the same market. We use this market identification for each type of services provided by the hospitals as defined by the three-digit DRG codes. Specifically, for each DRG code, we first identify each hospital's catchment areas using the information on the Statistical Location Area (SLA) of patients as given in the data. We regard a hospital's catchment as SLAs that supply three per cent or more of the total number of separations handled by the hospital for a given DRG. Next, based on the list of catchments areas (in terms of SLAs) of a given hospital, another hospital is regarded as a competitor if that hospital is drawing more than 3% of its patients from any SLA in the given hospital's catchments areas.[8]

Once we define the markets and competing hospitals, we can construct the SLA-DRG specific HHI (HHI_{SLA}^{DRG}) using the usual definition of the index for each competing hospital as follows:

$$HHI_{SLA}^{DRG} = \sum_{h} \left(S_{h,SLA}^{DRG} \right)^2 \tag{2}$$

where $S_{h,SLA}^{DRG}$ denotes hospital h's share of separations in that market and the summation is with respect to all hospitals competing in the (SLA-DRG) market.

In other words, HHI_{SLA}^{DRG} measures the extent of market competition for all hospitals operating in that SLA-DRG market. We next aggregate the index up to the DRG level by using the number of separations in each SLAs as weights. Finally, we construct the overall hospital competition measure (i.e., hospital-specific HHI) by aggregating up the DRG-specific HHI using the number of separations within each DRG as weights.

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[7] For further discussion, see Rhoades (1995).

[8] This choice is rather arbitrary but we choose to follow the limit used by Zwanziger and Melnick (1988).

Unplanned readmission as an indicator of hospital quality

One of our contributions to the literature on efficiency and competition is the incorporation of hospital quality in measuring hospital efficiency. Existing studies often exclude hospital quality in estimating hospital efficiency, a practice that is tantamount to assuming that quality is constant across hospitals and time, or that there is no trade-off between quality and output. Although many studies examine the relationships between competition and technical efficiency, technical efficiency and quality, and competition and quality (e.g., Dalmau-Matarrodona and Puig-Junoy, 1998; Propper *et al.*, 2004; Laine *et al.*, 2005; Kessler and Geppert, 2005; and studies reviewed by Gaynor, 2006), few examine the relationship between competition and technical efficiency with quality taken as another dimension of hospital output. We also note that the use of quality as a control variable in the efficiency regression (equation 1) is not appropriate if quality is endogenous. Our approach avoids this problem.

However, quality is difficult to measure especially in health care. Empirical studies based on data on specific type of patients such as those with cardiovascular diseases often use risk-adjusted mortality rates as the main indicator of hospital quality. For examples, 25 out of 37 studies on the link between hospital ownership and quality of care reviewed by Eggleston *et al.* (2008) use mortality as the indicator of quality, likewise for studies that examine the link between hospital competition and quality (e.g., Escarce *et al.*, 2006 and the studies surveyed by Gaynor, 2006). Other indicators used by a smaller number of studies include in-hospital adverse events and to a lesser extent, unplanned readmission.

We use risk-adjusted rate of unplanned readmission instead of mortality or adverse events for two reasons. First, this study is based on all hospital patients with all kinds of diagnoses. As explained in the next section, in estimating the efficiency of the hospitals, we use aggregate production inputs such as number of doctors and nurses and total pharmaceutical expenditures. We do not have separate estimates of these inputs for each DRG or different type of patients, thus we are unable to derive disease-specific efficiency measures. We are therefore unable to conduct the study at the disease level. This restriction effectively rules out measures such as mortality rates because different diseases can have vastly different mortality rates.

Second, unplanned readmissions are not only readily available from the database but more importantly have been shown to be a good indicator of hospital quality. Ashton *et al.* (1997) surveyed existing evidence and concluded that "[t]he risk of early readmission is increased by 55% when care is of relatively low quality." In comparison, Thomas and Hofer

(1999) found that the "predictive error" of mortality risks of patients when linked to the quality of hospitals was 55% and concluded that "[r]eports that measure using risk-adjusted mortality rates misinform the public about hospital performance."

In order to control for variation in the risk of readmission due to disease and patient characteristics, we use the separation-level data to estimate a panel regression model with an indicator of unplanned readmission as the dependent variable and patients' demographic and diagnostic information as the explanatory variables. We estimate the following regression:

$$r_{hst} = \alpha_{ht} + I_{hst}\xi + d_{hst}^{DRG}\delta + \mu_{hst}, \tag{3}$$

where $r_{hst} = 1$ indicates a specific (first) separation *s* of any hospital patient in a given DRG and at hospital *h* in period *t* which was subsequently identified as an unplanned readmission within 28 days after the separation, I_{hst} denotes a vector of patient's characteristics such as age and gender as well as the number of diagnoses recorded (a measure of co-morbidity or complexity of the patient's disease) for that particular separation, d_{hst}^{DRG} represents a vector of three-digit DRG dummy variables, and α_{ht} denotes hospital fixed effects.[9]

We estimate (3) using the regular fixed-effect panel regression instead of a logit regression in order to retain hospitals without any unplanned readmissions in the sample. Since our main interest is in obtaining a proxy for hospital quality, we think the advantage of a clearer interpretation of the logit model does not outweigh the advantage of retaining hospitals with no unplanned readmission.[10] In order to control for the possibility of other factors besides hospital quality accounting for a patient's unplanned readmission, we only examine the subsequent episode following a patient's first admission (within a specific three-digit DRG and within the last three year) to a particular hospital in period *t*. The estimated fixed effects capture the rate of unplanned readmission adjusted for types of diseases (DRG), patient's demographics, and the severity/complexity of disease.

Technical Efficiency

We use a non-parametric technique in the form of Data Envelopment Analysis (DEA) to measure relative technical efficiency levels of the hospitals in the sample. This technique has been used extensively in studies of the performance of health care services since the mid-

[9] We use evidence from existing studies such as Ashton *et al.* (1987) and Milcent (2005) as our guide in selecting control variables. This equation will be estimated for each financial year (*t*) separately so that we have only two vectors of hospital fixed effects with α_{h1} and α_{h2} as their components.

[10] This problem is moot if mortality rate is used to proxy quality in high-risk diseases such as cardiovascular disease because it would be extremely rare to find hospitals with no fatality.

1980s (Hollingsworth *et al.*, 1999). A typical example is Dalmau-Matarrodona and Puig-Junoy (1998) who studied the relationship between market structure and hospital efficiency by regressing DEA efficiency scores on market structure measures in a censored-regression framework.

One reason for the popularity of DEA in hospital performance studies is its ability to deal with multiple outputs in measuring output productivity, a characteristic of the health care industry. Furthermore, unlike its parametric counterparts, DEA does not impose a specific functional form on the production technology, which in the case of hospital care, can be extremely complex. For this reason, efficiency estimates from parametric approaches such as ordinary least squares and stochastic frontier analyses could be sensitive to model specification (Street, 2003). We believe the complexity of hospital production technology is a more important issue to control for than the potential problem arising from the uncertainty in our data (Lovell, 2006). However, a major potential drawback of DEA is its deterministic nature, meaning that the results could be sensitive to outliers in the data, although this problem is not just confined to DEA (see Jacobs, 2001; and Lovell, 2006). To address this shortcoming of DEA, we utilise a relatively recent bootstrapping technique by obtaining bias corrected efficiency estimates and statistically valid confidence intervals for the main estimates (see Simar and Wilson, 1998 and 2007). [11]

In DEA and in frontier analysis in general, productive performance is often defined with respect to an unknown population production frontier which represents the most efficient input-output combination. The sample of input-output combinations in the data is used to estimate the population frontier and then each sample observation is measured relative to this frontier. In particular, for each hospital h in a given period we compute Farrell input-oriented efficiency measure, defined as

$$F_i(x, y) = \min\{\lambda : \lambda x \in L(y)\} \tag{4}$$

where $y \in \Re^M$ is a *M*-vector output, $x \in \Re^N$ is a *N*-vector input, and $L(y) = \{x : x \text{ can produce } y\}$ is the associated input requirements set representing the production technology.[12] As defined above, $F_i(x, y)$ measures the amount by which hospital h can reduce its inputs yet still produce the same amount of output. If we assume

[11] Jacobs showed that while stochastic frontier analysis and DEA may measure different aspects of productive efficiency, their differences are more likely due to noises and data deficiencies. Related to this, Linna (1998) reported that both techniques compare well in terms of efficiency estimates in their study of hospital efficiency.
[12] See Farrell (1957).

constant returns to scale (C) and strong disposability of both inputs and outputs (S), we can compute $F_i\left(x^{h'}, y^{h'}\right)$ as the solution to the following linear programming problem:

$$
\begin{aligned}
&F_i\ \left(x^{h'}, y^{h'} \mid C, S\right) = \min \lambda \\
&s.t. \\
&\sum_{h=1}^{H} v_h y_{hm} \geq y_{h'm}, m = 1, \ldots, M \\
&\sum_{h=1}^{H} v_h x_{hn} \leq \lambda x_{h'n}, n = 1, \ldots, N \\
&v_k \geq 0, h = 1, \ldots, H
\end{aligned}
\tag{5}
$$

where H is the total number of hospitals. $F_i\left(x^{h'}, y^{h'}\right)$ in (5) is our biased efficiency estimator, denoted as $\hat{E}_{ht}$ earlier. Using existing studies as a guide and given data availability, we use the following output and input measures summarized in Table 1 to compute $F_i\left(x^{h'}, y^{h'}\right)$.[13]

Table 1: Output and Input Measure for DEA

Output measures:

Total Weighted Inlier Equivalent Separations (WIES)
Quality (based on 28-day risk-adjusted rates of unplanned readmission)

Input measures:

Full time equivalent (FTE) doctors
FTE nurses
FTE registered and other nursing staff
FTE administrative, domestic, and other staff
Expenditures on drug, medical, and surgical supplies
Number of beds

As discussed earlier, the DEA technique is inherently deterministic in nature and may suffer from data problems such as outliers and measurement errors. In order to minimize these problems, we utilise Simar and Wilson's (1998) bootstrapping method to obtain bias-corrected efficiency scores. These bias-corrected scores are then used as the dependent variable in a truncated regression model, with measures of competition as explanatory variables. The statistical significance of the coefficients of the truncated regression model is bootstrapped using the technique of Simar and Wilson (2007). This approach is similar to that of Pilyavsky *et al* (2006), except that we follow Simar and Wilson’s (2007) suggestion of using truncated regression models instead of the censored (Tobit) regression of Pilyavsky *et*

[13] See, for examples, the review by Hollingsworth (2003). Unfortunately, due to data unavailability, we do not have any measure of capital inputs for the efficiency estimates.

al (2006), since the assumed data generating process is more consistent with truncated rather than censored regression.

4. Data

The source for the hospital separation data is the Victorian Admitted Episodes Dataset (VAED) covering the time period 1996-97 to 2004-05. These annual data are linked across the years using de-identified patient identification number.[14] The dataset contains hospital level information such as hospital identification number, hospital teaching status, ownership (public versus private) and separation level information such as admission and separation dates, length of stay, diagnostic codes, DRG codes, age, marital status, and the usual residence of the patient.

The source of the hospital level input data is the Hospital Annual Report Database. This database is available from 1998-99 to 2004-05 and only covers public hospitals. However, only data for the latest two years, i.e., 2003-04 and 2004-05, are useable for our purpose.[15] The information available in the database includes hospital full-time equivalent (FTE) labour inputs of doctors, nurses, medical support officers, ancillary support officers, and other workers (hotel, allied health, administration and clerical workers) and financial information such as total expenditure in drug supplies, medical, surgical supplies and prostheses, pathology, etc.

Table 2 summarises the sample data used for the estimation of (1)-(5). Based on the provided hospital codes, there are a total of 123 public hospitals and 133 and 142 private hospitals in respectively 2003-04 and 2004-05.[16] Public hospitals recorded an average of 9,949 and 10,243 separations each year for respectively 2003/04 and 2004/05. As shown in Table 2, we also computed weighted separations using the cost weights (WIES) provided in the database. Private hospitals reported fewer separations, regardless if weights are used.[17] Furthermore, in terms of unplanned readmissions within 28 days, the average percentage is 0.12 in 2003/04 and 0.16 in 2004/05. The maximum recorded unplanned readmission rate

[14] For more information on the data linking process see, for example, Sundararajan et al. (2002).

[15] Even then, not all public hospitals were reported. The useable data are only available for 36 hospitals in 2003-04 and 58 hospitals in 2004-05. Fortunately, this incomplete database is used only for the estimation of efficiency using DEA, where by the relative nature of the measures, the undesirable effects of an incomplete sample are not as strong as for the case when we want to identify hospitals' competitors.

[16] Due to confidentiality, we were not able to identify whether or not the increase in the number of hospitals from 133 to 142 represent genuine entrants, mergers or splits, or statistical artefacts.

[17] Zero weighted separations appearing as a minimum value are due to hospitals which all separations have zero WIES value (approximately 6% of the separations). In the DEA analysis, we drop separations with zero values when weighted separations are used as an output measure.

approximately doubled from 3.13 per cent to 6.62 per cent over the two years. Unlike the VAED data which cover all hospitals, the annual report data only cover some public hospitals.[18] Finally, Table 2 also shows that the sample of public hospitals for which we have

Table 2: Descriptive summary of the hospital separation and annual report data

	2003/04				2004/05			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Hospital separation data								
Public hospitals								
Number of hospitals*	123				123			
Number of separations								
Simple count	9949	16246	40	89081	10243	16897	19	93122
Weighted (WIES)	6969	12915	0	58716	7096	13153	0	61407
Private hospitals								
Number of hospitals*	133				142			
Number of separations								
Simple count	5119	6956	85	49872	4961	6807	42	50147
Weighted (WIES)	3506	6786	0	43994	3,345	6636	0	44623
28-day unplanned readmission (%)	0.12	0.39	0	3.13	0.16	0.59	0	6.62
Public hospital annual report								
Number of hospitals**	36				58			
Number of separations†								
Simple count	10952	10590	40	47560	19588	20751	95	93122
Weighted (WIES)	7508	8596	123	41167	13993	16541	5	61406
28-day unplanned readmission (%)†	0.223	0.287	0	1.282	0.200	0.228	0	1.031
Number of beds	137.7	140.3	4	476.7	389.1	404.6	10	1352
Full time equivalent (FTE)***								
Doctors[19]	32.5	66.1	0.01	351.4	92.6	146.9	0.0	648.0
Nurses	242.1	251.3	9.5	906.4	421.1	476.9	6.2	2031.1
Medical & ancillary support	94.6	143.6	1.96	632.0	118.3	166.4	1.3	724.1
Administrative, domestic, and other staffs	166.9	184.1	11.2	825.1	259.1	314.9	2.7	1351.2
Expenditures on drug, medical, and surgical supplies (AU$ 000)	1856	2928	17	14786	5007	8603	13	45197
Competition ($= 1/_{HHI}$)[20]	2.273	1.039	1.249	5.988	2.759	1.114	1.285	6.214
Number of competitors								
All hospitals	3.082	1.840	1.346	8.826	4.040	2.032	1.277	8.702
Public hospitals	2.145	0.745	1.234	3.936	2.376	0.711	1.241	3.663
Private hospitals	0.936	1.195	0.031	4.890	1.664	1.460	0.036	5.142
Teaching hospital	0.167	0.378	0	1	0.345	0.480	0	1
Average time in ICU (hr)	0.845	1.644	0	7.437	1.148	1.833	0	8.911
Old age ratio	0.136	0.109	0.004	0.65	0.141	0.115	0	0.558

Note: *These are the complete list of hospitals used in measuring competition levels and hospital quality. **These are hospitals with complete input data for our purpose and used in the estimation of efficiency and regressions of efficiency on hospital competition and other characteristics. ***As of the month of June of each respective financial year. †Based on hospital separation data of this subset of public hospitals.

18 In theory, the annual report database covers all public hospitals. However, many hospitals have missing values in the variables of interest.

19 The hospital employment data that we used showed that one small regional hospital had 0.01 FTE doctors in 2003/04 and two had 0.0 FTE doctors in 2004/05 in the reference month (June). One could interpret these low numbers as an absurd indication that these hospitals did not use the service of any doctor. Unfortunately, given the lack of any alternative information, we could not make any appropriate correction to data if they simply meant that the number of doctors was misreported. Nevertheless, as can be seen in Appendix Table 1 (compared to Tables 3 and 4 below), our analysis appear to be robust to the exclusion of these hospitals. See also Appendix Table 2 for the effects of removing the hospitals with low FTE doctor from the sample to estimate efficiency.

20 This variable is also known as the "numbers-equivalent" index, namely the number of equal-size hospitals that would yield the given HHI; see Adelman (1969), cited in Rhoades (1995).

complete data vary from small hospitals with low number of doctors and nurses to very large hospitals employing a large number of doctors and nurses. More importantly, one or more large hospitals reported in 2004-05 were not reported in 2003-04, indicating potentially important missing observations. Due to lack of any other alternative, we assume that the missing observations are due to some random causes. In addition, in the efficiency regressions, which use the pooled data, we include a year dummy as another control variable.

5. Results

The main estimation results are summarized in Tables 3 and 4. Both tables present the coefficient estimates and the corresponding asymptotic standard errors of the truncated regression model of hospital efficiency on competition and other control variables. In addition, the bootstrapped 90% and 95% confidence intervals using Simar and Wilson's (2007) approach with the recommended 2000 replications are also included. The model presented in Table 3 uses inverted HHI and the average number of hospitals in the same market as the main explanatory variables, whereas the model in Table 4 substitutes the number of hospitals with the number of private hospitals to investigate if public hospitals 'behave' differently with respect to competing private hospitals. In each case two model specifications are estimated, one treating quality as exogenous while the other includes quality as an additional endogenous output variable. Beside measures of competition, other explanatory variables that may explain the variation in hospitals' use of inputs in delivering their output(s) unaccounted for in the estimation of efficiency are included in both models, namely: hospital teaching status, average length of the use of the Intensive Care Unit (ICUs), and proportion of old patient.[21] Statistically significant estimates are indicated by the shaded cells of the tables.

Table 3 shows a statistically significant (at 10% or lower significance level) positive relationship between competition intensity (as measured by the inverse of the HHI) and the measured hospital efficiency only when quality is treated endogenously in the measurement of efficiency. The positive coefficient of competition level in Model 2 is statistically significant after controlling for hospital characteristics such as teaching status, hospital size and variables that proxy the severity of cases handled by the hospitals (e.g., the proportion of old age patients). The coefficient for competition level is statistically significant based on the

[21] Studies indicate that healthcare costs may increase with age or with proximity to death (see, for examples, Zweifel et al. (1999, 2005) and Palangkaraya and Yong (forthcoming)).

asymptotic standard error and, to a lesser degree, the bootstrapped confidence intervals (at the 10 per cent level).

Table 3: Truncated regression model estimates

Explanatory Variables	Model 1: quality is exogenous						Model 2: quality is endogenous					
			Bootstrap						Bootstrap			
			95% CI		90% CI				95% CI		90% CI	
	Coef.	S.E.	Lo	Hi	Lo	Hi	Coef.	S.E.	Lo	Hi	Lo	Hi
Competition level (inverse of HHI)	0.015	0.031	-0.031	0.060	-0.023	0.051	0.068	0.035	-0.037	0.186	-0.018	0.167
No. of competing hospitals	-0.010	0.019	-0.038	0.017	-0.034	0.013	-0.042	0.021	-0.103	0.007	-0.094	-0.002
Teaching hospital dummy	-0.057	0.046	-0.126	0.010	-0.115	-0.002	-0.022	0.049	-0.140	0.090	-0.120	0.073
Average ICU hours	-0.019	0.010	-0.033	-0.005	-0.031	-0.008	-0.009	0.010	-0.032	0.012	-0.028	0.009
Old age ratio	-0.684	0.131	-0.894	-0.501	-0.852	-0.528	-0.252	0.147	-0.701	0.105	-0.624	0.046
Year 04/05 dummy	-0.012	0.032	-0.058	0.031	-0.050	0.025	-0.037	0.034	-0.172	0.081	-0.150	0.060
Quality[22]	-4.481	1.906	-7.452	-1.990	-7.091	-2.516						
Constant	5.265	1.860	2.797	8.121	3.298	7.770	0.874	0.053	0.645	1.119	0.681	1.082
$\hat{\sigma}_{\varepsilon}$	0.125	0.011	0.078	0.108	0.081	0.105	0.129	0.014	0.079	0.137	0.083	0.133
Sample size	94						94					
Log likelihood	72.6						79.6					

Note: Shaded rows indicate statistically significant effect at l0 or 5% level of significance. $\hat{\sigma}_{\varepsilon}$ is the estimated standard deviation of the assumed right-truncated normal distribution of ε_{ht} in equation (1).

Table 4 presents the estimation results of the same truncated regression but with the number of competing hospitals replaced with the number of competing private hospitals. The estimation results show a relatively stronger positive link between competition and efficiency. Perhaps due to a less severe degree of collinearity between the number of competing private hospitals and the inverse of HHI, the coefficient for the latter in both Models 1 and 2 is positive and statistically significant based on the bootstrapped confidence intervals. However, if we were only looking at the estimated asymptotic standard errors, the results in Table 4 mimic the results in Table 3.

A significant and interesting finding in Model 2 shown in Table 4 is that the number of competing private hospitals is negatively correlated with public hospital efficiency and this relationship is statistically significant no matter how quality is treated, especially when we look at the bootstrapped confidence intervals. We are, however, unable to provide a definitive explanation on the positive relationship between competition and quality on the one hand,

[22] Risk adjusted rate of 28-day unplanned readmission.

while a negative relationship exists between competition and the number of competing private hospitals on the other hand.[23] A possible explanation for the latter negative relationship is the coefficient may capture the negative effects arising from 'medical arms race,' which may occur between public and private hospitals. We may reasonably expect the arms race effects be reflected in the number of competitors rather than in market shares (as captured by the HHI) since more hospitals imply greater demand for medical personnel, all else being equal. In comparison, a lower degree of competition with no change in the number of hospitals (say, through market share redistribution) is less directly linked to the demand for medical personnel.

Table 4: Truncated-regression estimates - effects of private hospitals

Explanatory variables	Model 1: quality is exogenous						Model 2: quality is endogenous					
			Bootstrap						Bootstrap			
			95% CI		90% CI				95% CI		90% CI	
	Coef.	S.E.	Lo	Hi	Lo	Hi	Coef.	S.E.	Lo	Hi	Lo	Hi
Competition level (inverse of HHI)	0.031	0.026	-0.004	0.067	0.003	0.061	0.066	0.029	-0.011	0.153	0.002	0.139
No. of competing private hospitals	-0.032	0.023	-0.064	-0.003	-0.060	-0.008	-0.061	0.025	-0.124	-0.012	-0.115	-0.020
Teaching hospital dummy	-0.045	0.043	-0.105	0.013	-0.095	0.003	-0.026	0.045	-0.124	0.068	-0.109	0.051
Average ICU hours	-0.017	0.010	-0.031	-0.005	-0.029	-0.007	-0.008	0.010	-0.028	0.010	-0.025	0.007
Old age ratio	-0.729	0.135	-0.931	-0.556	-0.892	-0.579	-0.332	0.151	-0.718	-0.008	-0.661	-0.057
Year 04/05 dummy	-0.009	0.031	-0.051	0.032	-0.044	0.026	-0.029	0.033	-0.117	0.052	-0.104	0.037
Quality	-4.392	1.903	-7.165	-2.051	-6.809	-2.535						
Constant	5.144	1.858	2.807	7.768	3.278	7.436	0.815	0.058	0.662	0.953	0.684	0.924
$\hat{\sigma}_{\varepsilon}$	0.124	0.011	0.073	0.101	0.075	0.099	0.127	0.014	0.082	0.132	0.085	0.128
Sample size	94						94					
Log likelihood	73.4						80.71					

Note: Shaded rows indicate statistically significant effect at l0% or 5% level of significance.

As mentioned above, the dependent variable in the truncated regression reported in Tables 3 and 4 is obtained from the DEA as specified in (4), with bootstrapping to correct for bias in the efficiency estimates. We compute the input-oriented hospital technical efficiency scores for each financial year. The scores are summarized in Table 5.

[23] Rhoades (1995) found a similar result for the banking markets.

Table 5: Hospital Farrell input-oriented efficiency scores

	2003-04				2004-05			
	Mean	Min	Max	Std. Dev.	Mean	Min	Max	Std. Dev.
Efficiency scores								
Single output (no quality*)								
Original score	0.868	0.529	1	0.144	0.812	0.004†	1	0.187
Bias corrected**	0.770	0.481	0.897	0.112	0.725	0.003†	0.916	0.154
Two output (with quality)								
Original score	0.910	0.594	1	0.126	0.856	0.446	1	0.155
Bias corrected	0.821	0.560	0.926	0.100	0.782	0.407	0.928	0.128
Sample size	36				58			

Note: Quality is defined as (1 - risk-adjusted rate of unplanned readmission). **Bias correction is done via bootstrapping following Simar and Wilson (1998) with 1000 as the number of replications and Silverman's (1986) bandwidth. †The minimum score corresponds to a single hospital. The next lowest hospital score is similar to the 2003-04 minimum score.[24]

Comparing the summary statistics for total weighted separations (WIES) of the 94 public hospitals in (the DEA sample) to those of the full sample in Table 2, we find that they are broadly similar; the most notable difference is that the DEA sample have a significantly higher average total WIES in 2004/05 than in 2003/04 (13,609.8 compared to 7,096). Unfortunately we do not observe the input variables for all hospitals in the sample, thus we are unable to determine the direction of the bias in efficiency estimates due to sample selection. To control for this potential bias, we estimate the efficiency scores using DEA for each year separately and include a year dummy variable in estimating the truncated regression model in (1) using pooled data. It should also be noted that the efficiency scores were obtained from the DEA that also accounts for hospital quality as an output. The quality measure is obtained from an unplanned readmission regression model as specified in (2). The coefficient estimates are presented in Table 6.

The dependent variable of the unplanned readmission regression summarised in Table 6 is binary. We defined the value of the dependent variable as one if the patient in the first separation in a specific DRG is admitted again under the same DRG to any hospital within 28 days with no indication that the readmission was a planned one. The model is estimated using ordinary panel regression with hospital fixed effects. Included in the regression but not reported in the table are a set of DRG dummy variables. Overall, the signs of estimated coefficients are as expected especially for the number of diagnoses - more complex cases with a higher number of diagnoses have greater risk of unplanned readmissions. We take the hospital fixed effects as the risk-adjusted rates of unplanned readmissions. The hospital

[24] In Appendix Table 3, we summarise the regression estimates when we exclude the specific hospital with the lowest efficiency score (0.004 original score). The results are similar.

quality measure is constructed by setting the minimum hospital fixed effects in Table 6 to zero and define quality as one minus the shifted fixed effects.[25]

Table 6: Unplanned readmission panel regression estimates

	2003-04			2004-05		
	Coefficient		Std. error	Coefficient		Std. error
Number of diagnostics	0.00015	***	0.00004	0.00014	***	0.00004
Age (year)	0.00000		0.00000	0.00000		0.00000
Married (1=married)	-0.00033		0.00021	-0.00031		0.00021
Male	0.00079	***	0.00020	0.00043	**	0.00020
Hospital fixed effects						
Mean	0.00000			0.00000		
Min	-0.02584			-0.02176		
Max	0.04342			0.05330		
R-square						
Within	0.0349			0.0314		
Between	0.4953			0.5306		
Overall	0.0452			0.0418		
Number of observations	1,446,198			1,447,086		
Number of groups (hospitals)	256			265		
Corr(α_{ht} , $I_{hst}\xi$)	0.2090			0.2330		

** (***): statistically significant at the 5 (1) per cent level; 401 DRG dummy variables are included but not shown.

6. Conclusion

This paper examined the relationship between competitive pressure and hospital efficiency using public hospital data from the state of Victoria in Australia. We measured hospital competition using two measures: the weighted averages of diagnosis related group (DRG)-level Hirschman-Herfindahl indices, and the number of competing hospitals. We linked these two measures to hospital technical efficiency scores that we compute using data envelopment analysis.

We found a statistically significant positive relationship between competition level measured by SSI and efficiency. The positive relationship is consistent with a recent finding of Abraham *et al.* (2007), which showed that entry in the hospital markets benefited consumers because it increased quantity of output and reduces hospital profits. However, we also found a statistically significant negative relationship between the number of competing hospitals and efficiency. In both cases the competition effects were stronger we used the number of competing private hospitals instead of the number of all competing hospitals, and especially when quality was treated as an endogenous variable incorporated in the efficiency estimation.

[25] In essence, hospital quality is taken as the proportion of separations that did not result in unplanned readmissions within 28 days (conditional on the risk of such readmissions).

In terms of the estimation methods of the impacts of competition on efficiency, we found that the asymptotic standard errors obtained from a regular maximum likelihood estimator for truncated regression model appeared to provide consistent statistical inference to the one provided by the more elaborate specification using the bootstrapping approach recommended by Simar and Wilson (2007). In fact, in general, the asymptotic standard errors appeared to be more conservative in terms of the implied statistical significance.

This study can potentially be extended in different directions. Firstly, the sample of hospitals is very limited. In particular, only public hospitals were included in the estimations of efficiency and the relationship between efficiency and competition. Even then, only a subset of public hospitals was available with useable inputs data. Expanding the sample with private hospitals and the rest of public hospitals will be useful in ascertaining the robustness of the findings. Secondly, we note that our competition measure is computed based on DRGs. It is quite plausible that different DRG codes entail similar medical services (i.e., requiring similar type of doctors, nurses, or drugs) so that they could be combined. Thirdly, the market competition measures can be improved by utilizing the choice-based model to estimate hospital market share as per Kessler and McClellan (2000). Lastly, when a longer panel becomes available, it would be possible to investigate the relationship between changes in competition and changes in productivity in a panel data setting using measures such as the DEA-based Malmquist index (Färe et al., 1994).

Appendix Table 1: Truncated regression model estimates (Excluding hospitals with <0.01 FTE doctors)

Explanatory Variables	Model 1: quality is exogenous				Model 2: quality is endogenous			
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Competition level (inverse of HHI)	0.014	0.030	0.028	0.025	0.064	0.034	0.063	0.028
No. of competing hospitals	-0.008	0.019			-0.039	0.020		
No. of competing private hospitals			-0.028	0.022			-0.057	0.024
Teaching hospital dummy	-0.053	0.045	-0.042	0.042	-0.023	0.047	-0.027	0.044
Average ICU hours	-0.017	0.010	-0.016	0.009	-0.008	0.009	-0.008	0.009
Old age ratio	-0.670	0.128	-0.710	0.132	-0.243	0.142	-0.318	0.146
Year 04/05 dummy	-0.009	0.031	-0.005	0.031	-0.036	0.033	-0.029	0.033
Quality	-4.308	1.847	-4.231	1.845				
Constant	5.076	1.803	4.969	1.802	0.860	0.051	0.806	0.056
$\hat{\sigma}_{\varepsilon}$	0.122	0.011	0.122	1.802	0.127	0.013	0.125	0.013
Sample size	91		91		91		91	
Log likelihood	70.3		71.0		76.2		77.3	

Note: Shaded rows indicate statistically significant effect at l0 or 5% level of significance. $\hat{\sigma}_{\varepsilon}$ is the estimated standard deviation of the assumed right-truncated normal distribution of ε_{ht} in equation (1).

Appendix Table 2: Hospital Farrell input-oriented efficiency scores (Excluding hospitals with <0.01 FTE doctors)

	2003-04				2004-05			
	Mean	Min	Max	Std. Dev.	Mean	Min	Max	Std. Dev.
Efficiency scores								
Single output (no quality*)								
Original score	0.865	0.529	1	0.145	0.805	0.004	1	0.187
Bias corrected**	0.759	0.478	0.892	0.109	0.717	0.003	0.911	0.154
Two output (with quality)								
Original score	0.907	0.594	1	0.127	0.853	0.446	1	0.155
Bias corrected	0.814	0.557	0.920	0.099	0.774	0.404	0.923	0.128
Sample size	35				56			

Note: Quality is defined as (1 - risk-adjusted rate of unplanned readmission). **Bias correction is done via bootstrapping following Simar and Wilson (1998) with 1000 as the number of replications and Silverman's (1986) bandwidth.

Appendix Table 3: Truncated regression model estimates (Excluding a single hospital with 0.004 efficiency score)

Explanatory Variables	Model 1: quality is exogenous				Model 2: quality is endogenous			
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Competition level (inverse of HHI)	0.033	0.025	0.039	0.021	0.084	0.033	0.075	0.027
No. of competing hospitals	-0.016	0.015			-0.046	0.020		
No. of competing <u>private</u> hospitals			-0.030	0.018			-0.062	0.023
Teaching hospital dummy	-0.054	0.037	-0.051	0.034	-0.028	0.045	-0.037	0.041
Average ICU hours	-0.014	0.008	-0.013	0.008	-0.007	0.009	-0.007	0.009
Old age ratio	-0.546	0.109	-0.587	0.111	-0.119	0.140	-0.201	0.144
Year 04/05 dummy	-0.009	0.025			-0.027	0.031	-0.021	0.030
Quality	-2.986	1.498	-2.946	1.485				
Constant	3.749	1.464	3.681	1.452	0.825	0.048	0.771	0.053
$\hat{\sigma}_{\varepsilon}$	0.103	0.009	0.102	0.009	0.119	0.012	0.117	0.012
Sample size	93		93		93		93	
Log likelihood	84.1		84.9		84.1		84.9	

Note: Shaded rows indicate statistically significant effect at l0 or 5% level of significance. $\hat{\sigma}_{\varepsilon}$ is the estimated standard deviation of the assumed right-truncated normal distribution of ε_{ht} in equation (1).

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