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Measuring bank efficiency: tradition or sophistication? – A note

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Abstract

The recent literature on measuring bank performance indicates a preference for sophisticated techniques over simple accounting ratios. We explore the results and relationships between bank efficiency estimates using accounting ratios and Data Envelope Analysis (DEA) with bootstrap among Jamaican banks between 1998 and 2007. The results indicate different outcomes for the traditional accounting ratios and the sophisticated DEA methodology in the measurement of bank efficiency. GLS random effects two-variable regression tests for superiority using a risk index for insolvency suggest an advantage in favour of the DEA.

Key Words

Bank efficiency, Jamaica, Accounting Ratios

JEL Codes

G21, G28, G29

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1. Introduction and Background

This note explores whether the use of sophisticated modelling techniques add value to the analysis of bank efficiency in Jamaica relative to comparatively simpler ratio constructs traditionally used by banks and regulators. Could bank management and regulators enhance the quality of their intelligence by investing in more sophisticated techniques that could potentially lead to improved levels of performance and possibly secure banks' survival in the face of worldwide financial disequilibrium? The correlation between an efficient financial system and the benefits to the real economy are now well-established (see, for example, Berger *et al.*, 2004). This issue is of particular relevance to Jamaica where the banking environment has changed markedly over the last decade as a result of crisis. Discussing the crisis, Daley *et al.* (2008:295) note that '... the likelihood of failure in any year, t , is significantly related to the ...the level of efficiency with which management conducts its affairs in $t-3$ and in $t-1$...'.¹

2. Measuring bank efficiency: Theory, hypotheses, model strategy and results

The 'traditional' efficiency ratio (ER) is generally regarded as a critical tool for analysis and decision making. It has also been used as a basis for measuring bank efficiency in empirical analysis.² We have adopted the definition by the United States Federal Financial Institutions Examination Council (FFIEC) for all Jamaican banks between 1998 and 2007.³

$$ER = \frac{C}{II + NII} \quad (1)$$

where C is non-interest expenses, II is net interest income and NII is non-interest income.

¹ Efficiency was measured using the accounting ratio.

² See, for example, Li *et al.*, (2001), Marcus (2001), Forster and Shaffer (2005), and Liebscher (2005). Some Jamaican banks also use an accounting ratio akin to this to monitor efficiency <http://mycmmmb.com/docs/SMW/SMW%202006/February%202006/SMR090206.pdf>.

http://www.jncb.com/corp_info/news.asp?Story=275, <http://www.capital-credit-mbank.com/viewnews.aspx?ID=60>

³ <http://www.ffiec.gov/PDF/UBPR/06UBPRS31.pdf>. 'Banks' refer to deposit-taking entities that may be commercial banks or merchant banks.

Smaller values of this ratio are more desirable as they suggest greater efficiency in producing a given output with fewer inputs or utilising a given set of inputs to produce greater output.⁴

This model has been challenged by a strand appearing in the empirical literature on the grounds that while ratios are useful and give some indication of the level and changes in efficiency over time, they represent a final outcome and do not allow for identification of the sources of inefficiency and where improvements are necessary. For example, Berger *et al.* (2009:116) caution that:

Ratio analyses do not control for individual bank outputs, input prices, or other exogenous factors facing banks in the way that studies using modern efficiency methodology do, and so may give misleading results. To illustrate, a cost-efficient bank may have relatively high cost ratios because it is producing a high cost output bundle (e.g. more loans, fewer liquid assets) or faces high input prices, and so may be incorrectly identified as a poor performer.

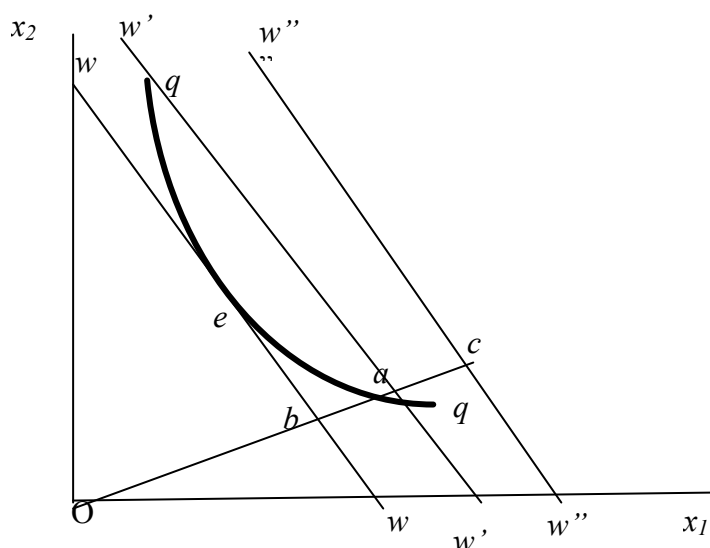
The alternative is to shift the paradigm to neoclassical production theory where performance is evaluated by assessing a bank as an economic unit or firm transforming inputs into outputs. Here, managers may isolate and evaluate the efficiency of the banks by cost, technical or allocative efficiency. With this distinction, inefficiency can be specifically targeted and addressed. Figure 1 explains the distinction, assuming constant returns to scale (CRS).⁵

The figure shows the isoquant qq for the production of a given output, with inputs x_1 and x_2 . The ratio of input prices is traced along the isocost, ww . The most efficient cost minimising position occurs when ww is tangential to qq , at point e . The fully cost efficient (CE) point, e , defines the point of minimum cost as well as optimal factor mix. If a bank utilises a factor combination of x_1 and x_2 at, say, point c , the actual cost to the bank is shown by $w''w''$ and is not fully CE. We can express CE formally by the ratio of Ob/Oc . At point c the bank is also technically inefficient because it uses more inputs than is necessary to produce at a point on the isoquant, q .

⁴Forster and Shaffer (2005) note that this ratio has sometimes been used to infer evidence of scale economies or diseconomies.

⁵Casu and Molyneux (2003) argue that using CRS when banks are not operating at optimal scale might be inappropriate and that the alternative assumption of variable returns to scale (VRS) produces efficiency scores that are greater than or equal to those obtained under CRS. We use CRS because of the limitations imposed by our data set.

Figure 1 Decomposing Efficiency



The bank will be fully technically efficient (100%) only if it produces at a point on the isoquant, for example point *a*. We can therefore derive a formal measure of technical efficiency (TE) by using the ratio Oa/Oc . A fully technically efficient bank will shrink its usage of factors from point *c* to point *a*, and TE will be =1. Notably, the bank may be producing the optimal level of output but not using the optimal mix of input. For example, at point *a* where the bank is fully technically efficient, it is not fully cost efficient because the actual cost to the bank is shown by $w'w''$ instead of ww . Point *a* is said to exhibit allocative inefficiency. Allocative efficiency (AE), defined by the ratio of Ob/Oa , is achieved when the reduction in inputs results in movement along the isoquant from point *a* to point *e*. We can therefore decompose CE into TE and AE as follows:

$$CE = AE * TE$$

Within this paradigm, the intermediation approach and the production approach are used to classify inputs and outputs: the former assesses deposit-taking entities as financial intermediaries that utilise labour and capital to transform deposits into loans and other earning assets; the latter is predicated on the entity as a producer of loan and deposit services

from labour and capital (see, for example, Drake, 2003).⁶

These approaches are associated with empirical research on bank efficiency utilising frontier parametric and non-parametric techniques. Data Envelopment Analysis (DEA) is a mathematical programming technique grounded in the principle of benchmarking that seeks to identify the most efficient entity based on a ‘frontier’ constructed over the data using the data in the sample.⁷ Because this frontier analysis technique provides an objectively determined numerical efficiency value using multiple inputs and outputs, Berger and Humphrey (1997:2) suggest that it may be ‘particularly valuable in assessing and informing government policy regarding financial institutions’ and, hence, its recommendation as a viable alternative to ratio analyses. However, Coelli *et al.* (2005:199) note that the flexibility of the DEA ‘...can also create problems, especially when dealing with small data sets.’ This caution bears particular relevance to developing countries that face a continual challenge of accessing sufficient, accurate and reliable data for empirical analyses.

The standard DEA model outcome for efficiency is a value between 0 and 1 (0% and 100%) indicating the degree of efficiency from least efficient to fully efficient. Let there be N banks. Let x_i represent the input matrix of the i^{th} bank and y_i represent its output matrix. Let the $K \times N$ input matrix be denoted as X and the $M \times N$ output matrix be denoted by Y . The efficiency measure for each of the N banks is maximised by the DEA searching for the ratio of all weighted outputs over all weighted inputs where the weights are selected from the dual of the linear programming problem conventionally represented as:

⁶ The choice of approach may result in different efficiency scores but the conclusions should be similar (see, for example, Berger *et al.*, 1997).

⁷ See, for example, Coelli *et al.* (2005). The basis of DEA is an extension by Charnes *et al.* (1978) who popularised the method. Other commonly applied techniques are the stochastic frontier approach (SFA), the Distribution-Free Approach (DFA) and the Thick-Frontier Approach (TFA).

$$\begin{aligned} \min_{q,i} \quad & \mathbf{q} \\ & -y_i + Y\mathbf{f} \geq 0 \end{aligned} \quad (2)$$

subject to

$$\begin{aligned} \mathbf{q}x_i - X\mathbf{f} & \geq 0 \\ \mathbf{f} & \geq 0 \end{aligned} \quad (3)$$

where \mathbf{f} is an $N \times 1$ vector of constants (reflecting the number of banks), \mathbf{q} is a scalar and is the economic efficiency score of the i^{th} bank ($0 < \mathbf{q} < 1$).

We hypothesize, consistent with the extant literature, that sophisticated measurement techniques should add informational value over simpler ratios. To test our hypothesis, accounting ERs are compared with efficiency scores from 2,000 non-parametric DEA bootstraps for each bank in each year.⁸ Variations of the intermediation approach employed to explore robustness are summarised in Table 1.

Table 1 Modelling strategy

EFFICIENCY APPROACH	MODEL DESCRIPTION		
Accounting	ER - US FFIEC definition $\frac{\text{Non-interest expenses}}{(\text{Non-interest income} + \text{net interest income})}$		
Frontier	NON-PARAMETRIC DEA BOOTSTRAP		
	Model	Inputs	Outputs
	Model 1	1. Operating Costs 2. Deposits	1. Total Net Interest Income 2. Non-interest income
	Model 2	1. Operating Costs 2. Deposits	1. Gross Loans 2. Investments
	Model 3	1. Operating Costs 2. Deposits	1. Gross Loans – NPL (net) 2. Investments
	Model 4	1. Operating Costs 2. Deposits	1. Net Loans + Investments 2. NPL ⁻¹

To formally explore our hypothesis, we compute Spearman's Rank Correlation for efficiency

⁸ A brief description of the bootstrapping procedure may be found in Simar and Wilson (2000). Hall (1986) suggests that 1,000 bootstraps to ensure adequate coverage of the confidence intervals.

scores from the model comparisons and report these results in Table 2. We do this to identify whether there is any relationship between the ranks generated from the DEA efficiency scores and the ranks generated from the accounting ratios.

A negative sign is expected on the Spearman's rho since a lower ER is preferred, while a higher value on the DEA suggests greater efficiency. Table 2 shows no discernable pattern as it relates to the sign on the correlation coefficient for any of the models. Furthermore, the *p*-values are not statistically significant at conventional levels; the occasional occurrences are most likely random. We therefore cannot reject the null hypothesis of independence between the ER and the DEA results for any of the models.

Table 2 Correlation results – Accounting ratio and DEA models

Spearman's ρ	Model 1	Model 2	Model 3	Model 4
1998	-0.1364	-0.3273	-0.3909	0.0091
1999	-0.2364	0.2818	-0.0182	0.0364
2000	-0.6626**	0.1394	-0.0303	0.1515
2001	-0.4000	-0.4364	-0.0455	0.1727
2002	-0.3371	0.2551	-0.0866	-0.6119**
2003	-0.4167	-0.0667	0.1333	0.4000
2004	-0.6000*	-0.3500	-0.3500	-0.6500*
2005	-0.4545	-0.0545	-0.0182	-0.1702
2006	0.2121	-0.5471*	-0.5471*	-0.5106
2007	-0.5000	-0.1500	-0.2833	-0.1167

Note: *Significant at the 0.10 level, ** Significant at the 0.05 level

We further tested whether this independence suggested superiority in favour of either technique using a two-stage approach. First, we constructed a risk index along the lines of the probability for insolvency described in Hannan and Hanweck (1988). This risk index, equivalent to the inverse of the probability of insolvency described in Hannan and Hanweck (1988), is represented as follows:

$$\frac{E(p/A) + K/A}{S_{p/A}} \quad (4)$$

where $E(p/A)$ is the 5-year moving average for the ratio of profit (*p*) to assets (*A*) (return on

assets) for each bank and K/A , is the capital (K) to asset ratio for each bank in a particular year, and $s_{p/A}$ is the standard deviation of the return on assets over the 5 years. A greater value for expression (4), suggests a lower probability of insolvency. Therefore, the ER will be negatively correlated with the risk index but the DEA efficiency will be positively correlated with the index. Using Generalised Least Squares (GLS) random effects regression, we test for association between each efficiency measure and the risk index. The results for the two-variable equation are summarised in Table 3.⁹ Evidently, there is a statistically significant relationship between two of the four DEA models and the risk index at conventional levels. Model 4 is marginally significant, while there is no statistical significance as it relates to Model 1 or the accounting ER. These results suggest an advantage in favour of some DEA models that are worthy of further investigation.

Table 3 GLS regression results – Risk index and efficiency models

	ER	Model 1	Model 2	Model 3	Model 4
Coefficient	-0.0339	0.0639	0.0964**	0.112*	0.068
	(0.447)	(0.160)	(0.055)	(0.042)	(0.121)

Note: p -values in parentheses. *Significant at the 0.10 level, ** Significant at the 0.05 level

3. Concluding remarks

This note was motivated by the growing trend in the empirical literature towards sophisticated methodologies for measuring bank efficiency. Our examination, in the light of the challenge of sufficient appropriate data, suggests independence of the model results among Jamaican banks between 1998 and 2007. Regressions tests for association with a risk index imply an advantage in favour of some DEA models. Intuitively, the options of using multiple inputs and outputs and of decomposing DEA scores imply significant value-added from the use of the bootstrapping technique with non-parametric DEA over traditional ratio analysis. This further suggests significant potential enhancements to the management of bank

⁹ The Breusch-Pagan test for random effects against pooled rejected pooled as did the F test for fixed effects against pooled. However the Hausman test was unable to distinguish between the random effects and fixed effects. For robustness, we also tested the association with both the accounting ratio and each DEA model in each equation. These results were statistically insignificant and have not been reported and are available from the authors upon request.

efficiency in Jamaica. However, these findings point to the need for more comprehensive future research on the subject.

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