University of New England

School of Economic Studies

Allowing for nondiscretionary factors in data envelopment analysis: A comparative study of NSW local government

by

Andrew Worthington and Brian Dollery

No. 99-12 – December 1999

Working Paper Series in Economics

ISSN 1442 2980

http://www.une.edu.au/febl/EconStud/wps.htm

 ISBN 1 86389 655 4

Allowing for nondiscretionary factors in data envelopment analysis: A comparative study of NSW local government

Andrew Worthington and Brian Dollery[**]

Abstract

Using the planning and regulatory function of one hundred and seventy-three NSW local governments, several approaches for incorporating contextual or nondiscretionary inputs in data envelopment analysis (DEA) are compared. Nondiscretionary inputs (or factors beyond managerial control) in this context include the population growth rate and distribution, the level of development and non-residential building activity, and the proportion of the population from a non-English speaking background. The approaches selected to incorporate these variables include discretionary inputs only, nondiscretionary and discretionary inputs treated alike and differently, categorical inputs, 'adjusted' DEA, and 'endogenous' DEA. The results indicate that the efficiency scores of the five approaches that incorporated nondiscretionary factors were significantly positively correlated. However, it was also established that the distributions of the efficiency scores and the number of councils assessed as perfectly technically efficient in the six approaches also varied significantly across the sample.

Key Words: data envelopment analysis, productive efficiency, local government

---

[**] Andrew Worthington is a Senior Lecturer in the School of Economics and Finance, Queensland University of Technology, and Brian Dollery is an Associate Professor in the School of Economic Studies, University of New England. Contact information: School of Economic Studies, University of New England, Armidale, NSW 2351, Australia. Email: bdollery@metz.une.edu.au.

ALLOWING FOR NONDISCRETIONARY FACTORS IN DATA ENVELOPMENT ANALYSIS: A COMPARATIVE STUDY OF NSW LOCAL GOVERNMENT

1. INTRODUCTION

Local public sector reform has been underway for more than a decade in many advanced countries, including the United Kingdom, Canada, New Zealand and Australia. The similarities in the local public sector reform programs followed in these countries, with their typical mix of commercialisation, corporatisation, deregulation of public sector management, performance monitoring and contracting-out, clearly all seek to enhance efficiency in the local public sector. Evaluating the success of these programs therefore depends crucially on how accurately and appropriately efficiency can be measured, and this has formed the basis of a small, but steadily increasing empirical effort (Chalos and Cherian 1995, Worthington 1999). However, it is only relatively recently that attempts have been made to apply the more advanced econometric and mathematical frontier techniques to the measurement of the efficiency of local governments in the provision of public services. One possible reason for this neglect is that it has generally been argued that there are several aspects of local governmental services that may make it difficult to develop accurate measures of efficiency, especially for the purposes of comparative performance measurement and process benchmarking.

First, the outputs of a service provider may be complex and/or multiple, and there may be difficulty in establishing cause and effect between the activities of a service and the final outcomes it seeks to influence, and these may be evident only after considerable time. Second, local government organisations may encounter problems in identifying the cost of producing and delivering services. For example, there may be difficulty apportioning costs across different services or the costs of a given program over long periods of time. Third, complexity in local government services may exist due to the interplay of related services and. For instance, efficiency indicators may need to capture the positive and negative externalities of service provision. Fourth, there are potentially many users of local governmental performance information. Different lines of accountability and the disparate informational requirements of governments, taxpayers, employers, employees, consumers and contractors create additional complications in efficiency measurement. Finally, a number of restrictions placed by these stakeholders may impinge upon the theoretical ability of local government entities to improve efficiency. For example, several commentators have argued that the intergovernmental mandating of expenditures and intergovernmental grant provisions may restrict the ability of local government bodies to modify behaviour efficiently.

A common theme that runs through these various dimensions of local government services is that the discretionary and non-discretionary resources available to a particular local government may have an important influence on its relative performance if other providers are operating in different environments. These environmental (or contextual) factors may encompass both physical environmental circumstances, as well as constraints arising from organisational and managerial policies. Ignoring these imposed factors may lead to disingenuous efficiency measures. For example, the socioeconomic profile and topography of a given local government area is not controlled by local authorities, yet directly affects the ability of councils to provide human, community and economic services. Similarly, contextual information in the form of statutory and professional standards or social norms may dictate the quantity and/or quality of output. Numerous examples exist in the form of mandated environmental and building standards.

The question arises as to how these differences in operating environment may be best incorporated into microeconomic efficiency analyses, especially those employing data envelopment analysis or DEA. The use of DEA as a technique for measuring the efficiency of government service delivery is now relatively well-established in Australia and several other advanced countries. For example, in the case of Australia, the Steering Committee for the Review of Commonwealth/State Service Provision (1998) presents the results of five case studies where DEA has been applied. These case studies cover Victorian hospitals, Queensland oral health services, and NSW corrective services, police patrols, and motor registries. However, to date little empirical work has been directed at applications of DEA to local government. There is an obvious need for empirical studies to examine the possible use of such techniques in improving performance in government-funded service delivery at the local level.

However, there is an even more compelling need to investigate how imposed contextual factors may impact upon these measures of relative efficiency. This is especially the case when the diversity that exists in Australian local government is recognised. For example, apart from the diversity implied by seven separate state-based legislative systems, Australian councils also vary significantly in population size and area, level of financial self-sufficiency, geophysical characteristics, and the degree of remoteness from major urban centres (Worthington 1999). Inexorable demographic, employment and infrastructural trends will ensure that this diversity is likely to continue.

The paper itself is divided into five main sections. Section II focuses on the alternative theoretical methods of incorporating contextual factors in DEA. Section III deals with the actual specification of the alternative approaches, and Section IV examines the specification of inputs and outputs to be used in each approach. Section V presents the resultant indices of efficiency and compares the results across the approaches used. The paper ends with some brief concluding remarks in the final section.

II. ALTERNATIVE TREATMENTS OF CONTEXTUAL FACTORS IN DEA

There are two main approaches to incorporating contextual factors in DEA. The first approach evaluates all variables simultaneously, incorporating discretionary and non-discretionary factors as variables endogenous to the efficiency model. This type of approach is largely confined to non-parametric techniques, such as DEA, which readily permit the inclusion of categorical and non-discretionary variables, and those denoted in different units of measurement. The second approach employs a single-stage analysis where the results from a model using only controllable inputs and outputs are subsequently adjusted for contextual factors in a second or even third stage analysis. This multi-stage adjustment process is available to both parametric and non-parametric approaches to efficiency measurement.

Within the single stage approach, a number of different techniques have been used. One method is to ignore differences in the contextual environment across the entire sample (Fried *et al*. 1995). That is, both controllable and uncontrollable factors are treated as discretionary inputs and outputs, or excluded from the analysis entirely, and thereby no specific allowance is made for factors beyond managerial control. Where there is only a slight degree of heterogeneity in inputs and outputs, both discretionary and nondiscretionary, the bias in efficiency measures thereby introduced may be relatively small. Where this is not the case, "including nondiscretionary inputs in the LP model for DEA amounts to an assumption of free disposability of these inputs. This is not necessarily a realistic assumption" (Ray 1988: 170). Examples of studies using this technique in local public services include Bessent *et al*. (1982), Cook, Roll and Kazakov (1990), and Parkin and Hollingsworth (1997) .

A second technique only compares organisations which operate in a similar operating environment. For example, comparisons may be made only among observations with a strictly identical technology. For instance, Cook, Kazakov and Roll (1993) examined the efficiency of local authority road patrols across privatised and non-privatised operations, and differing traffic levels. Similarly, Domberger *et al*. (1986) compared the cost efficiency differences between competitively tendered refuse collection services and those provided 'in-house'. However, whereas this method substantially decreases the amount of bias in efficiency results, it dramatically reduces the lessons that may be learned from dissimilar operating environments, and slows the spread of innovation (Fried *et al*. 1995; Rouse *et al*. 1996). Moreover, reducing the number of observations in nonparametric approaches to efficiency measurement substantially increases the likelihood a given observation will be judged relatively efficient (Banker 1993; 1996).

The third single-stage technique is only to compare organisations with other organisations in a similar or less favourable operating environment (Ali and Seiford 1993). For instance, suppose that an input variable can assume one of a number of levels. These values typically partition the entire reference set of decision-making units or DMUs into a number of categories. Now assuming that there is a natural nesting or hierarchy of the categories, each DMU should be only compared with DMUs in its own and more disadvantaged categories. For example, the relevant contextual input may the proportion of the population suffering from socioeconomic disadvantage. However, if this natural hierarchy assumption does not hold, then separate analyses are normally performed for each category. Empirical work using this technique includes Banker and Morey's (1986) and Ruggiero's (1996) study of New York local education authorities.

The final technique is to incorporate the contextual information directly into the DEA calculation. In the case of input-orientated (output-orientated) models, it is not relevant to maximise (minimise) the proportional decrease (increase) in the entire input (output) vector, rather maximisation (minimisation) should only be determined with respect to the sub-vector that is composed of discretionary inputs (outputs). Thus, the contextual information contributes to the constraints placed upon decision-making units, not the posited efficiency improvements. Studies using this technique in local public services include Worthington (1999) and Duncombe, Miner and Ruggiero (1997).

The main alternative to these single-stage methods is to employ the two-step (or stage) procedure which uses econometric methods to estimate the relationship between the characteristic and the efficiency scores. The efficiency scores and/or ranks can then be adjusted on the basis of this information. The main advantages are that a large number of characteristics can be accommodated, it makes no assumptions about the directional influence of contextual information, and allows for statistical tests of significance. Ray (1988: 175) argues *inter alia*:

> The advantage of second stage regression is that it allows one to leave the functional form of $f(x)$ unspecified and still determine the (stochastically) maximum output level producible from an observed input bundle for any level of the nondiscretionary inputs. Inclusion of the nondiscretionary inputs at the same level as the discretionary inputs does not permit one to identify the maximal output with reference to the discretionary inputs alone.

Ray (1988; 1991) employed a non-positive disturbance term to ensure that predicted efficiency never falls below observed efficiency when using ordinary least squares for this purpose, whilst Lovell, Walters and Wood (1993) used tobit regression to address the truncation problem found in efficiency scores. Alternatively, Rouse, Putterill and Ryan (1997) proposed a DEA model which initially includes controllable outputs, but only environmental factors as inputs. Rouse, Putterill and Ryan (1997: 8) have argued that:

> The output values of each inefficient DMU are adjusted up to frontier by the radial and non-radial slacks to ensure all DMUs operate on an equal footing with regard to the environmental factors. The adjusted outputs and controllable inputs are then included in the second stage DEA model to produce efficiency scores adjusted for environmental differences.

The multiplicity of approaches used to incorporate contextual information into efficiency analyses suggests the need for a critical appraisal of these techniques (Fried *et al*. 1995). Two motivations are evident. The first is that different econometric and mathematical programming techniques are likely to yield different absolute and relative measures of efficiency. A rigorous empirical comparison is therefore likely to highlight some of problems encountered in using alternative approaches, and whether the selection of one method over another would result in erroneous conclusions. The second motivation is that policymakers' attitudes towards environmental factors are a matter of general concern. There is scope to investigate the process of formulating information on contextual factors, and seeing how this fits into a system of intergovernmental relations. This is particularly pertinent for the system of intergovernmental grants and concomitant efforts by the funding government's efforts to enforce performance standards across jurisdictions.

III. SPECIFICATION OF THE ALTERNATIVE APPROACHES

The approaches selected for application to the local government data set are as follows (with notation): (i) a single-stage input-orientated DEA model incorporating discretionary inputs only (*A*); (ii) an identical DEA model incorporating both nondiscretionary and discretionary inputs (*B*); (iii) a DEA model constructed so as to permit the differential treatment of discretionary and nondiscretionary inputs (*C*); (iv) a DEA model that allows for categorical inputs (*D*); (v) a two-stage approach where efficiency scores constructed on the basis of discretionary inputs in the first stage are regressed against nondiscretionary inputs in a second stage (*E*); and (vi) a two-stage input adjustment approach where only nondiscretionary inputs are used in the first stage, and form the basis for adjusting outputs in a second stage calculation using discretionary inputs (*F*).

The base linear programming models for the following analysis consists of the input-orientated constant returns-to-scale (CRS) formulation of Charnes, Cooper and Rhodes (1978) and the input-orientated variable returns-to-scale (VRS) formulation following Banker, Charnes and Cooper (1984) [the notation used below follows Coelli *et al*. (1999)]. We limit our discussion to the VRS envelopment and follow the work of Charnes *et al*. (1993). Assume that the input (*I*) variables may be partitioned into subsets of discretionary (*D*) and nondiscretionary (*N*) variables:

$$I = \{1,\ 2,\ \ldots,\ n\} = I_D \cup I_N,\ I_D \cap I_N = \varnothing \qquad (1)$$

Assume there is data on K inputs and M outputs on each of N councils, and for the i-th council these are represented by the vectors x_i and y_i, respectively. The data of all N councils in the sample is denoted by a $K \times N$ discretionary input matrix, X, and an $M \times N$ output matrix, Y. The nondiscretionary inputs are denoted by the $L \times 1$ vector z_i for the i-th council and the $L \times N$ matrix Z for the full sample. The envelopment form of the problem used for approaches (A) and (B) is :

$$\begin{aligned} &\min_{\theta,\lambda} \theta \\ \text{s.t. } & -y_i + Y\lambda \geq 0 \\ & \theta x_i - X\lambda \geq 0 \\ & \theta z_i - Z\lambda \geq 0 \\ & N1'\lambda = 1 \\ & \lambda \geq 0 \end{aligned} \qquad (2)$$

where θ is a scalar and λ is a $N \times 1$ vector of constants. The value of θ will be the efficiency score for a particular council. It will satisfy $\theta \leq 1$, with a value of 1 indicating a point on the frontier, and hence a technically efficient council. The value of $\theta \leq 1$ identifies the amount of any inefficiencies that may be present.

Discretionary inputs and outputs

In the case of approach (A) only the subset of discretionary input variables I_D is used (the line involving Z is removed). Put simply, the influence of nondiscretionary variables is excluded from the analysis, and amounts to an assumption that these factors are constant across the sample. A large number of past DEA studies have followed this approach, including Johnes and Johnes' (1995) analysis of tertiary education in the U.K., Deller and Nelson's (1991) study of U.S. municipal road maintenance, and Thompson's *et al*. (1996) inquiry into natural resource use in the U.S. On the other hand, approach (B) includes the nondiscretionary input variables I_N (the line involving Z is included) though these are treated in exactly the same manner as the discretionary variables. The model formulation detailed above implicitly assumes that all inputs are discretionary (ie. controlled by the management of each council and varied at its discretion). Thus, in the case of the input-orientated models, maximisations are determined with respect to the entire vector of inputs that is composed of both discretionary and nondiscretionary inputs. Early approaches, which treated both controllable and environmental factors as discretionary inputs and outputs, include Bessent *et al*. (1982), Chalos and Cherian (1995) and Bates (1997).

Nondiscretionary inputs

The third approach (*C*) rests on the assumption that for an input-orientation it is not relevant to maximise the proportional decrease in the entire input vector. Maximisation should be determined only with respect to the subvector composed of discretionary inputs. Reproducing (2) we have:

$$\begin{aligned} &\min_{\theta,\lambda} \theta \\ \text{s.t.} \; -y_i + Y\lambda &\geq 0 \\ \theta x_i - X\lambda &\geq 0 \\ z_i - Z\lambda &\geq 0 \\ N1'\lambda &= 1 \\ \lambda &\geq 0 \end{aligned} \qquad (3)$$

The main difference in the above formulation is that value of theta, θ, to be minimised appears only in the constraints for the discretionary variables, whereas the constraints for *the* nondiscretionary variables operates only indirectly because the input levels are not subject to managerial discretion. Viewed as a two-step procedure, after the value of θ is determined for the discretionary inputs, we then solve the appropriate envelopment problem. The specific formulation employed to incorporate non-discretionary variables in the input-oriented BCC model may be found in Charnes *et al*. (1993) and Ali and Seiford (1993).

Categorical inputs

The fourth approach (*D*) rests on the assumption that an input variable can assume one of *L* levels (1, 2, . . . *L*). These *L* values typically partition the entire reference set of councils into a number of categories. Specifically, the set of councils $D = \{1, 2, \ldots n\} = D_1 \cup D_2 \ldots \cup D_C$, where $D_k = \{i \mid i \in D$, input value is k, and $D_j \cap D_k = \emptyset$, $j \neq k$. Now assuming that there is a natural nesting or hierarchy of the categories, each councils should be only compared with councils in its own and other more disadvantaged categories. Returning to the model and following Banker and Morey (1986) we can write:

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta \\
\text{s.t. } & -y_i + Y_{i \in U_{k=1}^{K} D_k} \lambda \geq 0 \\
& \theta x_i - X_{i \in U_{k=1}^{K} D_k} \lambda \geq 0 \\
& N1' \lambda = 1 \\
& \lambda \geq 0
\end{aligned}
\tag{4}
$$

Thus, all units $l \in D_1$ will be evaluated against the units in D_1, all units $l \in D_2$ will be evaluated against $D_1 \cup D_2$, all units $l \in D_3$ will be evaluated against $D_1 \cup D_2 \cup D_3$, and so on. Ruggiero (1996) used a similar model to incorporate nondiscretionary categorical inputs, namely a proxy for parental education in a study of New York state school districts, whereas Rouse *et al.* (1997) categorised environmental factors pertaining to local authority road maintenance in New Zealand.

'Adjusted' data envelopment analysis

The fifth approach (*E*) is a two-stage technique where efficiency scores are first calculated in an identical manner to (*A*): that is, using discretionary inputs (I_D) only. The scores thus obtained are then regressed against the set of nondiscretionary inputs (I_N) using the tobit regression model. The predicted scores from this second stage analysis "are 'averages' and the relative position of an individual councils vis-à-vis their predicted counterparts reflects their success or failure in coping with their environment" (Rouse *et al*. 1997: 8). Studies using this type of approach include Lovell, Walters and Wood (1994) and McCarty and Yaisawarng's (1993) studies of New York state school districts.

'Endogenous' data envelopment analysis

The final approach (*F*), follows the work of Rouse *et al*. (1996) which provides an adjustment to controllable inputs to allow for the influence of non-favourable operating environments. The first stage includes the vector of outputs, but only the nondiscretionary inputs (I_D). After running this program, the values of each council are adjusted towards the frontier to ensure that all councils operate on an equal footing with regard to the environmental factors. These adjusted outputs are then included in an identical DEA model in combination with the discretionary inputs I_D to produce what Rouse *et al*. (1997: 8) refer to as "efficiency scores adjusted for environmental differences".

IV. SPECIFICATION OF INPUTS AND OUTPUTS

The data set used in applying these alternate models relates to New South Wales local governments' planning and regulatory function. The planning and regulatory function is not only one of local governments' most important economic roles, but it is also the most frequent focus of contention between local councils and their communities (NSWDLG 1998). For example, of the 1307 complaints directed to the NSW Department of Local Government's Investigations and Review Branch concerning individual local councils during 1996/97, 378 complaints or allegations (some 30 percent) corresponded to planning associated matters, and 69 complaints (slightly more than 5 percent) to building associated matters (NSWDLG 1997: 52). Moreover, the NSW Department of Local Government (1998: 52) has noted that these complaints are usually distributed across a relatively small number of councils:

> The complaints were spread over 132 councils compared to 138 councils last year. Approximately 50% of all matters received by way of complaints/allegations involved 20 councils. The Department did not receive complaints on 45 councils compared to 39 last year.

All data corresponds to the year ending 31 December 1993 and is obtained from the NSW Department of Local Government (NSWDLG), the NSW Local Government Grants Commission (NSWLGGC), and the Australian Bureau of Statistics (ABS). The data applies to a sample of 173 local governments.

The set of discretionary and nondiscretionary variables themselves are included in Table 1. The first set of variables are the 'environmental' or 'contextual' factors hypothesised as affecting the provision of planning and regulatory services. These correspond to the vector of 'expenditure disabilities' used by the NSWLGGC as the basis for the Financial Assistance Grant (FAG) relativities. The NSWLGGC (1994: 11) specifies these environmental disabilities using the following criteria:

> For each function the Commission has identified a number of variables which are considered to be the most significant in influencing a council's expenditure on that particular function. A council may have a disability because of inherent factors such as topography, climate, traffic, duplication of services etc. In addition to disabilities identified by the Commission, 'Other' disabilities relating to individual councils may be determined from council visits or submissions.

Table 1. *Variables and descriptive statistics, planning and regulatory services*

Variable	Description	Mean	Std. dev.	Min.	Max.
Non-discretionary inputs					
x_1	Population growth rate	0.0084	0.0015	-0.0335	0.0466
x_2	Development index	11.7460	29.6300	3.9500	395.870
x_3	Heritage/environmental sensitivity	1.844	0.8616	1.0000	5.0000
x_4	Non-residential building activity	2.3768	2.4662	0.0000	30.5760
x_5	Population distribution	4.8172	6.8277	0.0000	50.4760
x_6	Non-English speaking background	0.0836	0.0933	0.0042	0.4378
Discretionary inputs					
x_7	Planning and regulatory expenditure	0.59E+06	0.88E+06	1000.00	0.41E+07
x_8	Legal expenditure	56015	0.11E+06	0.0000	0.68E+06
x_9	Full-time equivalent staff	8.3985	13.283	0	107
Discretionary outputs					
y_1	Number of BAs determined	748.49	985.02	0.0000	5083.00
y_2	Number of DAs determined	280.90	329.77	0.0000	1760.00

The ‘disabilities’ correspondingly chosen are: (i) average population growth over the previous five years (x_1); (ii) a regression-based index of development activity (x_2); (iii) the NSWLGGC’s subjective assessment of the areas subject to heritage/environment sensitivity (x_3); (iv) the proportion of properties classified as ‘commercial or industrial’ (x_4); (v) population distribution (x_5); and (vi) a disability factor indicating the proportion of the population from a NESB (x_6). All other things being equal, these factors indicate the need for higher inputs imposed upon a council’s planning and regulatory function by additional costs in development control (development activity), forward planning (population growth), the provision of supplementary information (NESB), the duplication of services and staff travel (distribution), and additional complexities related to plan preparation and development control (heritage/environment) (NSWLGGC 1994). Approaches (*B*) and (*F*) incorporate these variables in single-stage and second-stage estimations respectively denoted as discretionary inputs, (*C*) also includes these same variables, though they are treated as nondiscretionary, (*E*) uses the variables as a vector of exogenous explanatory factors in a second-stage analysis. Approach (*A*) excludes these contextual variables as per the preceding discussion. Summary details of the six alternative approaches are presented in Table 2.

Table 2. *Discretionary and nondiscretionary inputs and outputs*

	Variable description	A	B	C	D	E	F
			Single-stage			*Two-stage*	
x_1	Population growth rate		●	○		○	●
x_2	Development index		●	○		○	●
x_3	Heritage/environmental sensitivity		●	○		○	●
x_4	Non-residential building activity		●	○		○	●
x_5	Population distribution		●	○		○	●
x_6	Non-English speaking background		●	○		○	●
x_7	Standardised unit cost percentile				○		
x_8	Planning and regulatory expenditure	●	●	●	●	●	●
x_9	Legal expenditure	●	●	●	●	●	●
x_{10}	Full-time equivalent staff	●	●	●	●	●	●
y_1	Number of BAs determined	■	■	■	■	■	□
y_2	Number of DAs determined	■	■	■	■	■	□

Notes: ● discretionary input; ○ nondiscretionary input; ■ discretionary output; □ adjusted discretionary output.

An alternative method of incorporating contextual information is employed in the fourth approach (*D*). Here the standardised unit cost for planning and regulation is used to construct ten percentile categories (x_7). The standardised unit cost is based upon a subjective weighting of contextual factors by the LGGC, and indicates the expenditure disabilities imposed upon a given council relative to the state standard. In turn, this measure is used as the basis for intergovernmental grant relativities. It is assumed that the categories thus obtained form a natural nesting or hierarchy in local government operating environments. For example, those councils in the tenth (lowest) percentile of unit costs will be compared against other councils in that percentile, and all other percentiles. Councils in the twentieth (next to lowest) percentile will also be compared against themselves, but the remaining percentiles will exclude those in the tenth percentile. This process will be replicated up to where those councils in the ninetieth (highest) percentile will only be compared with other councils in the same percentile. Although standard cost is only an expression of a complex set of factors, its incorporation in the categorical model ensures that individual local governments are only compared with others facing similar or more difficult environments. It is also important to note that standard unit costs are independent of a council's actual costs and relate only to state averages and the imposed contextual factors.

The next group of variables are treated as discretionary inputs by all six approaches. However, in the two-stage approaches they are included in only one stage. Approach (*E*) includes the variables in the first stage, combined with discretionary outputs, whilst (F) uses them in the second-stage in conjunction with adjusted discretionary outputs. The inputs are: (i) planning and regulatory expenditures (x_8); (ii) the expenditures by the planning and regulatory function on legal costs (x_9) (as an indicator of the level of disputation in the planning process); and (iii) the number of full-time equivalent staff employed in the planning and regulatory function (x_{10}). A relatively efficient council *ceteris paribus* will therefore minimise the costs associated with planning and regulation, the amount of staff employed, and the level of legal disputation involved.

The outputs selected for the planning and regulatory function are made in the light of the ongoing attempts by the NSWDLG to: (i) remedy shortcomings in planning procedures and address specific service-related complaints without the need for a formal investigation process; (ii) the review of processes to handle major developments; (iii) the review and improvement in procedures for the handling of development and building applications (particularly relating to notifications); and (iv) the monitoring and enforcement of associated conditions (NSWDLG 1997). The outputs thus employed are twofold. The first of these is the number of building applications (BAs) determined and approved (y_1); and the second is the number of development applications (DAs) similarly determined and approved (y_2). The four single-stage approaches (A, B, C and D) incorporate these as discretionary outputs, whereas (E) employs these variables only in the first stage. The second two-stage approach (F) adjusts the original data on BAs and DAs for a second-stage analysis.

IV. COMPARISON OF EFFICIENCY SCORES

Table 3 summarises the results of the alternative approaches to incorporating contextual information. These approaches entail alternative treatments of discretionary and nondiscretionary inputs, discretionary outputs, and categorical inputs within either single or two-stage mathematical programming formulations. All variables relate to the planning and regulatory function of 173 New South Wales local governments in 1993. The discretionary inputs are planning and regulatory expenditure, legal expenditure relating to planning decisions, and the number of full-time equivalent planning staff. Discretionary outputs are measured by the number of building and development approvals determined and processed. The nondiscretionary inputs consist of a vector of socioeconomic, demographic and geographic variables hypothesised as influencing the efficiency of local public service provisions. These are the population growth rate, an index of development activity, a measure of the environmental/heritage sensitivity of the local government area, and measures of the extent of non-residential building activity, population distribution, and the proportion of the population from a non-English speaking background. The categorical variable summarises these nondiscretionary inputs with an index calculated using the New South Wales LGGC's percentiles of standard costs for the planning and regulatory function.

The summary statistics contained in Table 3 indicate that the differing assumptions required by each of the six approaches are likely to result in varying distributions of the efficiency scores. The base case formulation (*A*), where only discretionary inputs and outputs are included, suggests that the typical council in New South Wales could become purely technically efficient in the provision of planning and regulatory services by reducing inputs to 60.6 percent of their current level, and that inefficiencies arising due to the presence of scale effects account for 27.8 percent of observed inefficiency. In formulation (*B*), where the vector of environmental inputs are included (though still as discretionary), the mean level of pure technical efficiency increases to 94.5 percent (or a productivity loss of 5.5 percent), whereas those for the nondiscretionary (*C*) and categorical (*D*) approaches have mean levels of efficiency compared to best-practice of 94.8 and 70.5 percent respectively. However, this is to be expected due to the incorporation of additional constraints in the linear program (Ali 1993). In general, the mean efficiency scores for approaches (*B*), (*C*) and (*D*) show a substantial improvement in overall efficiency over the base case (*A*), once environmental factors are considered in the evaluation. Likewise, since the efficiency scores for the nondiscretionary model are always lower than the discretionary model, scores from the categorical approach that are greater than this must be due to the effects of the categorical measure (Rouse *et al*. 1996: 13).

Table 3. *Summary statistics for efficiency measures*

	A		B		C		D		E		F	
	Pure	*Scale*	*Pure*	*Scale*	*Pure*	*Scale*	*Pure*	*Scale*	*Pure*	*Scale*	*Pure*	*Scale*
Mean	0.6061	0.7216	0.9453	0.9177	0.8438	0.9488	0.7058	0.6523	0.6170	0.7000	0.5287	0.6283
Std. Dev	0.2795	0.2025	0.1301	0.1518	0.2450	0.1225	0.2846	0.2292	0.0854	0.1002	0.3071	0.2927
Minimum	0.1106	0.2364	0.2246	0.3068	0.1205	0.2729	0.1106	0.1627	0.1105	0.2643	0.0784	0.1181
Maximum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.7509	0.8410	1.0000	1.0000
Skewness	0.1174	-0.4714	-2.7581	-2.4688	-1.2685	-3.1789	-0.3812	0.0123	-2.1358	-0.8994	0.4097	-0.1035
Kurtosis	-1.2370	-0.5521	8.1028	6.1518	0.1317	10.5398	-1.2832	-1.1131	7.6463	1.5336	-1.2805	-1.5453
# Efficient	36	10	135	91	109	95	61	14	0	0	33	11
% Efficient	20.81	5.78	78.03	52.60	63.01	54.91	35.26	8.09	0	0	19.08	6.36

Similarly, the inclusion of the vector of contextual variables in various forms has an impact on the number of councils assessed as perfectly efficiency, both in technical and scale terms. In the base case, 36 councils (or 20 percent) are pure technically efficient. The inclusion of environmental factors as discretionary inputs increases the proportion of technically efficient councils to 78 percent, as nondiscretionary inputs to 63 percent, and as a categorical input to 35 percent. The number of scale efficient councils ranges from less than 6 percent in the base case, to more than 50 percent where the nondiscretionary inputs are included. Finally, the shape of the efficiency distribution varies across the single-stage approaches. With negative skewness indicating a distribution with an asymmetric tail extending towards more negative values, the approaches incorporating the vector of environmental inputs have a large number of councils with very low efficiency scores. This is especially the case where the environmental inputs are categorised as 'discretionary'. Likewise, with positive kurtosis indicating a relatively peaked distribution, we find that the second and third approaches have a large number of councils concentrated about the mean, in terms of both technical and scale efficiency.

The columns listed under (*D*) in Table 3 contain the predicted efficiency scores from a regression of DEA scores on the contextual factors detailed above. A significant part of the variation in efficiency scores is explained by the second-stage tobit regressions. Estimated coefficients, standard errors and elasticities (calculated at the means) of these regressions are detailed in Table 4. For pure technical efficiency, the signs on the coefficients of the environmental variables are as expected. The results suggest that the greatest marginal effects on planning and regulatory efficiency are imposed by a council's heritage/environmental sensitivity, the proportion of the population from a non-English speaking background (NESB), and the dispersion of the population. However, levels of significance are generally low. One reason could be the high correlations that exist between the contextual variables. For example, there is a high correlation between growth and development (as in fringe LGAs and rural areas with significant growth), and a similarly high correlation between non-residential building activity and the proportion of the population from a NESB (as in the case of inner metropolitan developed councils). However, in general the efficiency scores and the number of councils assessed as being purely efficient are much lower than those obtained from the single-stage techniques. The main reason for this is that the second-stage approach effectively captures the effect of omitted contextual factors and other stochastic influences.

Table 4. *Second-stage non-controllable input coefficients*

	Nomalised coefficient	Standard error	Regression coefficient	Elasticity
Constant returns-to-scale				
CONS.	2.4629	0.2747	0.5906	
GRO	-0.0059	0.0695	-0.0014	-0.0035
DEV	-0.0007	0.0057	-0.0002	-0.0047
HER	-0.1379	0.1001	-0.0331	-0.1421
NR	-0.0238	0.0686	-0.0057	-0.0310
DIS	-0.0160	0.0117	-0.0038	-0.0421
NES	-0.0288	0.0094	-0.0069	-0.1318
Variable returns-to-scale				
CONS.	2.0699	0.2751	0.6754	
GRO	0.0813	0.0707	0.0265	0.0397
DEV	-0.0005	0.0057	-0.0002	-0.0029
HER	0.0798	0.1027	0.0260	0.0684
NR	-0.0315	0.0693	-0.0103	-0.0340
DIS	-0.0085	0.0118	-0.0028	-0.0186
NES	-0.0260	0.0094	-0.0085	-0.0989

The final two columns in Table 3 report the two-staged ‘endogenous DEA’ approach, where the first stage consists of combining environmental factors as discretionary inputs and the discretionary outputs, and adjusting the observed outputs to the frontier by means of the total slacks. These adjusted outputs are then incorporated in a second-stage program along with the discretionary inputs to obtain the requisite efficiency scores. In contrast to the previous approaches, the mean level of efficiency is very low and the number of councils assessed as being purely efficient, whether in technical or scale terms, is also very low. In fact, the distributional statistics detailed in Table 3 suggest that the results from the endogenous DEA approach are very similar to those obtained where only discretionary inputs and outputs are included.

At least three considerations exist in selecting alternative DEA-based methodologies for the purposes of evaluating the efficiency of local public service provision. First, Rouse *et al*. (1996: 20) argue *inter alia* that the underlying rationale for the single-stage approaches “lies in the notion for performance measures to be meaningful, controllable inputs and outputs together with all pertinent environmental factors must be considered simultaneously”. Given that there are strong *a priori* reasons to think that the vector of environmental factors affects the efficiency of public service provision, Rouse *et al*. (1996: 20) also conclude that “efficiency cores obtained where the environment is missing have little or no usefulness, i.e. no information value”. This criticism would thus apply to the approaches where nondiscretionary contextual information is either excluded entirely (as in the first approach), or where the information is included in such manner as to render nondiscretionary factors subject to managerial discretion (as in the second technique). Second, a corollary is that two-stage approaches that use these functionally ‘misspecified’ efficiency scores are likewise subject to severe limitations. Rouse *et al*. (1996: 20) argue that “the value of such scores used as dependent variables in any subsequent analysis is so flawed as to render any results from it moot”. On this basis, the results using the two-stage approach employed in the fifth technique must also be examined with caution.

The final consideration relates to possible misspecification in the use of nondiscretionary continuous or categorical inputs. One question that is of considerable interest here is whether a set of variables is significant at the margin in characterising the production correspondence between inputs and outputs. Using Banker’s (1996) test statistics, the null hypothesis that the vector of environmental variables detailed has no marginal effect on production is rejected, assuming both an exponential [T_{EXP} = 7.1979] and half-normal distribution [T_{HN} = 11.7450]. A further important question is whether a single aggregate variable sufficiently captures the impact of a vector of variables on a set of computed inefficiencies. Using similar tests, the null hypothesis that the categorical variable in the fourth approach sufficiently captures the impact of this same vector of inputs is also rejected, assuming an exponential [T_{EXP} = 6.7103] and half-normal [T_{HN} = 10.5858] distribution. We may therefore conclude that although the vector of environmental inputs is significant at the margin in influencing the efficiency of local governments, summarising these factors in a single discrete measure is likely to result in misspecification.

Table 5. *Correlation matrix for pure technical efficiency*

Pearson product moment correlation						
A	1.0000					
B	0.3554	1.0000				
C	0.5739	0.6728	1.0000			
D	0.8534	0.4245	0.6266	1.0000		
E	0.2868	-0.1922	-0.0930	0.1820	1.0000	
F	0.8594	0.2968	0.4891	0.7044	0.1697	1.0000
Spearman rank correlations						
A	1.0000					
B	0.2609	1.0000				
C	0.4904	0.6861	1.0000			
D	0.8343	0.3838	0.5918	1.0000		
E	0.2564	-0.1869	-0.0416	0.0880	1.0000	
F	0.8487	0.2258	0.4057	0.7094	0.1705	1.0000
	A	*B*	*C*	*D*	*E*	*F*

A different means by which the alternative methodologies may be contrasted is to review the correlations between the efficiency scores: that is, how consistently do the alternative approaches rank councils in terms of their efficiency. Table 5 contains the Pearson product moment and Spearman rank correlations between the various approaches measures of pure technical efficiency. As inferred from the earlier discussion, there is a high degree of correspondence between the efficiency measures provided by the discretionary input, discretionary output only approach, and the two-stage endogenous DEA formulation (critical values are 0.1251, 0.1490 and 0.1958 at the .10, .05 and .01 levels respectively). There is a similarly high degree of positive correlation between (*D*) and (*F*) (that is, between the categorical input approach and the endogenous DEA formulation) and between the two approaches which include the environmental factors, whether as discretionary (*C*) or nondiscretionary (*B*) inputs.

A second approach to testing differences in efficiency is to use Banker's (1996) asymptotic test statistics, assuming both an exponential and half-normal distribution of inefficiencies relative to the *F*-distribution with ($2N_1$, $2N_2$) and (N_1, N_2) degrees of freedom respectively. The relevant test statistics are presented in Table 6. The null hypothesis in both tests is that each of two approaches have the same inefficiency distribution (H_0: $\sigma_1 = \sigma_2$), with the alternate being that the first approach yields, on average, a lower level of efficiency than the second ($H_1: \sigma_1 < \sigma_2$). The only instances where the null hypothesis is not rejected on the assumption of an exponential distribution of inefficiencies is between the base DEA approach (*A*) and the remaining approaches, and similarly on the basis of a half-normal distribution.

Table 6. *Summary of statistical test results, pure technical efficiency*

Banker's asymptotic test (exponential)						
A	–					
B	0.13893	–				
C	0.39654	2.85426	–			
D	0.74699	5.37676	1.88377	–		
E	0.97221	6.99785	2.45172	1.3015	–	
F	1.1964	8.61157	3.0171	1.60163	1.2306	–
Banker's asymptotic test (half-normal)						
A	–					
B	0.08514	–				
C	0.3611	4.24113	–			
D	0.71783	8.43086	1.98788	–		
E	0.66103	7.76384	1.8306	0.92088	–	
F	1.35657	15.9329	3.75675	1.88983	2.0522	–
	A	*B*	*C*	*D*	*E*	*F*

Finally, an ANOVA table is used to reject the null hypothesis that the mean efficiencies of all the approaches are the same [F_{STAT} = 77.181] at the .01 level, while Bartlett's test that the variances of these distributions are the same (χ^2_{STAT} = 338.42) is also rejected at the same level. Very different results are observed on the basis of the Pearson and Spearman correlation matrices for scale efficiency outlined in Table 7. Unlike the findings for pure technical efficiency, where a high degree of positive correlation existed between the alternative approaches, in the case of scale efficiency several significant negative correlations, both rank and product moment, are also observed. For example, the scale efficiency indices for approach (*A*) are positively correlated with approaches (*D*), (*E*) and (*F*), and negatively associated with (*B*) and (C). Similarly, approaches (*C*) and (*D*) both attempt to incorporate environmental or contextual factors as discretionary inputs, either continuously or categorically, yet there is a negative rank correlation between the two approaches. This would seem to suggest that although councils are ranked fairly consistently on the basis of pure technical efficiency regardless of the approach used (at least on the basis of correlation), the results from a comparison of scale efficiencies are much less certain. That is, councils assessed as relatively scale efficient on the basis of either the discretionary categorical single-stage formulation, or the two-stage approaches, would be relatively less efficient on the basis of single-stage approaches, using contectual factors either as discretionary or nondiscretionary inputs.

Table 7. *Correlation matrix for scale efficiency*

Pearson product moment correlation						
A	1.0000					
B	-0.2475	1.0000				
C	-0.1227	0.4768	1.0000			
D	0.8432	-0.2236	-0.0615	1.0000		
E	0.3783	-0.2873	-0.1596	0.2873	1.0000	
F	0.6250	-0.2756	-0.1761	0.4892	0.5801	1.0000
Spearman rank correlations						
A	1.0000					
B	-0.2307	1.0000				
C	-0.1639	0.8819	1.0000			
D	0.8459	-0.1849	-0.1343	1.0000		
E	0.4022	-0.2107	-0.1177	0.3000	1.0000	
F	0.6095	-0.2540	-0.1695	0.4883	0.6016	1.0000
	A	*B*	*C*	*D*	*E*	*F*

Banker's asymptotic tests of efficiency differences verify that the different approaches provide conflicting measures of relative efficiency. The test statistics are presented in Table 8. Assuming both and exponential and half-normal distribution, only in the pairings of approaches (*B*) and (*C*) and (*D*) and (*E*), does the null hypothesis of the same inefficiency distribution fail to be rejected. Likewise, the results of an ANOVA table (F_{STAT} = 86.317) reject the null hypothesis of the equality of the means, and Bartlett's homogeneity of variance test (χ^2_{STAT} = 338.42) also rejects the null hypothesis of the joint equality of the variances.

A number of points emerge from the present study. Firstly, whereas the best-practice calculations indicate that many New South Wales local governments operated at a high level of pure technical efficiency in 1993, for the average council a proportional reduction of inputs up to fifty-two percent of the current level is indicated. Depending upon the approach employed, up to eighty-one percent of councils were technically inefficient in the provision of planning and regulatory services. Secondly, the results also suggest that inefficiencies derived from an incorrect scale of operations in planning and regulatory services far outweigh technical inefficiencies. All other things being equal, many more councils are pure technically efficient than scale efficient, irrespective of the approach employed. Once again depending upon the approach employed, less than six percent of councils were scale efficient in planning and regulatory services.

Table 8. *Summary of statistical test results, scale efficiency*

Banker's asymptotic test (exponential)						
A	–					
B	0.29581	–				
C	0.18388	0.62161	–			
D	1.24912	4.22271	6.79323	–		
E	1.07766	3.64307	5.86074	0.86273	–	
F	1.33546	4.51459	7.26278	1.06912	1.23923	–
Banker's asymptotic test (half-normal)						
A	–					
B	0.25111	–				
C	0.14826	0.5904	–			
D	1.46385	5.82943	9.87374	–		
E	0.84533	3.36632	5.7018	0.57747	–	
F	1.88882	7.52177	12.7402	1.29031	2.23441	–
	A	*B*	*C*	*D*	*E*	*F*

Finally, these results are highly dependent upon the approach employed, and especially on how environmental or contextual factors are incorporated into the analysis. Six approaches were empirically tested in the current study: that is, two approaches where contextual factors were either ignored or assumed discretionary, two approaches where the contextual factors were incorporated as several nondiscretionary inputs or a single categorical input, and two remaining approaches, a modified DEA and an endogenous DEA formulation. In general, the results indicated *ceteris paribus* that the efficiency scores of all of the approaches which incorporated nondiscretionary factors were significantly positively correlated. However, it was also established that the distributions of the efficiency scores and the number of councils assessed as perfectly efficient in the six approaches also varied significantly across the sample.

V. CONCLUDING REMARKS

In so far as the current study is concerned, the issues highlighted concerning the incorporation of contextual information in local public sector efficiency analyses are at least threefold. First, overwhelming evidence exists, largely on a theoretical level, that for efficiency measures to be meaningful, all inputs and outputs, must be considered. This includes the nondiscretionary environmental or contextual factors that are hypothesised to exert an influence on the production correspondence relating inputs to outputs. Second, while recognising the need for incorporating all pertinent information, it is difficult to reconcile the two main approaches to incorporating such information in nonparametric analyses (Fried *et al*. 1995). Proponents of a single-stage approach argue, largely on a theoretical level, that only the simultaneous consideration of both discretionary and nondiscretionary inputs and outputs will produce conceptually sound measures of efficiency. Advocates of a two-stage approach counter this criticism with the argument that the advantage of a second-stage regression is that it has significantly greater levity in the specification of environmental influences, even if one accepts that these factors are 'inputs' into the production process.

The final issue concerns whether it is possible, on both a theoretical and an empirical level, to choose between alternative approaches to incorporating contextual information. Rouse *et al*. (1996: 22) argue *inter alia* that "policymaker's attitudes [to environmental factors must be clearly understood] before any firm conclusion is reached on the choice of methodology and interpretation of results". Matters of importance in this regard include the improved focus of benchmarking exercises if nondiscretionary factors are more clearly understood, and whether or not purported nondiscretionary factors may be subject to at least some alteration. By way of an alternative, there is an evolving empirical literature, largely based on the work of Banker and Chang (1995) and Banker (1996), concerning the development of statistics to test hypotheses about the characteristics of the production frontier, such as model specification. One problem here is that whilst Monte Carlo studies developed on the basis of these DEA tests appear promising, Banker (1996: 157) argues that it is not yet possible to identify all those "conditions under which the DEA-based tests perform well and conditions under which they do not". Despite this, where "the components reflecting potential improvement are understood and consensus has been obtained on the influence of nondiscretionary factors ... single stage approaches would appear to have a comparative advantage over multi-stage methods" (Rouse *et al*. 1996: 24).

REFERENCES

Ali, A.I. and Seiford, L.M. (1993) 'The mathematical programming approach to efficiency analysis', in H.O. Fried, C.A.K. Lovell and S.S. Schmidt, eds. *The Measurement of Productive Efficiency*, 120–159, Oxford University Press, New York.

Banker, R.D. (1993) Maximum likelihood, consistency and data envelopment analysis: A statistical foundation, *Management Science*, 39(10), 1265–1273.

Banker, R.D. (1996) Hypothesis tests using data envelopment analysis, *Journal of Productivity Analysis*, 7(2-3), 133–159.

Banker, R.D. and Chang, H. (1995) A simulation study of hypothesis tests for differences in efficiencies, *International Journal of Production Economics*, 39(1-2), 37–54.

Banker, R.D. and Morey, R.C. (1986) The use of categorical variables in data envelopment analysis, *Management Science*, 32(12), 1613–1627.

Banker, R.D. Charnes, A. and Cooper, W.W. (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis, *Management Science*, 30(9), 1078–1092.

Bates, J.M. (1997) Measuring predetermined socioeconomic 'inputs' when assessing the efficiency of educational outputs, *Applied Economics*, 29(1), 85–93.

Bessent, A. Bessent, W. Kennington, J.and Reagan, B. (1982) An application of mathematical programming to assess productivity in the Houston independent school district, *Management Science*, 28(12), 1355–1367.

Bessent, A. Bessent, W. Kennington, J.and Reagan, B. (1982) An application of mathematical programming to assess productivity in the Houston independent school district, *Management Science*, 28(12), 1355–1367.

Chalos, P. and Cherian, J. (1995) An application of data envelopment analysis to public sector performance measurement and accountability, *Journal of Accounting and Public Policy*, 14, 143–160.

Charnes, A. Cooper, W.W. and Rhodes, E. (1978) Measuring the efficiency of decision making units, *European Journal of Operational Research*, 2(6), 429–444.

Coelli, T. Prasada Rao, D.S. and Battese, G.E. (1999) *An Introduction to Efficiency and Productivity Analysis*, 3rd print, Kluwer, Boston.

Cook, W.D. Kazakov, A. and Roll, Y. (1993) 'On the measurement and monitoring of relative efficiency of highway maintenance patrols', in A. Charnes, W.W. Cooper, A.Y. Lewin and L.M. Seiford, eds. *Data Envelopment Analysis: Theory, Methodology and Applications*, 195–210, Kluwer, Boston.

Cook, W.D. Roll, Y. and Kazakov, A. (1990) A DEA model for measuring the relative efficiency of highway maintenance patrols, *Informational Systems and Operational Research*, 28(1), 113–124.

Deller, S.C. and Nelson, C.H. (1991) Measuring the economic efficiency of producing rural road services, *American Journal of Agricultural Economics*, 72(1), 194–201.

Domberger, S. Meadowcroft, S.A. and Thompson, D.J. (1986) Competitive tendering and efficiency: The case of refuse collection, *Fiscal Studies*, 7(4), 69–87.

Duncombe. W. Miner, J. and Ruggiero, J. (1997) Empirical evaluation of bureaucratic models of inefficiency, *Public Choice*, 93(1), 1–18.

Fried, H.O. Schmidt, S.S. and Yaisawarng, S. (1995) *Incorporating the Operating Environment into a Measure of Technical Efficiency*. Paper presented to the Bureau of Industry Economics Seminar, Canberra.

Johnes, J. and Johnes, G. (1995) Research funding and performance in U.K. university departments of economics: A frontier analysis, *Economics of Education Review*, 14(3), 301–314.

Lovell, C.A.K. Walters, L.C. and Wood, L.L. (1993) 'Stratified models of education production using modified DEA and regression analysis', in A. Charnes, W.W. Cooper, A.Y. Lewin and L.M. Seiford, eds. *Data Envelopment Analysis: Theory, Methodology and Applications*, 329–351, Kluwer, Boston.

McCarty, T.A. and Yaisawarng, S. (1993) 'Technical efficiency in New Jersey school districts', in H.O. Fried, C.A. Lovell and S.S. Schmidt, eds. *The Measurement of Productive Efficiency: Techniques and Applications*, Oxford University Press, New York.

NSW Department of Local Government (1997) *Annual Report 1996/97*, Department of Local Government, Sydney.

NSW Department of Local Government (1998) *Comparative Information on NSW Local Government Councils 1995/96*, Department of Local Government, Sydney.

NSW Local Government Grants Commission (1994) *Annual Report 93/94*, Department of Local Government, Sydney.

Parkin, D. and Hollingsworth, B. (1997) Measuring production efficiency of acute hospitals in Scotland, 1991-94: Validity issues in data envelopment analysis, *Applied Economics*, 29, 1425–1433.

Ray, S.C. (1991) Resource-use efficiency in public schools: A study of Connecticut data, *Management Science*, 37(12), 1620–1628.

Ray, S.C. (1988) Data Envelopment Analysis, Nondiscretionary inputs and efficiency: An Alternative Interpretation, *Socioeconomic Planning Services*, 22(4), 167–176.

Rouse, P. Putterill, M. and Ryan, D. (1996) *Methodologies for the Treatment of Environmental Factors in DEA*, Department of Accounting and Finance Working Paper, University of Auckland.

Ruggiero, J. (1996) On the measurement of technical efficiency in the public sector, *European Journal of Operational Research*, 90(3), 553–565.

Steering Committee for the Review of Commonwealth/State Service Provision (1998) *Data Envelopment Analysis: A Technique for Measuring the Efficiency of Government Service Delivery*, Canberra, AGPS.

Thompson, R.G. Dharmapala, P.S. Rothenberg, L.J. and Thrall, R.M. (1996) DEA/AR efficiency and profitability of 14 major oil companies in U.S. exploration and production, *Computers and Operations Research*, 23(4), 357–373.

Worthington, A.C. (1999) Performance indicators and efficiency measurement in public libraries, *Australian Economic Review*, 32(1), 31–42.