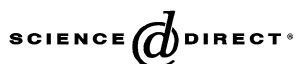




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How to better identify the true managerial performance: State of the art using DEA[☆]

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Abstract

Our motivation is to detail a potential improvement on the three-stage analysis published by Fried et al. [Accounting for environmental effects and statistical noise in data envelopment analysis. *Journal of Productivity Analysis* 2002;17:157–74] that can distinguish true performers from those that may be advantaged by favourable environments or measurement errors. The method starts with data envelopment analysis (DEA), and continues with stochastic frontier analysis to explain the variation in organisational performance in terms of the operating environment, statistical noise and managerial efficiency. It concludes with DEA again using adjusted data to reveal a measure of performance based on management efficiency only. Our proposed contributions include (i) a comprehensive approach where total input and output slacks are identified simultaneously for radial and non-radial inefficiencies before levelling the playing field, (ii) identifying percent adjustments attributable to the environment and statistical noise, and (iii) using a fully units-invariant DEA model.

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1. Introduction

The purpose of this paper is to detail a potential improvement to the performance evaluation method by Fried et al. [1] that can help identify the true managerial performance in an organisational unit once the playing field is levelled. The method consists of a three-stage analysis that starts with data envelopment analysis (DEA). The second stage is a stochastic frontier analysis (SFA) to explain the variation in organisational performance measured in the first stage in terms

of the operating environment, statistical noise, and managerial efficiency. The third stage concludes with DEA of organisational performance using adjusted data from the second stage that have been purged of the influence of the operating environment and statistical noise.

The three-stage sequential DEA/SFA approach highlights a partnership between non-parametric and parametric techniques. For instance, SFA efficiency measures are based on the estimated average parameter values in the regression equation. Thus, these efficiencies are not very sensitive to large data changes at the unit level, which is an advantage over DEA in the presence of measurement errors. On the other hand, SFA may be inappropriate if the structural form imposed on the analysis does not represent the behaviour of the organisation under study, whereas the non-parametric

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nature of DEA makes the technique less susceptible to specification errors regarding the production technology. In short, DEA and SFA both have some non-testable assumptions that represent the core weaknesses of these techniques. For example, in DEA, we assume that there are no measurement errors, whereas in SFA, we assume a particular structure. It is also recognised in literature that neither method, that is, parametric vs. non-parametric, is superior to the other [2]. Furthermore, "...unlike parametric frontier models, the incorporation of environmental variables in DEA models is a field still being researched..." [3, p. 896].

As any honest manager would admit, performance of a business unit depends as much on managerial efficiency as on the operating environment and measurement errors. While managerial efficiency is mostly a controllable component of performance evaluation, the latter two components are beyond the control of management. The stochastic analysis in stage 2 of the three-stage analysis, in this paper, is designed to capture the influence of the operating environment and statistical noise. Potentially, the technique can be used to test the contentions of those managers who attribute the lacklustre performance of their organisational units to the operating environment, or the contentions of those who claim all the credit for the good performance of their units.

The rest of the paper is presented as follows. Section 2 reviews how the impact of environmental factors in DEA has been addressed in the past. Section 3 provides an overview of Fried et al.'s [1] approach, DEA and SFA. Section 4 details the research design of the proposed improved three-stage analysis. Section 5 concludes the paper with a summary of the key potential contributions of the paper to measurement of organisational performance and efficiency measurement literature, and directions for future research.

2. A review of accounting for the impact of the environment in DEA

DEA (see the seminal papers by Charnes et al. [4] and Banker et al. [5]) has been applied across a wide-range of industries as well as in not-for-profit organisations. For brevity, we provide a short introduction to DEA and refer the reader to the authoritative book by Cooper et al. [6].

DEA is a non-parametric linear programming technique that computes a comparative ratio of weighted outputs to weighted inputs for each unit, which is reported as the relative efficiency score. The efficiency

score is usually expressed as either a number between 0 and 1 or as a percentage. A decision-making unit with a score less than one is deemed inefficient relative to other units. Traditionally, DEA has been used to measure the technical efficiency of organisational units (or in DEA jargon, decision-making units, DMUs) as opposed to their allocative efficiency. In the context of DEA, allocative efficiency is defined as the effective choice of inputs vis-à-vis prices with the objective of minimising production costs, that is, selection of an effective production plan, whereas technical efficiency investigates how well the production process converts inputs into outputs; the latter is the focus of DEA in this paper.

The key limitation of DEA is that it assumes data to be free of measurement error and thus, it is more sensitive to the presence of measurement error than parametric techniques. Another problem that has led to various approaches being developed involves dealing with the impact of environmental factors. While this is not a limitation specific to DEA, we consider accounting for the influence of environmental factors an important part of DEA where reliable findings are expected. We now continue to review the latter issue first before we detail in Sections 3 and 4 how to deal with both issues.

It is possible that some of the DMUs in the same sample operate in different environments. For example, in measuring literacy and numeracy in primary schools we need to consider the educational background of parents of children in each school. Failure to account for such an external factor may well discriminate the DEA results in favour of those schools located in better-educated neighbourhoods. The implied link here is that schools that draw their students from educated families are expected to show higher literacy and numeracy levels due to additional resources available to those children.

In a real life analysis, failure to account for environmental factors is bound to confound the DEA results and lead to unreliable economic decisions. There are at least two main approaches to incorporating uncontrollable or non-discretionary inputs in DEA. As part of a single-stage adjustment, the uncontrollable input can be included in DEA in such a manner that it becomes a constraint in linear programming (see [7,8]). However, the single-stage approach to account for environmental factors runs into difficulty where we have no pre-test understanding of the direction of their influence on efficiency.

The multiple-stage approach can entail a number of methods. A common practice is to run DEA where all the inputs are treated as controllable and then, in stage two, regress the emerging efficiency scores on non-discretionary inputs. However, DEA efficiency scores

are censored. Thus, in this case, the Tobit model outlined in Greene [9] has been regarded as more appropriate than ordinary least-squares regression (e.g. see Fried et al. [10]).

Others who developed variations on the multiple-stage approach include Fried et al. [11], Bhattacharyya et al. [12], Fried et al. [10], Pastor [3] and Muniz [13]. Fried et al. [11] perform a two-stage approach that uses free disposal hull¹ to initially evaluate performance, followed by logistic regression to explain performance variation on environmental variables and features of credit unions. Bhattacharyya et al. [12] also implement a two-stage approach that uses variable returns to scale DEA to compute radial technical efficiency scores, which are then regressed on environmental variables through SFA to explain variation attributable to an ownership component, random noise, and a temporal component.

However, the main drawback of two-stage approaches that have dominated multiple-stage analyses is their inability to account for measurement error. In two-stage approaches, where both stages are DEA based, measurement error is not addressed at all and the approach is deterministic. Fried et al. [10] report a three-stage analysis that uses Tobit regression in the second stage to explain the impact of operating environment on unit performance (nursing homes), followed by the third stage where the first stage data are adjusted before a repeat of DEA. However, this study does not explain statistical noise in unit performance. This shortcoming was later addressed in Fried et al. [1] where the authors focussed on input slacks only through a three-stage analysis that used DEA and SFA (once again using nursing home data); this study is reviewed in more detail in the next section.

Similarly, a three-stage DEA/SFA approach is used by Pastor [3] to separate the impact of environment on the risk management efficiency of European banking systems. In Pastor's comparative study, findings indicate similar efficiency scores across two- and three-stage methods of accounting for the environment but different scores using the single-stage method. Using a sample of public high schools, Muniz [13] compares the single-stage approach of Banker and Morey [7] with the three-stage approach put forward by Fried and Lovell [14],² where the first stage DEA identifies slacks, the second stage DEA distinguishes between slacks

traceable to managerial inefficiency and non-controllable inputs, and the third stage DEA uses data adjusted for the impact of non-controllable inputs as part of the final analysis. The key finding is that the single-stage approach does not identify the efficient units as well as the three-stage approach because it fails to account for the nature of inputs. Muniz's study does not identify inefficiency attributable to statistical noise.

In summary, we can ignore neither the environment nor the measurement errors. Thus, performance evaluation should be purged of environmental impact and statistical noise, which is the main theme of this paper. Before proceeding to detail our proposed approach, we first provide an overview of Fried et al. [1] and the two techniques that lie at the heart of their study.

3. Overview of Fried et al.'s approach, DEA and SFA

Fried et al.'s [1] three-stage approach to purging performance evaluation of environmental factors and statistical noise begins with DEA. In the second stage, SFA is applied to trace components of performance attributable to the operating environment of the unit, statistical noise, and managerial efficiency. In the third and final stage of their approach, data entered into DEA in stage 1 are adjusted for the effect of the environment and statistical noise before repeating DEA. Thus, the evaluation emerging from stage 3 DEA is said to represent managerial efficiency only. Fried et al. [1] demonstrate their methodology with a cross-sectional data set on US nursing homes. Next, we detail each stage as per Fried et al. [1] and at the same time provide an overview of DEA and SFA following a brief historical comment.

SFA and DEA were developed in response to the challenge laid down by Farrell [15] about estimating the production function either through a parametric approach such as Cobb–Douglas functional form, or by using non-parametric piecewise linear technology. Aigner et al. [16], and Meeusen and van den Broeck [17] independently proposed SFA. A year later, DEA was formalised by Charnes et al. [4].

Returning to Fried et al. [1], in stage 1 they use input oriented variable returns to scale DEA with the conventional BCC model (Banker et al. [5]). The linear programming problem as outlined by the authors is

$$\begin{aligned} \min_{\theta, \lambda} \quad & \theta \\ \text{s.t.} \quad & \theta x^0 \geq X\lambda, \\ & Y\lambda \geq y^0, \\ & \lambda \geq 0, \\ & e\lambda = 1, \end{aligned} \tag{1}$$

¹ Fried et al. [11] refer to this as a generalised model of variable returns to scale DEA first proposed by Banker et al. [5].

² Although we contacted the authors, we were unable to acquire a copy of this working paper.

where $x \geq 0$ is a DMUs $N \times 1$ vector of inputs, $y \geq 0$ is a DMUs $M \times 1$ vector of outputs, $X = [x_1, \dots, x_I]$ is an $N \times I$ matrix of input vectors in the sample, $Y = [y_1, \dots, y_I]$ is an $M \times I$ matrix of output vectors in the sample, $\lambda = [\lambda_1, \dots, \lambda_I]$ is an $I \times 1$ vector of peer weights, $e = [1, \dots, 1]$ is an $I \times 1$ vector, and there are I DMUs in the sample. Inputs and outputs for the unit evaluated are indicated by the superscript “0” and the linear program is solved once for each unit in the sample. The optimal solutions to emerge from Eq. (1) are the preliminary performance evaluation scores that are likely to be confounded by environmental effects and statistical noise.

In stage 2, Fried et al. [1] focus on radial slacks, that is, input contraction $[x - X\lambda] \geq 0$ to emerge from stage 1 DEA (rather than non-radial slacks i.e. under-produced outputs, $[Y\lambda - y] \geq 0$). Using SFA, input slacks are regressed on observable environmental variables, and a composed error term that captures statistical noise due to measurement errors and managerial inefficiency. The main justification for SFA (rather than Tobit regression) is an asymmetric error term that allows for identification of the one-sided error component (i.e. managerial inefficiency) and the symmetric error term component (i.e. statistical noise).

It is common to assume a normally distributed error term for statistical noise and a half-normal or exponential distribution for managerial inefficiency [18]. Examples of statistical noise include a strike by staff, equipment failure, and errors in measuring variables in the model; instances of managerial inefficiency include incompetency, inadequate staffing, and inadequate equipment.

The general function of the SFA regressions is represented in Eq. (2a) for the case of input slacks and in Eq. (2b) for the case of output slacks:

$$\begin{aligned} s_{i,j}^- &= f^i(z_j; \beta^i) + v_{i,j} + u_{i,j}, \quad i = 1, \dots, N, \\ j &= 1, \dots, I, \end{aligned} \quad (2a)$$

where $s_{i,j}^-$ is the stage 1 slack in the i th input for the j th unit, z_j the environmental variables, β^i the parameter vectors for the feasible slack frontier and $v_{i,j} + u_{i,j}$ the composed error structure where $v_{i,j} \sim N(0, \sigma_{vi}^2)$ represents statistical noise and $u_{i,j} \geq 0$ represents managerial inefficiency

$$\begin{aligned} s_{r,j}^+ &= f^r(z_j; \beta^r) + v_{r,j} + u_{r,j}, \quad r = 1, \dots, M, \\ j &= 1, \dots, I. \end{aligned} \quad (2b)$$

The SFA regression model does not require specification of the direction of impact of environmental variables; this can be read from the signs of the parameters.

Following each regression, parameters $\beta^i, \mu^i, \sigma_{vi}^2, \sigma_{ui}^2$ are estimated and permitted to vary across N input slack regressions.

SFA enables hypothesis testing and estimation of standard errors using maximum-likelihood methods [19]. Econometrics computer programs such as LIMDEP (by Econometric Software) and FRONTIER (by Tim Coelli) can be used to estimate the parameters of SFA regression models. Details of how SFA results can be used to adjust data are provided in the next section.

In stage 3, Fried et al. repeat the DEA of stage 1 by replacing observed input data with input data that have been adjusted for the influence of environmental factors and statistical noise. Thus, the DEA analysis to emerge from stage 3 represents performance due to managerial efficiency only.

4. Proposed research design

This section continues to detail the research design put forward by Fried et al. [1] and the improvements suggested in this paper.

4.1. Stage 1: initial data envelopment analysis to measure input and output slacks

As mentioned before, Fried et al.’s [1] analysis begins with traditional DEA using the BCC model (refer back to Eq. (1)). However, the BCC model (or, the CCR model i.e. Charnes et al. [4]), while producing units-invariant (i.e. dimension free) radial inefficiency estimates, does not generate units-invariant estimates of non-radial inefficiency³ [20]. For consistent interpretation of DEA and SFA estimates, we need to choose a fully units-invariant DEA model. Such a solution exists within the slacks-based measure (SBM) of efficiency (see [6, p. 97; 21]).⁴ Here, it is possible to argue for either output maximisation or input minimisation; Fried et al. [1] arbitrarily select input minimisation and thus in stage 2 they focus only on input slacks. We propose a more comprehensive analysis where total input and output slacks of radial and non-radial nature are measured simultaneously against the same reference set, facilitated by a non-oriented SBM model that is fully

³ Non-radial inefficiency is traditionally known as ‘slacks’. For brevity, the term ‘slacks’ covers radial and non-radial inefficiency in the rest of our paper.

⁴ While the additive DEA model can also capture slacks, it is neither units-invariant nor able to generate a scalar measure of efficiency.

units-invariant. The fractional program for the non-oriented constant returns to scale SBM is shown below [21], where ρ is the scalar that captures radial and non-radial slacks.

$$\begin{aligned} \min \quad & \rho = \frac{1 - (1/N) \sum_{i=1}^N s_i^- x_i^o}{1 + (1/M) \sum_{r=1}^M s_r^+ y_r^o} \\ \text{s.t.} \quad & x^o = X\lambda + s^-, \\ & y^o = Y\lambda - s^+, \\ & \lambda \geq 0, s^- \geq 0, s^+ \geq 0, \end{aligned} \quad (3a)$$

where s^- and s^+ represent input and output slacks, respectively, and $X\lambda$ and $Y\lambda$ represent benchmark input consumption and output production (imposing the constraint $\sum_{j=1}^J \lambda_j = 1$ introduces variable returns to scale). Alternatively, Eq. (3a) can be transformed into

$$\rho = \left(\frac{1}{N} \sum_{i=1}^N \frac{x_i^o - s_i^-}{x_i^o} \right) \left(\frac{1}{M} \sum_{r=1}^M \frac{y_r^o + s_r^+}{y_r^o} \right)^{-1}, \quad (3b)$$

where the first term represents the mean contraction rate of inputs and the second term represents the mean expansion rate of outputs.

In Eq. (3a) the test DMU is deemed efficient if the optimal value for the objective function is unity. That is, for the test DMU to be efficient, all optimal input slack (input excess) and output slack (output shortfall) must equal zero. In the alternative formulation represented by Eq. (3b) we can see that SBM is the product of input and output inefficiencies. Environmental variables are omitted in stage 1 analysis.

4.2. Stage 2: purging stage 1 slacks through Stochastic Frontier analysis

The objective of stage 2 in Fried et al. [1] is to decompose stage 1 input slacks into environmental influences, statistical noise attributable to measurement errors in the original data, and managerial inefficiency. Input slacks are regressed through SFA on environmental variables. Fried et al. ignore output slacks because of their model's input orientation. However, they do acknowledge that a case can be made where both input and output slacks are explained through SFA, which is what we are proposing here and thus providing a more refined measure of organisational efficiency which can be incorporated into managerial decision-making with more confidence. We focus on stage 1 input slacks $s^- \geq 0$, and output slacks $s^+ \geq 0$. Thus, stage 2 analysis leads to an estimate of $N + M$ (i.e. inputs plus outputs) SFA regressions (refer back to Eqs. (2a) and (2b)) where slacks measured by SBM for each input (output) are regressed on environmental variables.

Next, the inputs of DMUs that have enjoyed an advantage by their relatively favourable operating environments or statistical noise are adjusted upwards, thus lowering efficiency scores. Fried et al. [1] propose that adjusting inputs upwards is preferred to the alternative method, where inputs are adjusted downwards for those DMUs disadvantaged by their relatively unfavourable operating environments or statistical noise, because some inputs may become negative after adjustments. Similarly, we adjust outputs upwards for those DMUs disadvantaged by their relatively unfavourable operating environments or statistical noise, thus raising efficiency scores. In this exercise of relocating DMUs in the efficiency space, we are levelling the playing field by bringing closer those DMUs advantaged and those DMUs disadvantaged by their operating environment or statistical noise. This is an improvement over Fried et al.'s [1] approach to levelling the playing field based on input slacks only.

Parameter estimates obtained from SFA regressions are used to predict input slacks attributable to the operating environment and to statistical noise. Thus, observed inputs can be adjusted for the impact of the environment and statistical noise by

$$x_{i,j}^A = x_{i,j} + \left[\max_j \{z_j \hat{\beta}^i\} - z_j \hat{\beta}^i \right] + \left[\max_k \{\hat{v}_{i,j}\} - \hat{v}_{i,j} \right], \quad (4a)$$

$i = 1, \dots, N, \quad j = 1, \dots, I,$

where $x_{i,j}^A$ is the adjusted quantity of i th input in j th unit, $x_{i,j}$ the observed quantity of i th input in j th unit, $z_j \hat{\beta}^i$ the i th input slack in j th unit attributable to environmental factors, and $\hat{v}_{i,j}$ the i th input slack in j th unit attributable to statistical noise.

$$x_{i,j}^A = (1 + \text{AdjFactorEnvironment}_{x_{i,j}} + \text{AdjFactorNoise}_{x_{i,j}}) x_{i,j}, \quad (4b)$$

where

$$\begin{aligned} \text{AdjFactorEnvironment}_{x_{i,j}} &= \left(\frac{\max_j \{z_j \hat{\beta}^i\}}{x_{i,j}} \right) \left(1 - \frac{z_j \hat{\beta}^i}{\max_j \{z_j \hat{\beta}^i\}} \right), \end{aligned}$$

$$\begin{aligned} \text{AdjFactorNoise}_{x_{i,j}} &= \left(\frac{\max_j \{\hat{v}_{i,j}\}}{x_{i,j}} \right) \left(1 - \frac{\hat{v}_{i,j}}{\max_j \{\hat{v}_{i,j}\}} \right). \end{aligned}$$

The first adjustment in Eq. (4a), $[\max_j \{z_j \hat{\beta}^i\} - z_j \hat{\beta}^i]$, levels the playing field regarding the operating environment by placing all units into the least favourable environment observed in the sample. The second adjustment

in Eq. (4a), $[\max_j \{\hat{v}_{i,j}\} - \hat{v}_{i,j}]$, places all units in the least fortunate situation (i.e. regarding measurement errors) found in the sample. Hence, DMUs enjoying relatively favourable operating environments and statistical noise would find their inputs adjusted upwards.

Eq. (4b) is our proposed transformation of Fried et al.'s approach to adjusting inputs, where the researcher is better able to see the degree of adjustments attributable to the operating environment and statistical noise. This is achieved by taking ratios instead of differences and arriving at an adjustment factor (e.g. 1.2) which multiplies the observed input. The first variable in Eq. (4b), i.e. *AdjFactorEnvironment*, represents the percent upward adjustment of the observed input for the impact of the environment, and the second variable, i.e. *AdjFactorNoise*, captures the percent upward adjustment attributed to statistical noise.

Similarly, DMUs suffering from relatively unfavourable operating environments and statistical noise would have their outputs adjusted upwards as shown in Eq. (5a) by comparing their slacks against those generated by the DMUs operating in the most favourable environment and the most fortunate situation. Eq. (5b) transforms Eq. (5a) similar to the example shown for Eqs. (4a) and (4b). The first variable in Eq. (5b) captures the percent upward adjustment of the observed output for the influence of the environment, and the second variable represents the percent upward adjustment attributed to statistical noise.

$$y_{r,j}^A = y_{r,j} + \left[z_j \hat{\beta}^r - \min_j \{z_j \hat{\beta}^r\} \right] + \left[\hat{v}_{r,j} - \min_j \{\hat{v}_{r,j}\} \right], \quad r = 1, \dots, M, \quad j = 1, \dots, I, \quad (5a)$$

where $y_{r,j}^A$ is the adjusted quantity of r th output in j th unit, $y_{r,j}$ the observed quantity of r th output in j th unit, $z_j \hat{\beta}^r$ the r th output slack in j th unit attributable to environmental factors, and $\hat{v}_{r,j}$ the r th output slack in j th unit attributable to statistical noise.

$$y_{r,j}^A = (1 + \text{AdjFactorEnvironment}_{y_{r,j}} + \text{AdjFactorNoise}_{y_{r,j}}) y_{r,j}, \quad (5b)$$

where

$$\begin{aligned} \text{AdjFactorEnvironment}_{y_{r,j}} &= \left(\frac{z_j \hat{\beta}^r}{y_{r,j}} \right) \left(1 - \frac{\min_j \{z_j \hat{\beta}^r\}}{z_j \hat{\beta}^r} \right), \\ \text{AdjFactorNoise}_{y_{r,j}} &= \left(\frac{\hat{v}_{r,j}}{y_{r,j}} \right) \left(1 - \frac{\min_j \{\hat{v}_{r,j}\}}{\hat{v}_{r,j}} \right). \end{aligned}$$

However, to use Eqs. (4a) or (4b), it is necessary to distinguish input-sourced statistical noise ($v_{i,j}$) from managerial inefficiency ($u_{i,j}$) in the composed error term of the SFA regressions. Once $v_{i,j}$ has been estimated for each unit, Eq. (4a) or (4b) can be implemented and observed input usage adjusted. Most researchers in this field (and LIMDEP software) use the method by Jondrow et al. [22] to separate the composed error term into its components. Hence, the input-sourced statistical noise is estimated residually by Eq. (6), where $\hat{E}[u_{i,j}|v_{i,j} + u_{i,j}]$ depends on $\hat{\beta}^i$, $\hat{\mu}^i$, $\hat{\sigma}_{vi}^2$, $\hat{\sigma}_{ui}^2$

$$\hat{E}[v_{i,j}|v_{i,j} + u_{i,j}] = s_{i,j}^- - z_j \hat{\beta}^i - \hat{E}[u_{i,j}|v_{i,j} + u_{i,j}], \quad i = 1, \dots, N, \quad j = 1, \dots, I. \quad (6)$$

That is, statistical noise attached to an input usage, which is conditional on the composed error structure, is estimated by subtracting from the stage 1 input slack the estimate of that input's slack for a given unit attributed to environmental factors and the conditional estimate of managerial inefficiency for the same input and unit. We extend Fried et al.'s [1] method by estimating statistical noise in output generation as well

$$\hat{E}[v_{r,j}|v_{r,j} + u_{r,j}] = s_{r,j}^+ - z_j \hat{\beta}^r - \hat{E}[u_{r,j}|v_{r,j} + u_{r,j}], \quad r = 1, \dots, M, \quad j = 1, \dots, I. \quad (7)$$

4.3. Stage 3: final data envelopment analysis with adjusted inputs and outputs

Stage 3 is a repeat of stage 1 analysis using input and output data adjusted in stage 2. The results of stage 3 analysis represent SBM DEA analysis of managerial efficiency purged of the influence of operating environment and statistical noise. That is, in this final stage of the three-stage efficiency analysis, all units are re-evaluated after inputs and outputs have been adjusted for influences of operating environment and statistical noise. Our proposed methodology is an improvement over Fried et al. [1] who base their analysis on comparing DMUs after adjusting inputs for radial slacks only and do not work with a fully units-invariant DEA model.

5. Summary and discussion

We detail a potential improvement on the performance evaluation method by Fried et al. [1] that can be used to measure an organisational unit's performance purged of the impact of environment and statistical noise, thus helping to identify the true managerial performance. Key contributions of this paper to the organisational performance measurement and efficiency

literature include, (i) a comprehensive approach where total input and output slacks are identified simultaneously against the same reference set for radial as well as non-radial inefficiencies before levelling the playing field, (ii) identifying percent adjustments attributable to the operating environment and measurement errors, and (iii) using a fully units-invariant DEA model i.e. SBM.

The three-stage analysis starts with the non-oriented slacks-based model of DEA. Concerned that some units may experience favourable (unfavourable) environments and statistical noise, thus distorting their performance measurement, we apply SFA in stage 2. SFA helps decompose stage 1 technical inefficiency (input and output slacks) into environmental influences, statistical noise attributable to measurement errors in the original data, and managerial inefficiency. Stage 3 concludes the analysis with the same DEA model as in stage 1 but uses adjusted inputs and outputs from stage 2 that have been purged of the impact of the operating environment and statistical noise. Without adjustments some units are likely to be penalised on their performance scores due to factors beyond managerial control, while others can be rewarded for operating in favourable environments.

The proposed improvements specifically designed to address the key limitation of DEA, namely the assumption of no measurement error, and the more general problem of how to account for environmental effects, create new opportunities for researchers to revisit their existing studies or design new studies from ground up. Researchers who have access to environmental data are encouraged to apply the three-stage method. Our own attempts with two separate data sets could not be reported here as empirical illustrations because the SFA regressions did not fully converge. Furthermore, Fried et al. [1] were not forthcoming when we requested the data to replicate their study. We hope that others will rise to the challenge by trying to test the research design developed in this paper.

Furthermore, there is usually greater variation in the operating environment between countries than within a country. Thus, accounting for differences in performance due to environmental factors gains added significance when cross-country comparisons are made. This line of research constitutes another fertile ground for future applications of the three-stage DEA/SFA methodology as outlined in this paper. Where panel data are available, SFA can be used to separate efficiency due to technological change (frontier shift) and technical efficiency (catching-up effect); such results can then be compared to Malmquist indices. Alternatively, a lesser known method is to capture temporal influences by

comparing cross-sectional results against a grand frontier built on panel data (e.g. see [12]).

Extensions of this paper can also include measuring goodness of fit where there are stochastic variations in input/output data. For example, Sengupta [23] demonstrates how conventional linear DEA models can be compared to non-linear models (that may better represent real-world situations) through an equation of explanatory power analogous to R^2 in regression. We also note that heterogeneous samples in DEA can suffer from the problem of heteroscedasticity where variances are not constant across sub-groups within the sample. The impact of this problem is a tendency toward more efficient DMUs as statistical noise can inflate variance [24]. According to Sengupta [24], statistical noise can be reduced by selecting an appropriate DEA model (e.g. quadratic or log linear) and by smoothing input/output data through exponentially weighted moving average. Sengupta observes that, for noisy data, smaller smoothing factors are more effective in reducing heteroscedasticity and generating more stable DEA efficiency estimates.

In conclusion, the three-stage method can potentially be used to test the contentions of those managers who attribute the lacklustre performances of their units to the operating environment, or the contentions of those who claim all the credit for good organisational performance. The method can also become part of the human resource management toolkit in, say, determining compensation for managers.

References

- [1] Fried HO, Lovell CAK, Schmidt SS, Yaisawarng S. Accounting for environmental effects and statistical noise in data envelopment analysis. *Journal of Productivity Analysis* 2002;17:157–74.
- [2] Tortosa-Ausina E. Bank cost efficiency and output specification. *Journal of Productivity Analysis* 2002;183:199–222.
- [3] Pastor JM. Credit risk and efficiency in the European banking system: a three-stage analysis. *Applied Financial Economics* 2002;1212:895–911.
- [4] Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. *European Journal of Operational Research* 1978;2:429–44.
- [5] Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* 1984;30:1078–92.
- [6] Cooper WW, Seiford LM, Tone K. *Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software*. Boston: Kluwer Academic Publishers; 2000.
- [7] Banker RD, Morey RC. Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research* 1986;34:513–21.
- [8] Banker RD, Morey RC. The use of categorical variables in data envelopment analysis. *Management Science* 1986;32:1613–27.

- [9] Greene WH. *Econometric analysis*. New York: Macmillan; 2003.
- [10] Fried HO, Schmidt SS, Yaisawarng S. Incorporating the operating environment into a nonparametric measure of technical efficiency. *Journal of Productivity Analysis* 1999;12:249–67.
- [11] Fried HO, Lovell CAK, Eeckaut PV. Evaluating the performance of US credit unions. *Journal of Banking and Finance* 1993;17:251–65.
- [12] Bhattacharyya A, Lovell CAK, Sahay P. The impact of liberalisation on the productive efficiency of Indian commercial banks. *European Journal of Operational Research* 1997;98:332–45.
- [13] Muñoz MA. Separating managerial inefficiency and external conditions in data envelopment analysis. *European Journal of Operational Research* 2002;143:625–43.
- [14] Fried HO, Lovell CAK. Searching the zeds. Working paper presented at the Second Georgia Productivity Workshop, Athens, GA; 1996 November 1–3.
- [15] Farrell MJ. The measurement of productive efficiency. *Journal of the Royal Statistical Society* 1957;120:253–81.
- [16] Aigner D, Lovell CAK, Schmidt P. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 1977;6:21–37.
- [17] Meeusen W, van Den Broeck J. Efficiency estimation from Cobb–Douglas production functions with composed error. *International Economic Review* 1977;18:435–44.
- [18] Jacobs R. Alternative methods to examine hospital efficiency: data envelopment analysis and stochastic frontier analysis. *Health Care Management Science* 2001;4:103–19.
- [19] Coelli T, Prasada RDS, Battese GE. *An introduction to efficiency and productivity analysis*. Boston: Kluwer Academic Publishers; 1998.
- [20] Lovell CAK, Pastor JT. Units invariant and translation invariant DEA models. *Operations Research Letters* 1995;18:147–51.
- [21] Tone K. A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research* 2001;130(3):498–509.
- [22] Jondrow J, Materov IS, Lovell CAK, Schmidt P. On the estimation of technical inefficiency in the stochastic frontier production model. *Journal of Econometrics* 1982;19:233–8.
- [23] Sengupta JK. Nonlinear measures of technical efficiency. *Computers and Operations Research* 1989;16(1):55–65.
- [24] Sengupta JK. Data envelopment analysis with heterogeneous data: an application. *Journal of Operational Research Society* 2005;56:676–86.