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**Cardiff Economics
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E2011/27

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ISSN 1749-6101
November 2011

Post-crisis cost efficiency of Jamaican banks

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October 2011

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**Abstract**

Deregulation, re-regulation and continuing globalisation embody an imperative that banks increase efficiency in order to survive. We employ the Simar-Wilson (2007) two-step double bootstrap Data Envelopment Analysis method to measure whether cost efficiency among Jamaican banks has improved between 1999 and 2009 following a number of post-crisis responses aimed at strengthening and improving the sector. Efficiency is extracted from a meta-frontier construction for the full sample period. In addition we conduct tests for unconditional *beta-* and *sigma-convergence* and overall, the results suggest that there has been a tendency towards improvement in bank efficiency levels for the industry as a whole but there is also evidence that foreign banks show a higher trend improvement in efficiency.

**Keywords**: Bank efficiency, DEA, bootstrap, convergence, Jamaica

**JEL Codes**: G21, G28

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We gratefully acknowledge funding support from The University of the West Indies, Mona Campus, and NCB Foundation.

## 1. Introduction

The Jamaican banking sector of today is largely the legacy of unprecedented financial crisis during the last decade of the twentieth century and has undergone many changes consequentially. The crisis resulted in a transformation of the sector in terms of number, types, and ownership of banks.[1] In addition, regulatory amendments imposed by the central bank and reporting changes imposed by an amended Companies Act and Jamaica's adoption of International Financial Reporting Standards (IFRS) have also had, as expected, significant impact of the reported performance of banks (see, for example, Jain, 2002).

While the explanations for Jamaica's past banking problems vary, there is tacit consensus that the macroeconomic environment as well as bank size, ownership and operational efficiency were among the most significant factors contributing to the failure of banks. We make a rigorous attempt to measure efficiency relative to best practice to answer this question: what statistical inference can we draw from point-estimates of efficiency provided by the use of bootstrapping technology? In our investigation of the post-crisis efficiency levels of individual Jamaican banks we implicitly address whether the hypothesis of greater correlation between efficiency and increased foreign ownership holds true for Jamaican banks.

We address the presumption that a sound regulatory framework can serve as a

[1] The number of banks was reduced due mainly to regulator-initiated closures and mergers.

bulwark from instability and engender increased operational performance within banks by implicitly investigating whether the profusion of post-crisis enhancements to the regulatory and supervisory framework is evidenced in improved operational efficiency among Jamaican banks. Specifically, has the regulatory reform focused on transparency and accuracy of non-performing loans (NPLs) influenced greater efficiency within banks? We examine this is by the treatment of NPLs as a bad output, in some of the models examined in this paper.

Another benefit of our paper is the information it provides from tests of convergence specified on the bank efficiency estimates. Utilising the concept of *β-convergence* and *σ-convergence* borrowed from the growth convergence literature, we examine for unconditional convergence among banks in the sample frame. Generally speaking, the findings are indicative of improvement in efficiency in general but that foreign owned banks are converging at a slower rate towards a higher trend improvement in cost efficiency.

The next section contextualises Jamaica's banking sector. Section 3 reviews the literature on bank efficiency for developing countries and the DEA methodology. Section 4 discusses model strategy and data. Section 5 presents the results, including a discussion of the convergence tests and section 6 concludes.

## 2. Efficiency and Jamaica's banking sector in context

Jamaica's banking environment has changed markedly over the last decade. In the early 1990s following a period of deregulation in the financial sector, there was a proliferation of banks in the island: 37 by 1993 of which 30 were locally owned.[2] However, a weak institutional and regulatory framework, regulatory forbearance and internal weaknesses within banks resulted in high levels of non-performing loans, poor capitalisation and inefficiency (Daley 2007).[3] By January 1997, the government was forced to intervene to mitigate the effects of a system-wide crisis.[4] Fourteen of the 21 bank failures in the period 1994-98 occurred in one year (1998). Daley (2007) argues that the peculiar features of the failed banks played a more significant role in the event of failure than did the 'macro' factors during that year that would have affected all banks. According to Daley *et al*. (2008) '… 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* …' (p.295).

Of course, there are significant potential welfare gains from efficiencies within the banking sector. The finance-growth nexus suggests strong positive correlation between financial market development and economic growth in developing countries where banks are

[2]'Banks' refer to deposit-taking entities that may be commercial banks or merchant banks. As a consequence of continual restructuring within the Jamaican banking sector, 5 of the 6 commercial banks operating at the end of 2007 had majority foreign ownership.
[3] Efficiency (or inefficiency) in this instance was measured by a higher ratios of expenses to income.
[4] See, for example, Duncan and Langrin (2004), Tennant (2006) and Daley (2007) for more detailed discussions of the crisis.

the primary intermediary, as capital markets tend to be thin and not well developed (see, for, La Porta example *et al*. 1998). The events taking place both within and outside of the Jamaican banking sector since the 1990s dictate the need for continued focused attention and examination of those factors that are significant correlates to banks' performance and ultimately banking and financial sector system stability.

The efficiency optimisation imperative is acknowledged and, indeed, well-understood in Jamaica, where efficiency is increasingly emphasised as a priority in performance targets. Unfortunately, banking efficiency in Jamaica remains under-researched. This is probably due to the relatively small number of banks and the inaccessibility to high-quality bank-specific data. While several authors make reference to efficiency in relation to bank spreads (for example, Tennant 2006) or bank failure (Daley 2007; Daley *et al*. 2008), Bailey (2006) is the only known study to have specifically examined efficiency in the Jamaican banking sector between 2005 and 2006. We contribute to the literature on banking efficiency in developing countries by examining the efficiency of Jamaican banks at the firm level between 1998 and 2009. This is the first work to our knowledge to examine efficiency in banking using non-parametric bootstrapping technology and to perform a test of convergence on bank efficiency for Jamaica.

**3. Bank efficiency literature and methodology**

Tennant's (2006) examination of interest rate spreads in Jamaica argues that interest rate spreads act as 'a key indicator of [an] institution's efficiency' (p.88), and reports from a survey of Jamaican financial sector stakeholders that recorded high spreads have been attributed to inefficiency, *inter alia*. Consequently, he notes the perception that increased operational efficiencies can help to reduce bank spreads.

According to Bailey (2006), technical efficiency for the Jamaican banking sector in general declined during 2006 relative to 2005. A Stochastic Frontier Approach (SFA) was applied to quarterly data for the period December 2004 to December 2006 and resulted in average technical inefficiency of 25.7% and 9% for commercial and merchant banks, respectively, in 2006 relative to 4.1% and 2.0%, respectively, in 2005.

Not surprisingly, extensive research has been conducted on bank efficiency using data for the United States of America. However, there is also a growing body of literature for developing countries with an increasing number of studies conducted using data for transition economies in Europe, for Pakistan, India and China (see, for example, Berger *et al*. 2009 for a brief survey). Generally speaking, the empirical findings relating to bank ownership and efficiency are mixed. Berger *et al*. (2009:115) note that: 'The most common findings for developing nations are that on average, foreign banks are more efficient than or approximately equally efficient to private [non-state] domestic banks. …there are variations on all of these findings.'

Perhaps it is as a result of the heterogeneity of the outputs and inputs related to banks why there is a lack of consensus in the literature as to their precise classifications. Consequently, the *intermediation* and *production* approaches are often utilised as classification guides. The intermediation approach assesses deposit-taking entities as financial intermediaries that utilise labour and capital to transform deposits into loans and other earning assets; the production approach is predicated on the entity as a producer of loan and deposit services from labour and capital (see, for example, Drake 2003). The choice of approach may alter the efficiency scores obtained but not the qualitative conclusions (see, for example, Berger *et al*. 1997).

The above approaches are now associated with empirical research on banking efficiency utilising frontier parametric and non-parametric techniques. The parametric approaches impose a structural form on the data and are subject to criticism. Despite certain drawbacks, non-parametric approaches are commonly used since they avoid the restrictions of a defined functional form and infer the results from the banks' output directly.

While bank efficiency has been measured by either parametric or non-parametric methods, there remains no consensus on the preferred method for determining the best-practice frontier against which relative efficiencies are measured. The parametric approach, such as the stochastic frontier approach (SFA), specifies a functional form and allows for random errors which follow a symmetric normal distribution while the inefficiencies are measured by a truncated distribution.

However, the parametric approach suffers from the problem of misspecification of the functional form, and possibly inefficiency and multi-collinearity. Usually a local approximation such as the trans-log is specified, which has been argued to provide poor approximations for banking data (see McAllister and McManus 1993; Mitchell and Onvural 1996). In theory, parametric estimators offer faster convergence and produce consistent estimates, but this would be true only if there is no misspecification of the functional form. In contrast, the nonparametric model, such as the conventional Data Envelopment Analysis (DEA), does not require the explicit specification of the form of the underlying production relationship, but at the cost of slower convergence rates and hence larger data requirements. The nonparametric approach also has been criticized for not considering errors due to chance, measurement errors, or environmental differences; hence all deviations are attributed to the measured inefficiency. The conflict between the nonparametric and parametric approaches is important because the two types of methods tend to have different degrees of dispersion and do not always produce a common ranking of the same financial institutions (Berger and Humphrey 1997). Bias, and large variance may be the result when the number of inputs and outputs is large, unless a very large quantity of data are available (Kneip, Park and Simar 1998). Also, the efficiency measure is sensitive to outliers and is upward biased by construction. The bootstrap provides an attractive alternative to the conventional DEA[5].

The essence of the bootstrap idea (Efron 1979, 1982; Efron and Tibshirani 1993) is to approximate the sampling distributions of interest by simulating, or mimicking, the data generating process (DGP). The bias in the DEA estimator then can be estimated and confidence intervals can be built by using this approximated distribution. Simar and Wilson (2007) propose a two-stage semi-parametric bootstrap model, which is capable of incorporating the effects of environmental variables in estimating efficiencies. Environmental factors are a set of factors that probably affect the production process, but are not under the control of firm's managers. These factors might reflect differences in ownership, size, market share, regulatory constraints, business environment, competition, *etc.* among the firms under analysis. Simar and Wilson (2007) cite 47 published papers that employed a two-stage approach wherein non-parametric, DEA efficiency estimates are regressed on a set of

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[5] The first application of the bootstrap method to frontier models dates to Simar (1992). Its use in non-parametric envelopment estimators was developed by Simar and Wilson (1998, 2000)

environmental variables in a parametric, second-stage analysis. The typical two-stage approaches do not provided a coherent description of a DGP, and the method of inference is flawed since the DEA efficiency estimates are biased estimates and are serially correlated, in a complicated, and unknown way.

In order to deal with the problem described above, Simar and Wilson (2007) define a DGP that provides a rational basis for regressing non-parametric, DEA efficiency estimates on some environmental variables in a second-stage analysis. In addition, they suggest bootstrap procedures to provide valid inference in the second-stage regression, as well as to increase the efficiency of estimation and correct the estimation bias[6].

Following Färe, Grosskopf and Lovell (1985) the efficiency of a firm can be defined and measured as the radial distance of its actual performance from a frontier. In the first stage, we employ the Tone (2002) new cost efficiency model, which allows for heterogeneity in unit prices of input. As a general rule, efficiency levels measured relative to one frontier cannot be directly compared with efficiency levels measured relative to another frontier. In order to make the later cross-time convergence analysis more sensible, we use a *meta-frontier* framework, wherein, efficiencies of all observations are measured relative to a common frontier for the full sample period. We chose to use the input oriented efficiency measure and constant return to scale (CRS) is assumed as an optimal scale in the long run.

[6] We adopt the algorithm 2 of the two-stage semi-parametric double bootstrapping method set out by Simar and Wilson (2007).

The cost efficiency $\hat{\rho}$ for the j-th bank is defined as;

$$\hat{\rho}_j = e\bar{x}_j^* / e\bar{x}_j \qquad (1)$$

where $e \in R^m$ is a row vector with all elements being equal to unity, and $\bar{x}_j^*$ is the optimal solution of the LP given below;

$$[\text{Cost}] \qquad e\bar{x}_j^* = \min_{\bar{\text{x}}, \lambda} e\bar{x}_j$$

$$\begin{aligned} s.t. \quad & \bar{x}_j \geq \bar{X}\lambda \\ & y_j \leq Y\lambda \\ & \lambda \geq 0 \end{aligned} \qquad (2)$$

where $\bar{X} = (\bar{x}_1, \ldots, \bar{x}_n)$, with $\bar{x}_j = (p_{1j}x_{1j}, \ldots, p_{mj}x_{mj})^T$, is the matrix of individual factor costs, and $Y = (y_1, \ldots, y_n) \in R^{s \times n}$ is a matrix of outputs.

The cost efficiency measure $\hat{\rho}_j \leq 1$ is the scalar efficiency score for the j-th bank. If $\hat{\rho}_j = 1$ the *i*-th bank is cost efficient as it lies on the frontier, whereas if $\hat{\rho}_j < 1$ the bank is inefficient and need a (1- $\hat{\rho}_j$) reduction in the total cost.

In the second stage, the efficiency estimates $\hat{\rho}_j$ are regressed on a set of environmental variables $z_j$ by using a maximum likelihood method. In practice, Shephard's (1970) definition of efficiency is used to avoid two boundaries points. Shephard's efficiency measure is merely the reciprocal of the conventional Farrell efficiency score ($\hat{\gamma}_j = 1/\hat{\rho}_j$), and can be treated as a measure of inefficiency. If $z_j$ is a vector of environmental variables for the $j^{\text{th}}$ bank and $\beta$ is a vector of parameters associated with each factor to be estimated, then equation (3) below describes the model to be estimated

$$\hat{\gamma}_j = z_j\beta + \varepsilon_j \geq 1 \qquad (3)$$

under (left normal) truncated regression (use only $\hat{\gamma}_j > 1$ in this step) and $\varepsilon_j$ is a truncated random error $N(0, \hat{\sigma}_\varepsilon^2)$, truncated at $(1 - z_j\hat{\beta})$. The algorithm steps are;

Step 1: bootstrap, for each $j = 1,...,n$, we draw $\varepsilon_j^*$ from the distribution $N(0, \hat{\sigma}_\varepsilon^2)$ with left-truncation at $(1 - z_j\hat{\beta})$ and compute $\gamma_j^* = z_j\hat{\beta} + \varepsilon_j^*$.

Step 2: construct a pseudo sample by setting $x_j^* = x_j\hat{\gamma}_j / \gamma_j^*$ for all banks and keep the output measure unchanged, $y_j^* = y_j$.

Step 3: re-estimate DEA cost efficiency $\hat{\gamma}_j^*$ by replacing $(x_j, y_j)$ by $(x_j^*, y_j^*)$.

Step 4: loop over this procedure 100 times ($L_1 = 100$), take the mean, $\bar{\hat{\gamma}}_j^*$, of 100 $\hat{\gamma}_j^*$ estimates, then compute the bias-corrected estimator $\hat{\hat{\gamma}}_j$ for each bank, such that $\hat{\hat{\gamma}}_j = 2\hat{\gamma}_j - \bar{\hat{\gamma}}_j^*$. The bias-corrected Farrell efficiency score can be easily obtained by taking the reciprocal of $\hat{\hat{\gamma}}_j$, that is $\hat{\hat{\rho}}_j = 1/\hat{\hat{\gamma}}_j$.

Step 5: re-estimate the marginal effects of environmental variables, $z_j$, using the bias-corrected efficiency estimate, $\hat{\hat{\gamma}}_j$, to obtained coefficients estimates $\hat{\hat{\beta}}$, by left-truncated regression with $L_2 = 1000$ bootstrap replications. Once the set of $L_2$ bootstrap parameter estimates for $\beta$ and $\sigma_\varepsilon^2$ have been obtained, the percentile bootstrap confidence intervals can then be constructed.

We hypothesize, consistent with the extant literature, that post-crisis regulatory enhancements leads to greater efficiency, and that the larger banks are more efficient as are banks with greater foreign ownership. We therefore report the efficiency of banks generally and in addition, we seek to identify whether there is discernable common speed of convergence across the banks.

## 4. Measuring bank efficiency: model strategy and data

Given the relatively virgin research ground in Jamaica, there is the potential to construct different models of varying specifications and sophistication that could be useful to a variety of policy decisions relating to banks. However, our final models – both in number and design – were determined by data availability. We utilise the full population of banks that existed during the period 1998 to 2009. Table 1 summarises the environmental variables used in step 5 of the algorithm outlined in the previous section and also sets out the four different models tested in the paper. In all four models the intermediation approach was taken and the common factor inputs to the cost efficiency construction were labour (number of bank personnel), real fixed assets, and real bank deposits. The unit costs of the factor inputs were given as unit price of labour (personnel costs divided by number of bank personnel), unit price of fixed assets (non-personnel costs divided by fixed assets) and unit cost of funds (interest costs divided by total bank deposits.

**Table 1 Variable Definitions**

| Category | Mnemonic | Description |
|---|---|---|
| **Environmental** | CATM | Dummy variable; Commercial bank = 1, zero otherwise |
| | COST | Cost-Income ratio |
| | SIZE | Logarithm of total assets deflated by consumer price index |
| | BR | Branches per bank as proportion of total branches |
| | GROWTH | Real GDP growth |

| | | |
|---|---|---|
| Inputs | GDP | Real GDP |
| | OWN | Dummy variable; Foreign owned/acquired = 1, zero otherwise |
| | CR3 | Three-bank concentration ratio |
| | LAB | Total number of personnel per bank |
| | FA | Fixed assets deflated by consumer price index |
| | DEP | Total customer deposits deflated by consumer price index |
| | PL | Personnel costs per bank divided by total number of personnel per bank |
| | PK | Non-personnel costs divided total fixed assets |
| | PF | Total interest costs per bank divided by customer deposits |
| **Model 1** | RLOAN | Total loans per bank deflated by consumer price index |
| | ROEA | Other earning assets per bank deflated by consumer price index |
| | RNONINT | Non-interest earnings deflated by consumer price index |
| **Model 2** | RLOAN-RNPL | Total real loans per bank less non-performing loans deflated by consumer price index |
| | ROEA | As above |
| | RNONINT | As above |
| | $(RNPL)^{-1}$ | Inverse of real non-performing loans (bad output) |
| **Model 3** | RLOAN-RNPL | As above |
| | ROEA | As above |
| | $(RNPL)^{-1}$ | As above |
| **Model 4** | RLOAN | As above |
| | ROEA | As above |

Model 1 is conventional in the literature and treats all loans as a good output. It also treats the non-interest income flows of a bank as an output. The traditional measure of bank income is interest income, but many banks de-emphasise the less profitable 'plain vanilla' banking function, to promote a broader role and emphasize a wider range of services[7] (for example, Drake 2003). Model 2 differs from model 1 in that it takes performing loans as an output so as to give zero weight to NPLs and following Thanassoulis *et al.* (2008) treats NPLs as a bad output by defining a variable that is its inverse. Model 3 removes non-interest earnings from the set of outputs but continues to treat only performing loans as a good output and NPLs as a bad output. Model 4 is a restrictive version of Model 1 and excludes non-interest earnings from the set of output.

We test our hypotheses using annual audited unconsolidated financial data for all Jamaican banks during the period 1998 to 2009 as available. Data were obtained from publicly available resources, including Bankscope, financial statements and Annual Reports, the website of the respective banks, the website of the Central Bank, and media reports.[8] Notably, all the banks now use International Financial Reporting Standards (IFRS) to report financial information.[9] In the final analysis we used an unbalanced panel of 12 banks with 108 bank-year observations.

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[7] Non-interest earnings are a flow of income which proxies the stock equivalent so that the integrity of the outputs as stocks is maintained.

[8] Bankscope database is a resource providing financial and other data for over 29,000 banks all over the world.

[9] IFRS was adopted or all financial reporting on or after July 1, 2002. Some financial statements have therefore been reported using the superseded local accounting standards (Local GAAP). Daley (2004), Jain (2002) and Daley (2002), for example, discuss the likely impact of the change.

## 5. Empirical Results

Table 2 presents the second stage of the double-bootstrap methodology of Simar and Wilson (2007). Each model utilises a common set of environmental variables. The table shows the point estimate of the coefficients and the lower and upper bound estimates at the 95 percentile.

**Table 2: Stage 2 regression model; upper and lower bound in parenthesis at 95th percentile**

| *Environmental Variable* | *Model 1* | *Model 2* | *Model 3* | *Model 4* |
|---|---|---|---|---|
| Intercept | 2.65 | 27.1 | 5.31 | 21.5 |
| | (1.28, 20.7) | (-11, 65) | (-21.7, 35.3) | (-15.7, 57.4) |
| CATM | 1.38* | 0.72 | 1.05 | 1.35 |
| | (0.04, 2.50) | (-1.25, 2.89) | (-.068, 2.72) | (-1.03, 3.50) |
| COST | 0.53 | 3.71 | -.275 | 4.37 |
| | (-2.4, 3.56) | (-1.9, 9.9) | (-5.3, 4.7) | (-2.5, 10.8) |
| SIZE | .001* | .001* | .001* | .001* |
| | (.000, .002) | (.000, .002) | (.000, .002) | (.000, .002) |
| BR | -7.8* | -10.3* | -13.9* | -13.5* |
| | (-1.2, -3.33) | (-19, -1.7) | (-22.5, -4.9) | (-22.3, -2.9) |
| GROWTH | -.19 | -.83* | -.41 | -.79* |
| | (-.04, 0.04) | (-1.5. -.3) | (-.09, .13) | (-1.47, -.15) |
| RGDP | -.10* | -.34* | -.14 | -.21 |
| | (-.02, -.002) | (-.06, -.11) | (-.03, .04) | (-.004, .04) |
| OWN | 2.57* | 1.91* | 3.16* | 2.67* |
| | (1.47, 3.66) | (.004, 3.71) | (1.19, 5.07) | (.022, 4.71) |
| CR3 | 0.09 | 0.051 | 0.11 | -.02 |
| | (-.002, 0.18) | (-.017, 0.28) | (-.007, .29) | (-.026, .19) |

* significant at the 5%

Bearing in mind that the dependant variable is the inverse of the cost efficiency measure (values greater than unity indicate inefficiency and values of unity indicate 100%

efficiency), Table 2 provides consistent results for the role of size, branch network and ownership. Size in terms of assets is associated with lower efficiency but banks with larger branch networks are associated with higher efficiency. Contrary to expectations, foreign ownership is associated with lower cost efficiency. One possible reason for this result is that foreign acquisition of domestic banks occurred in the aftermath of the 1998-2000 banking crisis picking up the weaker of the available banks. Macroeconomic factors play a role in some of the models but the influence is not robust.

Table 3 summarises the mean cost efficiency in groups of three-year intervals by model, for the conventional DEA result, the bootstrapped bias-corrected estimate, the average lower bound and average upper bound intervals at the 95$^{th}$ percentile.

**Table 3: Mean Cost Efficiency Scores; Mean percentage efficiency shown in parenthesis**

| Model | Year range | DEA Score | Bias-corrected | Lower bound | Upper bound |
|---|---|---|---|---|---|
| **Model 1** | 1998-2000 | 1.928* (51.9%) | 2.291$^{\#}$ (43.6%) | 2.079 | 2.529 |
| | 2001-2003 | 1.692 (59.1%) | 1.781$^{\#}$ (56.1%) | 1.541 | 2.034 |
| | 2004-2006 | 1.412 (70.8%) | 1.199 (83.4%) | 0.920 | 1.475 |
| | 2007-2009 | 1.271* (78.6%) | 1.044 (95.8%) | 0.614 | 1.234 |
| **Model 2** | 1998-2000 | 2.106*(47.5%) | 2.699$^{\#}$ (37.1%) | 2.477 | 2.923 |
| | 2001-2003 | 1.709 (58.5%) | 1.846$^{\#}$ (54.2%) | 1.583 | 2.107 |
| | 2004-2006 | 1.370 (73.0%) | 1.120 (89.2%) | 0.816 | 1.432 |
| | 2007-2009 | 1.350 (74.1%) | 1.119 (89.4%) | 0.795 | 1.422 |
| **Model 3** | 1998-2000 | 2.268 (47.5%) | 3.142$^{\#}$ (31.8%) | 2.196 | 3.311 |
| | 2001-2003 | 1.969* (50.8%) | 2.492$^{\#}$ (40.1%) | 2.235 | 2.703 |
| | 2004-2006 | 1.466 (68.2%) | 1.335$^{\#}$ (74.9%) | 1.057 | 1.627 |
| | 2007-2009 | 1.542 (64.8%) | 1.510$^{\#}$ (66.2%) | 1.217 | 1.812 |
| **Model 4** | 1998-2000 | 2.260* (44.3%) | 3.107$^{\#}$ (32.2%) | 2.899 | 3.291 |
| | 2001-2003 | 2.003* (49.9%) | 2.558$^{\#}$ (39.1%) | 2.328 | 2.774 |
| | 2004-2006 | 1.530 (65.4%) | 1.466$^{\#}$ (68.2%) | 1.218 | 1.735 |
| | 2007-2009 | 1.459 (68.6%) | 1.299$^{\#}$ (77.0%) | 1.018 | 1.599 |

*Significant bias at the 95$^{th}$ percentile; significantly different from unity at the 5 per cent

As averages of individual scores the bias-corrected scores can only be interpreted as indicative. However, they show that the bias in the plain DEA scores is not universally frequent. Often the simple DEA score is not significantly different from the bias-corrected score. However, the distribution of scores can confirm if the measured efficiency score is significantly different from the benchmark. One noticeable feature is that the measure of efficiency is lower in the models that include NPLs as a bad output. As a test for robustness we report the simple correlation of the scores between each model for comparison[10]. Table 4 shows the results.

**Table 4 Simple correlations of efficiency scores**

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Model 1 | 1.0000 | | | |
| Model 2 | 0.9565 | 1.0000 | | |
| Model 3 | 0.8717 | 0.9134 | 1.0000 | |
| Model 4 | 0.8947 | 0.8430 | 0.9315 | 1.0000 |

## 6. Tests for convergence

We borrow from the growth convergence literature of Barro and Sala-i-Martin (1992) to test for unconditional *$\beta$-convergence* and *$\sigma$-convergence*. *$\beta$-convergence* measures the speed of

[10] Results from a Spearman rank correlation were very similar.

convergence to the best practice frontier and $\sigma$ *-convergence* measures at which the dispersion of efficiency narrows to the mean.

Following Fung (2006) we estimate unconditional convergence using panel estimation techniques. Equation (1) below describes the basic model.

$$\Delta CE_{i,t} = \alpha + \beta TREND_t + \lambda CE_{i,t-1} + u_{i,t} \qquad (4)$$

Where *CE* = cost efficiency, *TREND* represents a time trend, and *u* is a stochastic disturbance. A negative value of $\lambda$ is a necessary condition for convergence. The larger the absolute value of $\lambda$, the faster the speed of convergence. Also the further a bank is from the benchmark the faster the speed of convergence. The coefficient on the *TREND* term identifies the steady-state efficiency improvement path for the industry as a whole. To allow for variable speed of adjustment speed between domestic banks and foreign owned banks and possible differences in the trend path of efficiency improvement, equation (4) is modified to be;

$$\Delta CE_{i,t} = \alpha + \beta TREND_t + \gamma TREND_t * OWN + \lambda\, CE_{i.t-1} + \vartheta CE_{i,t-1} * OWN + \epsilon_{i,t} \qquad (5)$$

The stead-state values of efficiency improvement for foreign banks $(CE_F^*)$ and domestic banks $(CE_D^*)$ is given as;

$$CE_F^* = -\frac{\alpha+(\beta+\gamma)TREND}{\lambda + \vartheta}$$

$$CE_D^* = -\frac{\alpha+\beta TREND}{\lambda}$$

To estimate cross sectional dispersion or *σ-convergence*, which is testing the convergence towards the industry average level of efficiency, we adopt the following autoregressive distributed lag model specification[11], following the specification for panel data used by Parikh and Shibata (2004).

$$\Delta E_{i,t} = \mu + \varphi E_{i,t-1} + \varepsilon_{i,t} \quad (6)$$

Where $E_{i,t} = CE_{i,t} - \overline{CE_t}$ , $E_{i,t-1} = CE_{i,t-1} - \overline{CE}_{t-1}$, and $\overline{CE}_t$ is the mean efficiency score at time t. A negative value for the parameter $\varphi$ implies unconditional $\sigma$ -*convergence*. The intercept $\mu$ indicates the average dispersion from the mean.

Table 5 below presents some selected results of *beta-convergence* for each model which, as described above, measures cost efficiency based on alternative output measures and Table 6 shows the results for *σ-convergence*.

We experimented with interactive terms to identify different speeds of adjustment for different groups of banks and for alternative steady-state efficiency improvement paths. It was found that an interactive adjustment response of efficiency in the post-crisis period (2001-2009) was not significant when included with the interactive adjustment response with ownership (*OWN*). This is very likely because a number of banks were foreign acquired post the crisis. The most important and consistent result to focus on is that the lag of technical efficiency is negative and strongly significant in all four models. The trend was negative and generally significant indicating an improving efficiency path for the industry. The interactive

[11] Similar specifications have been estimated, among others, by Fung (2006), Weill (2009) and Casu and Girardone (2010).

term of ownership and lagged cost efficiency suggests that the speed of convergence of the foreign owned banks is lower than domestic but an interactive term with the trend suggests that the trend efficiency path of average efficiency is marginally higher than the industry. The foreign banks have a slower speed of adjustment but the steady-state trend path shows a faster improvement in efficiency over time than domestic banks.

**Table 5: Tests for Beta-convergence in cost efficiency; Dependant variable $\Delta CE_{i,t}$**

| ***Variable*** | ***Model 1*** | ***Model 2*** | ***Model 3*** | ***Model 4*** |
|---|---|---|---|---|
| ***Intercept*** | 100.66** (0.038) | 110.97** (0.046) | 93.49 (0.135) | 152.0*** (0.006) |
| $CE_{i,t-1}$ | -.5868*** (0.000) | -.8370*** (0.000) | -.7178*** (0.000) | -.8301*** (0.000) |
| $TREND_t$ | -.0499** (0.039) | -.0549** (0.048) | -.046 (0.139) | -.0753*** (0.007) |
| $OWN{*}CE_{i,t-1}$ | 0.1499* (0.060) | 0.4293*** (0.000) | 0.4611*** (0.004) | 0.5576*** (0.000) |
| $OWN{*}TREND_i$ | 0.00002 (0.807) | -.00002* (0.096) | -.0004** (0.038) | -.0004*** (0.005) |
| ***Wald Chi(4)*** | 45.3 | 221.0 | 31.5 | 108.4 |

Note: GLS panel estimation, heteroskedastic adjusted standard errors, *p*-values in parentheses, *** significant at the 1%, ** significant at the 5%, * significant at the 10%

**Table 6: Tests for Sigma-convergence; Dependant variable $\Delta E_{i,t}$,**

| **Model** | $E_{i,t-1}$ | **Wald Chi-Sq(1)** |
|---|---|---|
| **Model 1** | -.4210*** (0.000) | 35.3 |
| **Model 2** | -.5853*** (0.000) | 94.3 |
| **Model 3** | -.2990*** (0.000) | 20.2 |
| **Model 4** | -.3922*** (0.000) | 36.0 |

Note: GLS panel estimation, heteroskedastic adjusted standard errors, *p*-values in parentheses, *** significant at the 1%,

Table 6 confirms the existence of *σ-convergence*, which says that the improvement in efficiency of banks in post-crisis Jamaica has also resulted in the narrowing of the dispersion of efficiency.

**6. Concluding Remarks**

Motivated by the potential impact of recent events on Jamaica's critical banking sector, this paper has presented a number of models for measuring individual bank efficiency in Jamaica. Frontier models show that the use of the bootstrapping technique mitigates bias and therefore show superiority in favour of the bootstrapping technique over the standard DEA. There were wide fluctuations in efficiency levels over the period 1998 to 2009 but there was a discernible trend towards improvement particularly for the foreign-owned commercial banks.

The inclusion of the non-performing loans as a bad output produced more telling results than its mere inclusion or exclusion. In general, efficiency levels declined when the bad output is introduced. With the introduction of IFRS, International Accounting Standard (IAS) 39 mandates guidelines and a rigorous approach to credit provisioning which must be observed. This increases the difficulty for banks to go undetected with under-provisioning as with previous accounting requirements. In line with expectations, the post-IFRS results appear to be more transparent and to better reflect the true economic value of assets and liabilities.

Issues regarding bank efficiency are of particular interest in Jamaica where there banks compete for a share of the small, open market. A bank's response to market conditions is likely to be better the more efficiently that bank operates. Reliable information about the level of efficiency and changes to these levels over time will assist bankers in determining how to ‘bundle,’ price, and market banking services. Furthermore, any long-term impact on bank profitability is likely to have relevance to customer welfare and economic development and therefore to policymakers in a wider sense. The results from this paper inform an exercise in measurement that may be used to improve managerial performance by highlighting banks that score high on best practices and also to address research issues such as the variation in efficiency based on different definitions of output. It is therefore useful for policymakers at both the micro and the macro levels. These results must be considered in relation to other factors such as banks’ productivity and the impact of accounting measures on reported financial data that are used to impute efficiency levels in frontier analysis.

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