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«Measuring efficiency from casemix funding in Victoria using the stochastic frontier»

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Abstract

The Australian state of Victoria experienced a fundamental change in public hospital funding in 1993 with the introduction of casemix funding using diagnosis related groups. One of the primary drivers of this altered funding regime was to introduce a mechanism by which public hospitals could be compared for costs. Cost comparisons would then create an incentive for efficiency improvements because efficient hospitals would attract increased funding. This paper applies stochastic frontier estimation of a production function to panel data for the period 92/93 to 95/96 in order to establish whether, in fact, efficiency improvements were realised over this period. The results show that there was no significant change to individual hospital efficiency levels.

JEL Codes: I11, I18
Keywords: stochastic frontier, casemix funding, efficiency measurement, Victoria.

Introduction

This paper investigates individual hospital's efficiency levels over time in order to determine whether the change to casemix funding of Victoria's public hospitals had the desired effect of improving efficiency. Casemix funding[1] was implemented in Victoria on 1 July 1993. It was the cornerstone of Victoria's health reforms which had the overall objective of reducing waiting lists, lowering costs and improving efficiency (Duckett, 1994). Duckett, 1999, p 107 states that under casemix funding using diagnosis related groups (DRGs) 'The hospital therefore becomes more clearly accountable for variation in the efficiency of the services it provides'. Also, 'Generally, case-mix funding is seen as being able to yield efficiency improvements more rapidly than negotiated funding…'. In this paper a technique known as stochastic frontier estimation[2] (SFE) has been adopted in order to show the effect of this policy change on hospital efficiency.

Traditionally, econometricians estimated production, cost and profit functions under the assumptions that producers operate *on* the functions and that they maximise or minimise accordingly. The SFE model recognises that these assumptions are

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[1] For an in depth look at Victoria's casemix funding arrangements and literature see Mangano (2007).
[2] The technique is also referred to as stochastic frontier analysis in the literature.

unrealistic; that, due to a number of reasons, not all producers are successful in minimising inputs or maximising profits. Modern efficiency measurement uses econometrics to reformulate the functions into frontiers. In the case of a production frontier, the model calculates the minimum input bundle required to produce a given output. Firms who do not restrict their inputs to this minimum bundle are identified as being inefficient; their production lies beneath an estimated production frontier. The distance from the frontier is measured using a *composed* error term. Part of the error term captures the traditional symmetric random noise (v), and the other part (u) captures the inefficiency component and is one-sided. For a production frontier the error term is ($v - u$), is negatively skewed and has a negative mean. The production frontier model is stochastic because it recognises the existence of *random* variation in the operating environment. The inefficiency component is one-sided due to various types of inefficiency (Kumbhakar and Lovell, 2000).

Work on modern efficiency measurement began with Farrell (1957) who drew upon the work of Debreu (1951) and Koopmans (1951) to define a simple measure of firm efficiency that could account for multiple inputs under the assumption of constant returns to scale. Banker, Charnes and Cooper (1984) advanced the original work by accounting for variable returns to scale. The refined stochastic frontier production function is parametric, and was independently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977), Battese and Corra (1977), and refined by Jondrow et al. (1982). This technique was initially developed for use as a cross-sectional approach to measuring inefficiency until it was further modified to allow for the use of panel data (Schmidt and Sickles, 1984). Another technique that has been applied to healthcare organisations is data envelopment analysis (DEA). This technique is non-parametric and involves the use of linear programming methods to construct a frontier over the data so that each firm's performance can be compared to this frontier (Coelli, 1996[b]). Both of these techniques have been applied to hospitals and other healthcare organisations outside of Australia, as evidenced by extensive literature.

Literature – healthcare applications of frontier methods
Zuckerman et al. (1994) use a cross-sectional stochastic frontier multiproduct cost function to derive hospital-specific measures of inefficiency. The authors recognise that one of the goals of Medicare's PPS in the United States is to '…promote

efficiency by rewarding hospitals that are able to keep their costs below PPS rates and penalizing those that are not' (Zuckerman et al., 1994, p 256). They also observe a wide range of profitability among hospitals in 1990, which they attribute in part to the changes in the way that hospitals are paid. The existence of high profits for some hospitals and losses for others, leads the authors to question whether profitable institutions are efficient, and those experiencing losses are not. If this is the case, it follows that inefficient hospitals should cut their costs and profitable hospitals should expand production (Zuckerman et al., 1994). Their stochastic frontier model measures the relative efficiency of hospitals so that they can better assess the relationship between profits and efficiency, thereby providing an answer to this question.

Among their findings, the authors conclude that inefficiency '…accounts for 13.6 percent of total hospital costs' (Zuckerman et al., 1994, p 255), and that the PPS, which rewards efficiency and penalises inefficiency, provides '…hospitals with appropriate incentives' (Zuckerman et al., 1994, p 275). This is because a reduction in inefficiency reduces costs. Their model shows that by removing the 13.6 percent estimated inefficiency this would have reduced hospital costs in the U.S. in 1991 by approximately \$31 billion (Zuckerman et al., 1994, p 274). The findings also indicate some specific relationships with inefficiency.

Firstly, the model shows that there is a negative relationship between profitability and inefficiency, with profit rates significantly higher among relatively less inefficient hospitals (Zuckerman et al., 1994, p 272). Furthermore, hospital occupancy rates are inversely related to inefficiency. An increase in occupancy is related to lower inefficiency and lower costs in the industry. Following on from that finding, therefore, a reduction in productive capacity of the average hospital, as well as a reduction in the number of hospitals per population, could reduce inefficiency (Zuckerman et al., 1994). With regards to the degree of competition in the market, the findings show '…weak evidence that competition from other hospitals is related to inefficiency' (Zuckerman et al., 1994, p 272). As expected, the authors find a positive relationship between average salaries paid and inefficiency. They note that this could be due to the fact that there are differences in the qualifications and mix of nursing staff, for example, employed at different hospitals. Despite the advantages of employing higher quality staff, the results would indicate that hospitals that pay higher average salaries are inefficient. This issue of quality difference is also relevant

to the number of staff per adjusted admission. The findings show a positive relationship between staff numbers, quantity of assets (intensity of input use), and inefficiency.

This issue of quality of care is dealt with by the use of 30-day post-admission Medicare mortality rates and board certification of medical staff. The authors acknowledge that quality is difficult to measure and they do not present their results as conclusive proof of their findings. In particular the authors examine the relationship between quality of care and inefficiency. In relation to this, the findings show that '…the least efficient group of hospitals is not staffed by a more highly board certified staff nor is it achieving a lower observed-to-expected mortality rate ratio than the most efficient group' (Zuckerman et al., 1994, p 273). This finding would imply that inefficiency is not associated with higher quality healthcare.

Their cost function, which relies on maximum likelihood estimators (MLE), includes direct measures of illness severity, output quality and patient outcomes to reduce the likelihood that the inefficiency estimates are capturing unmeasured differences in hospital outputs. In relation to output endogeneity, although the authors reject this hypothesis they do treat one output, namely inpatient days, as endogenous.

The motivation for Zuckerman et al. (1994) is that other studies of hospital efficiency estimation apply the DEA method, and many consider that method to be inferior to the stochastic frontier. Hofler and Folland (1991) [as cited in Zuckerman et al. (1994)], for example, note that the DEA, which estimates a deterministic frontier, does not necessarily identify truly efficient benchmarks in the data.

> As Hofler and Folland point out this is not entirely satisfactory because it assumes that some observed production process (or combination or processes) is efficient, while ignoring that the observations in any data set may be subject to random fluctuations. (Zuckerman et al., 1994, p 258).

This is particularly problematic when estimating cost functions, as it is not possible to establish what is the appropriate level of minimum costs, i.e. the benchmark. The stochastic frontier relaxes the implicit structure embodied in DEA, and allows the model to identify deviations from the frontier that are not due to a hospital's behaviour and, therefore, out of their control (Zuckerman et al., 1994). These deviations could be the result of unusually high rates of a particular illness or unexpected expenditures on plant and equipment, and could be misinterpreted as

inefficiency. Despite the obvious thoroughness of this paper, Skinner (1994) challenges the use of stochastic frontiers with cross-sectional data for hospital efficiency measurement.

Skinner (1994) presents an argument based on the efficacy of basing policy decisions involving 'millions of dollars' on a statistical assumption. Specifically, Skinner considers two scenarios; one where the stochastic frontier finds inefficiency where there is none, and one where it fails to distinguish inefficient from efficient industries either statistically or visually. The argument is based on the accuracy of the error term of the cross-sectional stochastic frontier model, which is decomposed into noise and inefficiency. In the first instance the occurrence of a random event that happens, for example building repairs, every 5 years, and that gives rise to increased costs, may be misinterpreted as inefficiency prevailing in an industry. The use of panel data overcomes this problem since the occurrence of a random event would not affect the results to any great extent. Secondly, Skinner (1994) notes that the distribution of noise and that of the total error term are visually not significantly different from each other, leading him to question whether policy recommendations involving health expenditure can be based on such an error term.

Skinner (1994) contends that a non-parametric DEA frontier model with panel data yields more robust estimates of cost differences among nursing homes or hospitals. It is Skinner's view that the use of panel data will allow researchers to estimate a fixed effect for each health facility. The author, therefore, prefers the non-parametric approach taken by Kooreman (1994[a]) in the same volume, notwithstanding the fact that it too uses cross-sectional data.

Kooreman (1994[a]) analyses the technical efficiency of Dutch nursing homes with respect to the use of labour inputs using the DEA production function technique. The data is based on a survey held in 1989 among all 320 nursing homes in The Netherlands. Missing observations for some homes reduce the sample to 292 homes. Kooreman states that an important advantage of DEA, in addition to not having to pre-specify a functional form for the production function, is that it is relatively easy to handle the case of multiple inputs and outputs. However, the author also states that DEA is a *relative* efficiency criterion. DEA does not detect inefficiency of the nursing home sector as a whole, but rather the performance of nursing homes relative to the sector's best performers.

Kooreman (1994[a]) differs from previous studies of the nursing home industry in that he estimates a primal production function whereas others estimate cost functions. He posits that technical efficiency is a prerequisite for cost efficiency, so it stands to reason that the technical efficiency estimates of the production function will also provide useful insights of cost efficiency in the nursing home industry. Another notable difference is that his data are taken from The Netherlands, whereas others use U.S. data.

The nursing home industry in The Netherlands is financed on the basis of prospective payments for the number of beds, treatment days and capital costs. The budget allocated to a nursing home may result in a surplus, which is available to the home for future expenditure (Kooreman (1994[a]). The system is regulated in that there is very little scope for a nursing home to select patients; rather an 'indication committee' of health care experts allocates patients to homes. This point alone makes any comparisons to the hospital sector rather weak since, in the former case, budgets are based on historical cost with no apparent incentives built in to the payment system to encourage technical efficiency. Nevertheless, the results are topical and relevant to the application of DEA in healthcare, and are reported here.

Kooreman (1994[a]) shows that the nursing home sector operates under constant or decreasing returns to scale. According to this assumption, the results also show that an unusually high number (50 percent of nursing homes) operate on the technically efficient DEA frontier (Kooreman, 1994[a], p 309). The stricter efficiency criterion of constant returns to scale produces a frontier with 21 percent of nursing homes operating efficiently. Since the constant or decreasing returns criterion eliminates the effects of size of home from the efficiency estimates, the author proposes that this one is more appropriate. In any event, the existence of government regulation reduces a home's ability to determine its own size (Kooreman, 1994[a]).

There is a second stage to Kooreman's analysis, which examines the characteristics of efficient nursing homes so that the causes of inefficiency can be identified. The author uses censored regression models, however he acknowledges that these models produce '…estimates that are asymptotically biased toward zero…' (Kooreman, 1994[a], p 310). The size of the nursing homes is explained using the number of beds, the number of beds squared, and the presence of day care facilities. The equation used (constant and decreasing returns), however, measures efficiency conditional on a given size, and eliminates size effects. The author notes that a high

occupancy rate would be translated into higher efficiency even though it could also be an indication of poor quality. This is because if the demand for beds increases suddenly, the inputs required (e.g. nursing staff) cannot be increased quickly. The efficiency score will improve because the ratio of inputs to outputs falls. Therefore, quality of care is inversely related with efficiency since higher quality requires more inputs for a given output level. The author includes quality variables such as presence of a patients' council, presence of a council of patients' relatives, presence of a procedure for handling complaints and a variable that indicates the absence of visiting hour restrictions, in order to determine this relationship (Kooreman, 1994[a]). The author also notes that the various care requirements of patients in nursing homes will determine the level of resource requirements. Volunteer staff provides some of these activities, and this would result in lower inefficiency. The author also controls for age of patients since, generally, older patients require more resource use. The results show that on average non-efficient homes use 13 percent more labour inputs per unit of output compared with efficient homes (Kooreman, 1994[a]).

However, Dor (1994), in reviewing the DEA and SFE techniques, observes that DEA does not include a stochastic error term. He states that in practice all random noise in the DEA is combined with the true inefficiency, resulting in suspect inefficiency scores. The SFE method, conversely, has an advantage over DEA in that it separates the two sources of error. Although Dor prefers the technique used by Zuckerman et al. (1994) outlined above, he acknowledges that an improved method would be to use panel data.

Dor's (1994) criticism of Zuckerman et at. (1994) is aimed at their use of cross-sectional data, and the necessary reliance on MLE. MLE have omitted variable problems in that omitted variables appear as inefficiency. Panel data estimators are preferable because they '…are less likely to yield biased estimates of the βs due to omitted variables, and because they require fewer distributional assumptions about the deterministic error (u_i)' (Dor, 1994, p 332). Another reason for using a panel data approach is that it allows the analyst to test for endogeneity of outputs directly, rather than having to cross to the ordinary least squares model and then back again to the SFE, as is the case in the cross-sectional approach taken by Zuckerman et al. (1994).

Newhouse (1994) looks at frontier estimation in health care and concludes that such estimates cannot be relied on when trying to apply these measures of efficiency to reimbursement decisions. He states that the major difficulty is the measurement of

output, which tends to be measures of patient days or stays. According to Newhouse, the generic problem is the variation in quality of the product and its dimensionality; frontier techniques, in his opinion, work best when the product is homogeneous and one-dimensional. Newhouse (1994) addresses the use of frontier estimation as generic, without acknowledging the strengths and weaknesses of both techniques and the different results obtained from both cross-sectional and panel data. He notes that omitted inputs appear as inefficiency, but this is only the case for the SFE using cross-sectional data. He also attributes differences in severity of illness between hospitals as being mistaken for differences in efficiency since the resources required for treatment also differ[3].

Kooreman (1994[b]), in reply to Dor (1994), Skinner (1994) and Newhouse (1994), suggests that DEA and SFE are complementary tools because each addresses a different question. DEA uses input and output quantities to determine the level of technical efficiency, and SFE uses input prices, output quantities and total costs to determine both technical and allocative efficiency. According to Kooreman the strengths of both techniques can be demonstrated in future research by using panel data. He agrees that DEA and SFE results should not be simplistically taken to determine hospital reimbursement levels. However, the fact that policymakers may prematurely base reimbursement decisions on the results of these methods '…does not impair the usefulness of DEA and SFE as descriptive and analytical tools' (Kooreman, 1994[b], p 346). The use of these methods and the results they produce, therefore, provide a mechanism for identifying hospitals where special circumstances have given rise to differences in efficiency scores. The author posits that once this is known, it is possible for policymakers to investigate those hospitals more closely before deciding on whether or not the hospital is operating inefficiently. 'Thus, in my view DEA and SFE primarily serve as signal devices' (Kooreman, 1994[b], p 346).

Following on from the above debate in 1994, another subsequent publication uses both techniques. Linna (1998) investigates the development of hospital cost efficiency and productivity in Finland in the period 1988-1994 by comparing both parametric and nonparametric panel models. The parametric panel methods use stochastic cost frontier models with a time-varying inefficiency component. The non-

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[3] These resource differences are addressed however by the adjustment of hospital separations for DRG weights.

parametric panel methods use various DEA models to calculate efficiency scores and the Malmquist productivity index.

Linna's main objective in undertaking this study was to determine if the use of panel data models would improve the estimates of individual efficiency scores, as compared to earlier cross-sectional analyses. The author finds that results using panel data suggest that a reduction in inefficiency will reduce total hospital costs by between '…1.0 [and] 1.2 billion Finnish marks annually' (Linna, 1998, p 425). These figures are slightly lower than those obtained using cross-sectional models, however the author notes that it is difficult to measure the significance of reliability improvement from cross-sectional data to using a panel. The results further indicate that the choice of modelling approach does not affect the results. SFE and '…DEA models were both able to reveal that productivity progress in 1988-1994 was due to both the exogenous rate of technical change and to the effect of time-varying cost efficiency' (Linna, 1998, p 425). The author finds, however, that SFE and DEA methods produce different average efficiency scores. Nevertheless, he concludes by saying that non-parametric and parametric methods used together with panel data provide a sufficiently clear understanding of the development of efficiency in hospital production to justify future studies of frontier models in health care.

In an earlier journal issue of the same year Puig-Junoy (1998) uses a cross-sectional DEA to examine technical efficiency among Intensive Care Units (ICUs) in Catalonia (Spain) using a two-stage approach.   In the first stage environmental factors, over which the ICU has no control, are ignored. In the second stage variation in operating efficiency is captured by a regression model. By focusing on the services provided by ICUs, the model alleviates the problem of measuring heterogeneous outputs, since all ICUs treat patients that are critically ill. Also, the analysis uses patient-level data rather than aggregate data, and incorporates quality measures, such as mortality probability.   Despite the emphasis on quality variables, the author acknowledges that the analysis does not attempt to measure whether patients receive an appropriate amount of care; rather it presents mortality probability data showing severity of illness at admission. Also, the outcomes for these patients are determined by survival status at discharge. The measurement of technical inefficiency requires that ICUs minimise inputs given the amount of outputs produced.   The paper acknowledges that measuring technical efficiency is adequate when comparing the

performance of not-for-profit institutions, such as those found in the hospital sector (Puig-Junoy, 1998).

The choice of input set for Puig-Junoy's model is made up of both patient illness characteristics and clinical practice characteristics (Puig-Junoy, 1998). The seven inputs are: survival probability at admission, mortality risk level, weighted ICU days, non-ICU hospital days, available nurse days per patient, available physician days per patient, and technological availability. The output set contains: the number of days surviving in the hospital, and the surviving discharge status (Puig-Junoy, 1998, p 268-9). Many of the inputs used by the study, such as availability of nurse days, are determined exogenously and termed 'non-discretionary' because they cannot be modified when taking decisions to treat a patient. Therefore, it is not the use of these non-discretionary inputs that is being examined for efficiency. The efficiency estimates are determined 'given' these input levels, and calculated as 'short run efficiency'. The question being asked, is therefore:

> Given the level of labour (nurses and physicians) and technology available in the hospital, which is the efficiency level of clinical management in the treatment of a critically ill patient?
> (Puig-Junoy, 1998, p 268).

The answer to this question is somewhat obvious. In his conclusion the author notes that higher risk patients are managed less efficiently than lower risk patients. The existence of high risk, critically ill patients indicates a need for more resource use, with the intention being to prevent impending death. The author posits that devoting more resources to patients who eventually die is a form of inefficiency, since death could have been predicted to some degree.

> These results indicate that changes in clinical decisions may improve efficiency, given that the present resource allocation decisions do not seem to be closely related to the expected outcome.
> (Puig-Junoy, 1998, p 275).

The thrust of Puig-Junoy's study is to determine efficiency levels of clinical managers in ICUs based on the fact that financing ICUs accounts for 1 percent of GDP and 28 percent of hospital costs in the U.S. (Puig-Junoy, 1998, p 263). Corresponding figures are not provided for ICUs' health expenditure share in Catalonia (Spain), the subject of this study. This could be a significant factor if the

financing and/or reimbursement methods in the two healthcare markets (US and Spain) differ.

Also, with the introduction of more radical surgery, made possible with better technology, the use of ICUs has been increasing (see Hayes, 1991). The result is that with technological change and an ageing population it is increasingly possible to use surgical interventions on patients who were not considered good candidates prior to the introduction of the latest technological innovation. This increases the reliance on ICUs to provide post-operative care. Puig-Junoy's analysis does not take this into account since it is based on resources used per patient. However, technological innovation clearly has an effect on total health expenditures which may be better explained using aggregate data.

The author outlines various limitations of using DEA, among which are omitted inputs and outputs, the assumption of no measurement error, and the assumption of no random fluctuations in the input-output set (Puig-Junoy, 1998, p 276). Another limitation of DEA applied to healthcare is that DEA may incorporate variables that attempt to measure quality requiring value judgments, and for which data are less reliable.

Street (2003) provides another application of stochastic frontier estimation to the hospital sector using cross-sectional data for English public hospitals. More specifically this paper compares the results obtained using corrected ordinary least squares (COLS) with results obtained using the SFE cost functions. There are two alternative results obtained for the SFE model since the model is run under two assumptions of the distribution of the inefficiency term, u_i. One of the SFE models assumes a half-normal distribution, and the other an exponential distribution. Furthermore, the author produces confidence intervals relating to each hospital's point estimate of relative efficiency. For the COLS model this shows the prediction error associated with uncertainty of parameter estimates. For the SFE models, the parameter estimates are taken as known. However the author imposes a distribution around the value of the inefficiency term conditional upon the total error term, ε_i. This provides critical values for the upper and lower bounds of u_i.

Findings from Street (2003) show quite different levels of efficiency for each technique. The COLS model suggests hospitals are on average 69 percent efficient, whilst the SFE model reports a mean efficiency of 90 percent (Street, 2003 p 904). Although both models agree on which hospital is the most efficient and which is the

least, the rate of efficiency varies, as does the ranking of hospitals in between these two extremes. Quite rightly, Street posits that '…if the objective is to set hospital specific efficiency targets, it would be inadvisable to rely on a single specification of the error distribution' (Street, 2003, p 904). Clearly the use of cross-sectional data in these models suffers from the same problems outlined previously, namely that omitted variables appear as inefficiency and that periodic expenditures, which are not spread evenly over many years, would also appear as inefficiency for hospitals where they occur in the year of observation. Street lists a number of other reasons why the error distribution cannot be relied on, without attributing these to the use of cross-sectional data. Rather, the reasons given are based specifically on the hospital sector's unique characteristics such as society, regulators and hospital management having different notions of what they consider to be 'efficiency', the existence of excess capacity to enable emergency admissions, the inaccuracy of coding practices, and different accounting practices throughout the sector.

Craycraft (1999) identifies the necessity for nonprofit organisations to measure efficiency due to the growing reliance, in particular in the US hospital sector, for government to base reimbursement on efficiency. The author notes that hospitals are reimbursed a fixed rate to compensate for efficient treatment. This, combined with the rapid increase in hospital costs, '…has put pressure on hospitals to improve efficiency' (Craycraft, 1999, p 19). This author's main concern is to show how important accurate efficiency measurement is in order to identify inefficiencies. This process in turn provides the information necessary to realise cost savings through targeted inefficiency reduction.

Craycraft (1999) reviews various statistical techniques used in previous research to measure efficiency in hospitals and analyses the strengths and weaknesses of each method. The techniques compared are Ratio Analysis, Regression Analysis, and Frontier Analysis (DEA and SFE). The author notes that measuring efficiency is difficult, and inaccurate measures of efficiency may lead to poor decisions. If efficiency is improperly measured, it may lead to a misallocation of resources among and within hospitals. If hospitals are considered inefficient when they are truly efficient, resources may be inappropriately allocated away from these hospitals.

Craycraft's overview on the SFE technique sets out its limitations when using cross-sectional data and promotes the use of panel data to overcome these limitations. Specifically, the use of panel data overcomes the need to impose a functional form on

the data. The author nevertheless states that caution should be exercised in basing policy decisions on the results from any of these techniques, but notes that the SFE compares favourably to other techniques.

> SFE allows better estimates of an individual hospital's efficiency measure and the sources of the inefficiency (whether technical or allocative). SFE also allows for the statistical and sampling errors common in empirical research. However, the lack of knowledge of the correct functional form to use or the effects of using an inappropriate functional form makes interpreting the results difficult. (Craycraft, 1999, p 25)

Clearly, the SFE with panel data is superior in measuring relative efficiency because it overcomes the main objection to using a cross-sectional SFE, which is to impose a functional form on the data. Also, panel data models require fewer assumptions because repeated observations on a number of decision-making units, such as hospitals, can take the place of strong distributional assumptions (Kumbhakar and Lovell, 2000).

Stochastic Frontier Estimation

The advantages of using SFE with panel data include being able to test for endogeneity of outputs directly, having a model that is less likely to yield biased estimates of the βs, and the requirement for fewer distributional assumptions about the inefficiency term (u) than would be required with a cross-sectional model. One possible limitation regarding the use of SFE is that it constructs a benchmark frontier. Farrell (1957) referred to the 'unfortunate psychological effects' when performances are measured against some unattainable ideal. Also, arguments against SFE (for producing measurement errors when using prices, costs and quantities together) only apply to estimating cost, revenue and profit frontiers. They do not apply to technical efficiency estimation using production frontiers, since input prices are not required in their estimation. This is the main reason for choosing to estimate the production frontier in this paper, and measuring technical efficiency, not allocative efficiency. The following discussion, therefore, is restricted to production frontier models using panel data.

The choices to be made when estimating a production frontier involve the decision on whether to allow technology to vary through time, or to assume constant technology, and whether to adopt a fixed-effects or a random-effects model. The

assumption of time-invariant technology is relaxed when using panel data. Nevertheless, it is interesting to observe the difference in the two models. Equation (1) shows a Cobb-Douglas production frontier with time-invariant technical efficiency, where producers $i = 1,...,I$, over time period $t = 1..., T$:

$$\ln y_{it} = \beta_o + \sum_n \beta_n \ln x_{nit} + v_{it} - u_i \tag{1}$$

Here the structure of the production technology (β_o) is assumed constant over time. Adapting the model for fixed-effects is straight forward and generates the simplest panel data model (Kumbhakar and Lovell, 2000). Equation (2) shows the time-invariant model in equation (1), with fixed-effects.

$$\ln y_{it} = \beta_{oi} + \sum_n \beta_n \ln x_{nit} + v_{it} \tag{2}$$

In this model $\beta_{oi} = (\beta_o - u_i)$ so that these are producer-specific intercepts. That is, the u_i are treated as fixed and are to be estimated along with the β_ns. Here there is no distributional assumption on the u_i, and the v_{it} are iid $(0, \sigma_v^2)$ and uncorrelated with the regressors. The u_i are allowed to be correlated with the regressors or with the v_{it} and are non-negative. Thus, in the fixed-effects model there will always be at least one producer assumed to be operating on the technically efficient frontier. All other producers are compared to this technically efficient producer (Kumbhakar and Lovell, 2000).

We can observe the random-effects model by allowing the u_i to be randomly distributed with constant mean and variance. In this case the u_i are uncorrelated with the regressors and with the v_{it}. There is still no distributional assumption on the u_i and they remain non-negative. Equation (1) is re-written as:

$$\begin{aligned}
\ln y_{it} &= [\beta_o - E(u_i)] + \sum_n \beta_n \ln x_{nit} + v_{it} - [u_i - E(u_i)] \\
&= \beta_o^* + \sum_n \beta_n \ln x_{nit} + v_{it} - u_i^*
\end{aligned} \tag{3}$$

In equation (3) the u_i are random and this allows for some of the x_{nit} to be time invariant (Kumbhakar and Lovell, 2000).

Time-varying technical efficiency is a more appropriate assumption for panel data particularly if the operating environment is competitive. Technical efficiency change was incorporated into models of productivity change by Bauer (1990). Earlier

work on productivity change referred to the residual between an index of the rates of growth of outputs and an index of the rates of growth of inputs as 'a measure of our ignorance' [(Abramovitz, 1956) cited in Kumbhakar and Lovell, 2000]. It is now well accepted that efficiency change is a source of productivity change, and Bauer (1990) was able to decompose these by deriving '…detailed primal and dual (cost) decompositions of productivity change' (Kumbhakar and Lovell, 2000, p 308). Thus, the assumption that technical efficiency is constant over time is too strong an assumption to make.

> The longer the panel, the more desirable it is to relax this assumption. (Kumbhakar and Lovell, 2000, p 108).

Incorporating time-varying technical efficiency requires Equation (1) to be adjusted in the following way:

$$\ln y_{it} = \beta_{ot} + \sum_{n} \beta_n \ln x_{nit} + v_{it} - u_{it}$$
$$= \beta_{it} + \sum_{n} \beta_n \ln x_{nit} + v_{it}$$

(4)

Equation (4) is the stochastic production frontier panel data model with time-varying technical efficiency. β_{ot} is the frontier intercept that is common to all producers in period t, and β_{it} is the producer specific intercept in period t, ie. $\beta_{it} = \beta_{ot} - u_{it}$. The introduction of time-varying technical efficiency has a cost in that additional parameters must be estimated. With an I x T panel it is not possible to obtain estimates of all $I \cdot T$ intercepts β_{it}, the N slope parameters β_n, and σ_v^2. Fortunately, this was addressed in the literature [Cornwell, Schmidt and Sickles (1990)] and the model was simplified somewhat to reduce the number of intercept parameters to $I \cdot 3$ as shown by equation (5).

$$\beta_{it} = \Omega_{i1} + \Omega_{i2}t + \Omega_{i3}t^2$$

(5)

As with the time-invariant model, the time-variant model is adjusted for fixed-effects and random-effects, and detailed in Kumbhakar and Lovell (2000) p 109-110. In addition, these authors set out a third approach to estimating time-varying and time-invariant technical efficiency; a maximum likelihood approach.

The MLE method can estimate the parameters of the stochastic production function by numerical maximisation of the likelihood function. Traditionally this method was computationally demanding, however the availability of econometric

software[4] has greatly simplified the process by automating the method (Coelli, Rao and Battese, 1998). According to Kumbhakar and Lovell, 2000, p 106 '…MLE is generally more efficient than either LSDV[5] or GLS[6], since it exploits distributional information that the other two do not.'

Battese and Coelli (1995) define a stochastic frontier production function using panel data to estimate technical inefficiency effects. The authors note that previous papers involve a two-stage approach to this estimation. The first stage involves estimating the stochastic frontier production function and predicting the technical inefficiency effects under the assumption that these inefficiency effects are identically distributed. In the second stage the *predicted* technical inefficiency effects are regressed. This contradicts the assumption of identical distribution made in the first stage. In their work the authors propose a one-stage model which allows for the estimation of both technical change in the stochastic frontier and time-varying technical inefficiencies. This is the model chosen to be applied in this paper for estimation of a production frontier using Victorian Hospital Comparative Data for the years 1992/93 to 1995/96.

Model

The one stage stochastic frontier production function proposed by Battese and Coelli (1995) takes the general form:

$$Y_{it} = \exp(x_{it}\beta + V_{it} - U_{it}) \tag{6}$$

Where Y_{it} = production at the t-th observation (t = 1,2,….T) for the i-th firm (i = 1,2,….N).

WIES have been chosen as the dependent variable since these are separations weighted by DRG.

x_{it} = a (1 x k) vector of values of known functions of inputs of production for the i-th firm at the t-th observation.

These independent variables (regressor variables) are average available beds, nursing staff, administration/clerical staff, medical support staff, hotel and allied staff and year of observation.

β = a (k x 1) vector of unknown parameters to be estimated.

V_{it} = assumed to be iid $N(0, \sigma_v^2)$ random errors, independently distributed of the U_{it}s.

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[4] For example, the LIMDEP and the FRONTIER computer programs are both able to estimate SFE parameters using MLE.
[5] Least squares with dummy variables.
[6] Generalised least squares.

U_{it} = non-negative random variables associated with technical inefficiency of production, which are assumed to be independently distributed, such that U_{it} is obtained by truncation (at zero) of the normal distribution with mean, $z_{it}\delta$ and variance σ^2 (Coelli, 1996[a]).

The inputs chosen for the stochastic frontier model all had available data for at least one year of observation, which is a requirement of the model. Staff numbers were chosen because they are a significant factor in a hospital's production. Labour is also an area where we would expect some variation between hospitals depending on hospital size and location. We would expect increased use of labour to have a positive effect on output due to the assumption of monotinicity in the properties of production functions (Chambers, 1997, p 9).

Average available beds were chosen since bed availability would be expected to vary among hospitals and be positively correlated with output. As above, we would expect that hospitals with larger bed numbers are able to support more weighted inlier equivalent separations. There is doubt in the literature as to the appropriateness of using available beds as a measure of hospital size. Butler (1995) states that this is an imperfect measure of the scale of a hospital's operations because beds are not all interchangeable. Butler cites Berki (1972) in pointing out that intensive care beds, paediatric beds and obstetric beds are not substitutable for medical or surgical beds. For the purpose of this study, however, WIES are a function of available beds, although it is possible for beds to be underutilised at any point in time.

The technical inefficiency effect, U_{it}, from model (6) is specified as:

$$U_{it} = z_{it}\delta + W_{it} \tag{7}$$

Where z_{it} is a (1 x m) vector of explanatory variables associated with technical inefficiency of production of firms over time.

δ is an (m x 1) vector of unknown coefficients.

W_{it} is the random variable defined by the truncation of the normal distribution with zero mean and variance, σ^2, such that the point of truncation is $-z_{it}\delta$, i.e., $W_{it} \geq -z_{it}\delta$.

The explanatory variables in the inefficiency model are three dummy variables, which have been used so that some explanation can be given for inefficiency. The first of these has hospitals grouped into Metropolitan with a value of 1 and Non-metropolitan with a value of 0. This explanatory variable will show

whether or not geographical location has any effect on inefficiency, given the different level of concentration in each location. Vogel and Miller (1995), a study of market concentration among hospitals, show that highly concentrated markets (monopolies) result in lower costs[7].

The second dummy variable groups hospitals into Teaching with a value of 1 and Non-teaching with a value of 0. Some metropolitan hospitals in this study are non-teaching, and one non-metropolitan hospital is a teaching hospital. This variable should also give an indication as to whether or not teaching responsibilities have an impact on inefficiency. The increased burden on teaching hospitals may impact on efficiency since it would involve increased costs of teaching and research not otherwise imposed on non-teaching hospitals (Duckett, 1999). However, there is evidence to suggest that, once adjustment is made for casemix, the existence of university funds (for staff salaries etc.) and the utilisation of lower paid students, the impact of teaching is not as significant as previously thought (Butler, 1995, p 247).

The final dummy variable is the year of observation. This will show how inefficiency has changed over time. As discussed, the objective of casemix funding is for hospitals to improve efficiency over time in order to secure increased funding. In this study, year of observation appears in both models (6) and (7). In the stochastic frontier model (6), the year variable accounts for Hicksian neutral technological change, and in the inefficiency model (7), the year of observation shows that the inefficiency effects may change linearly over time.

Within the inefficiency model we would expect larger metropolitan hospitals to be less inefficient than their regional counterparts, representing economies of scale in production. Since most teaching hospitals are located in the metropolitan area, we would expect that these are also less inefficient than non-teaching hospitals. Over time we would expect inefficiency to decline since casemix funding imposes pressure on hospitals to reduce input costs.

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[7] Vogel and Miller (1995) examine the variations in rural hospital costs using U.S. data, and find that hospitals located in highly concentrated rural communities have lower costs per day than other non-metropolitan hospitals. They also find that metropolitan hospitals follow a similar trend in that increased competition in this market leads to increased costs. Specifically, metropolitan hospitals exhibit cost-increasing competition due to what they term a 'technological arms race' (Vogel and Miller, 1995, p 81). This form of competition based on acquisition of the latest technology is not evident in highly concentrated rural communities. The authors also find, however, that in other non-metropolitan hospital markets (with > 1 hospital) increased competition brings about lower costs, which is consistent with economic theory.

Results

The results for the one stage model comprising both stochastic frontier production function and technical efficiency effects using the above variables are set out in Tables 1, 2 and 3. All variables in Table 1 have been logged so that coefficients may be read as elasticities.

Table 1: Stochastic Frontier

Explanatory Variables	Coefficient	Standard Error	t-ratio
Constant	4.2005	(0.138)	30.320
*l*n Average Available beds	0.797	(0.061)	12.905
*l*n Nursing Staff	0.178	(0.077)	2.301
*l*n Admin/Clerical Staff	0.271	(0.049)	5.527
*l*n Medical Support Staff	-0.005	(0.029)	-0.176
*l*n Hotel and Allied Staff	-0.196	(0.066)	-2.937
Year	-0.030	(0.017)	-1.707

Table 2: Inefficiency Model

Explanatory Variables	Coefficient	Standard Error	t-ratio
Constant	-0.357	(0.164)	-2.174
Metropolitan location	-3.275	(0.330)	-9.922
Teaching	-1.391	(0.239)	-5.815
Year	0.008	(0.058)	0.149

Table 3: Statistical Summary

Statistic	Coefficient	Standard Error	t-ratio
Log Likelihood Function	-108.45		
σ^2	0.412	(0.041)	9.984
est γ	0.9018	(0.0209)	43.025
L-R Test of one-sided error	114.69		

The signs from the results are mostly as expected. In the stochastic frontier model positive signs for average available beds, nursing staff and admin/clerical staff suggest that a one unit increase in each of these variables results in an increase in the WIES figure. The sign for medical support staff is small and negative; indicating negative marginal product, but the t-ratio is less than 2. The sign for hotel and allied

staff is also negative and shows that a one unit increase in this input results in a 0.19%
decrease in WIES. Although this is not a large percentage change, it suggests that this
input also has negative marginal product, which is a counterintuitive result.   The first
three inputs, and hotel and allied staff, are statistically significant with t-ratios
exceeding 2.

The majority of signs in the inefficiency model are as expected. The result for
Metropolitan location suggests that if a hospital is located in the metropolitan area, it
reduces the inefficiency effect by over 3 per cent. Teaching hospitals also have a
negative relationship and therefore teaching hospitals also reduce the inefficiency
effect compared to non-teaching hospitals. This is consistent with Butler's (1995)
findings. The fact that most teaching hospitals are located in the metropolitan area
may explain this result. Over time it is not evident whether the inefficiency effect
changes linearly since the result is not statistically significant.

The null hypothesis that the inefficiency parameters equal 0 ($\delta_1 = \delta_2 = \delta_3 = 0$)
is rejected at the $\chi^2_{0.95,\ 3}$ value[8]. In Table 3 the estimate for the variance parameter
(gamma) is close to 1; therefore, taken together, the inefficiency effects are likely to
be highly significant in the analysis of weighted inlier equivalent separations.

The δ parameter in equation (7) is a time-invariant parameter. In order to test
this assumption, an OLS model was estimated in three different specifications; one,
allowing δ to differ across four years for both variables and, for the two remaining
specifications, allowing δ to differ across four years for one and then the other
variable. The time variation in the parameter was tested by comparing the first
specification with each of the two restricted specifications. The F-test statistic fails to
reject H_o that the coefficients do not change over time. Thus, the null hypothesis is
accepted that the δs do not change significantly over the four years.

Table 4 sets out a summary of the technical efficiency estimates for the
hospitals in this study.

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[8] H_o: $\delta_1 = \delta_2 = \delta_3 = 0$ has a Log (Likelihood) = -131.073
Therefore: λ = -2{-131.073 – [-108.45]} = 45.22
Where $\chi^2_{0.95,\ 3}$ = 7.81, 45.22 > 7.81, therefore reject H_o.

Table 4:   Summary of Technical Efficiency Estimates by Year of Observation (Number and %)

Year		< 0.5	0.5	0.6	0.7	0.8	0.9	1	Total Hospitals
1	No.	5	9	11	26	31	34	0	116
	%	4.3	7.8	9.5	22.4	26.7	29.3		
2	No.	18	4	13	22	32	23	0	112
	%	16	3.6	11.6	19.6	28.6	20.5		
3	No.	10	8	6	26	22	30	0	102
	%	9.8	7.8	5.9	25.5	21.6	29.4		
4	No.	8	7	7	24	27	28	0	101
	%	7.9	6.9	6.9	23.8	26.7	27.7		

Note: Using a Chi-squared test, the null hypothesis was not rejected, indicating that there has not been any significant change in proportions over time.
$X^2 = 17.382 < X^2_{0.95, 15} = 24.996$

In Table 4 technical efficiency is a measure between 0 and 1, with 1 being technically efficient and 0 being technically inefficient. It is clear that no hospital lies on the efficiency frontier (= 1). Overall, the number of hospitals in the study fell from 116 to 101. This was due to hospital closures and amalgamations. Over the four year period, the number of hospitals that are 90 per cent efficient fell from 34 to 28. Similarly, the number of hospitals operating within the 80 per cent efficiency group fell from 31 to 27. These numbers as a percentage of the total do not change to any extent for both of these groups. Table 5 below shows hospitals' technical efficiency score results prior to closure or amalgamation.

Table 5: Efficiency Score Results of Hospitals Prior to Closure or Amalgamation

Hospital*	Year 1	Year 2	Year 3
31 $R^{\#}$	<0.5		0.7
34 R	0.5		
54 R	<0.5		
103 M	0.9		
4 R	0.8	0.6	
19 R	0.6	0.5	
24 R	0.7	0.6	
25 R	0.8	0.6	
37 R	0.8	0.8	
44 R	0.5	<0.5	
47 R	0.8	<0.5	
52 R	0.7	<0.5	
66 R	0.6	<0.5	
72 R	0.7	0.8	
107 R	0.9	<0.5	
28 R	0.9	<0.5	<0.5

* None of the above hospitals (except 31) was operating in Year 4.
\# Hospital 31 did not close, but data was not available for Year 2. It is included here so that total hospital numbers correspond with Table 4.
R = Regional Hospital   M = Metropolitan Hospital

With the exception of hospitals 37, 72 and 103, all hospitals that closed or amalgamated experienced declining efficiency just prior to ceasing operations. It is possible that either the threat of reduced funding, or the fact of it, has been the cause of these closures. Of the results shown in Table 5, none of the hospitals noted were teaching hospitals, and only one was located in the metropolitan area.

From Table 4 it is clear that the number of hospitals operating at <0.5 efficiency rose initially and then fell at the end of the period. The same can be said for those operating at 0.6 efficiency. The hospital numbers operating between 0.5 and 0.7 efficiency remained fairly stable over the period. These results also suggest that even the most efficient hospitals could reduce inputs by approximately 10 per cent and still maintain current output levels.

Conclusion

The central aim of this paper has been to analyse the Victorian public hospital sector and determine to what extent, if any, the introduction of casemix funding using DRGs has altered efficiency in that State's delivery of acute hospital services. In arriving at the conclusion that there does not appear to have been an improvement in individual hospitals' technical efficiency over time, it is still evident that casemix funding has altered the way that scarce resources (that is, government funding) are distributed to acute hospitals. Although this funding arrangement was originally designed, among other things, to improve efficiency, the evidence produced shows that this objective was not completely realised. If, in fact, overall cost savings were achieved in Victoria, they were due to closures and amalgamations of small regional hospitals during the period.

It is apparent from the literature that both DEA and SFE techniques have been applied to health data elsewhere. The techniques have been the subject of intense debate concerning their legitimacy in general, as well as in their application to healthcare. Clearly the importance of hospital funding to the provision of public health necessitates considerable scrutiny to ensure that efficiency measures provide policymakers with accurate information. The main advantage of SFE is that it is able to separate random noise from inefficiency through a decomposed error term. It has been shown that firms' operations are suboptimal and, therefore, analysis of production frontiers is more realistic than that of production functions. Also, the use of panel data provides richer results than cross-sectional data due to the data being broader.

The SFE results show that casemix funding does not appear to have had a positive effect on hospital efficiency over the four year period. It does appear, however, that casemix funding has had an effect on hospital closures in Victoria's regional areas. According to the results, efficiency gains were made only in metropolitan teaching hospitals. The stochastic frontier model shows a positive relationship between the first three inputs (average available beds, nursing staff and admin/clerical staff) and output, and a negative relationship between hotel and allied staff, and output, indicating negative marginal product for this input. Medical support staff also exhibits negative marginal product. This input, together with the year of observation, is not statistically significant and therefore not a good indicator of

production. The inefficiency effects model shows that hospitals in the metropolitan area and teaching hospitals reduce the inefficiency effect. That is, there is a strong relationship between geographical location and efficiency, and type of hospital and efficiency.

Tables 4 and 5 also show no support for technical efficiency improvement over time. The reduction in hospital numbers from 116 to 101 is a result of closures and amalgamations over the period, most of which occurred following a period of inefficiency. It is notable that most of the closures observed occurred in regional Victoria where hospitals are smaller and cater to a smaller and more widespread population. Also, there is only one teaching hospital located in the non-metropolitan area, suggesting that the lack of teaching facilities in regional Victoria corresponds with perceived inefficiency in those locations.

These results suggest that casemix funding benefits large metropolitan teaching hospitals, at the expense of small regional hospitals that are less capable of competing for government funding. The fact that casemix has been taken into account in this analysis suggests that hospitals have been compared on an equal footing. Nevertheless, geographical location, perhaps due to differences in concentration, population size, demographics, and hospitals' limited access to the pool of highly skilled nursing and administration staff, appears to have had a significant impact on these results.

The fact that the SFE model estimates the frontier from the data suggests that realistically hospitals have performed, at best, within 10 percent of achieving a position on the frontier. Continued cutbacks and expectations of efficiency improvements do not appear to be justified under this scenario since there does not appear to have been any significant improvement in efficiency in individual Victorian public hospitals following casemix funding. Cost savings, if any, are a direct result of closures and amalgamations that occurred in regional Victoria. These are typically small hospitals that are unable to expand due to the limited size of population and, consequently, their patient base, and lack of available doctors. In these circumstances, therefore, casemix funding using DRGs has not delivered the improvements that it promised. Future research should be directed at using SFE with panel data to analyse the implication of casemix funding applications Australia-wide.

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