Investigating the Relationship between Economic Factors & Bank Efficiency: The Case of Jamaica

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Abstract

This paper evaluates the impact of bank specific and macroeconomic variables on bank efficiency. A Translog Cost Function is estimated for commercial banks in Jamaica over the period 2000 – 2012, with efficiency estimates from the model improving across all banks. Furthermore, at the close of the period, each bank would only need to reduce costs by less than 5.0 per cent to operate as efficiently as possible. OLS estimates of the impact of economic factors on efficiency, showed similar results for large and small banks, with small banks showing much greater responsiveness to the variables examined. A VEC model was also utilized in investigating this relationship for the commercial bank sector. Findings from the model showed that innovations in GDP growth, the NPLs to total loans ratio and the HHI led to the strongest improvements in efficiency, with the capital to asset ratio also having a favourable impact on the variable. Regarding inflation, this factor contributed to an initial deterioration in efficiency, however, stimulated improvements in subsequent periods. Innovations in the interest rate variable led to deterioration in efficiency. The impact of innovations in NPLs to totals on bank efficiency may be reflective of longer-term benefits of stronger credit risk management by banks in allocating expenditure needed to improve the loan monitoring and risk mitigation process. Moreover, the findings of the study are useful in informing policymakers of the potential impact of the macroeconomic policy environment on the performance of banking institutions.

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† The views expressed are those of the authors and not necessarily those of the Bank of Jamaica.

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1. Introduction

Banking has experienced dramatic changes internationally over the last few decades. Deregulation and financial integration have featured as major forces impacting the performance of the banking sector. Moreover, in such a rapidly changing market worldwide, bank regulators, managers and investors are concerned about efficiency or how effectively banks transform their inputs into various financial products and services. It is generally accepted that efficiency in banking operations allows enterprises and households to enjoy higher quality services and lower prices. Furthermore, increases in banking sector inefficiency may not only raise the cost of services offered but also reduce the level of intermediation in the economy and impair economic growth. As such, an efficient financial sector is an important prerequisite for economic growth and development, especially in developing countries. Examination of the efficiency and performance of financial institutions is also relevant from a financial stability policy perspective, because as banks become better-functioning entities, it is expected to be reflected in strengthening capital buffer, safety and soundness of the financial systems.

In line with these developments, an extensive literature has evolved examining financial firm efficiency issues. The existence of banks of a similar size with diverging average operating costs has also caused a shift of focus towards a more accurate evaluation of the cost efficiency of banks. However, not as many studies have examined how risk and output quality factors influence efficiency levels. The measurement of the efficiency of banking institutions can serve two major purposes. It helps to benchmark an individual bank against a best practice bank and secondly, it helps to evaluate the impact of various measures on the efficiency and performance of these institutions. Measuring the efficiency of the banking system and analysing the factors that explain it can be very important for supervisory authorities in assessing emerging risks and has implications for pricing policies in the sector. Furthermore, a stable and efficient banking system helps to ensure an optimal allocation of capital resources in an economy which is an important pre-condition in fostering economic growth.

For Jamaica, Bailey (2009) estimated efficiency for dominant banks in the Jamaican commercial banking sector for the period 1989 to 2005 and found that, on average, dominant banks would need to reduce costs by roughly 7.0 per cent in order to operate as efficiently as possible. The paper further explored the relationship between efficiency, concentration and performance. Results from the Vector Autoregressive (VAR) model rejected the structure-conduct-performance (SCP) hypothesis, which indicates that stronger concentration leads to increased profits. Rather, improvements in efficiency contribute to increased profitability for the dominant banks. However, improvements in efficiency for these dominant banks may not be reflected in their pricing policies due to the absence of strong competition in the sector. Nonetheless, there has been no recent study in the Jamaican context that investigates the determinants of efficiency, in particular utilizing macroeconomic variables and other factors which impact operating performance in the commercial banking sector.

This study has two main objectives: first it aims to extend the established literature by examining the determinants of Jamaican banks' cost efficiency over the period 2000 to 2012, by estimating a Translog cost function. The Jamaican banking market has undergone substantial events impacting operating performance in the sector over the past 12 years, in particular more recently the Jamaica Debt Exchange Programme (JDX) and also the impact of the global crisis period. [2,3] OLS models were used to investigate the impact of economic factors on the efficiency of large and small banks. There was also an investigation of the impact of these factors on cost efficiency for the overall commercial banking sector by using a Vector Error Correction framework. The results of the study will also provide insight regarding the potential impact of economic policy on banking sector efficiency as well as the possible implications of these policies for consumer welfare.

The paper is organized as follows: Section 2 provides a review of the relevant literature. Section 3 discusses the methodology and data employed. Section 4 examines trends in efficiency estimates over the sample period while section 5 presents the findings of the models employed. The policy implications of the results and the conclusion are outlined in section 6.

[2] The JDX was launched on 14 January 2010 and involved the GOJ's debt re-profiling programme with investors voluntarily participating in a par-for-par exchange of domestic bonds for new notes of longer maturities and lower interest rates, strongly impacted the business model of Jamaica banks.

[3] More specifically, banks' investment profile and net earnings performance were substantially affected by the impact of the JDX on interest rates offered on domestic debt as well as the composition and maturity profile of the domestic debt stock.

2. Previous Literature

Measuring the efficiency of the banking system has been the subject of a large number of studies in the last 20 years, originally with emphasis on the US market, and then in recent years, on other markets of Europe and Asia. Many studies investigate the existence of economies of scale and scope, examining Cobb-Douglas production functions or applying Translog cost functions, while a number of studies have employed the Data Envelopment Analysis Technique (DEA), which does not require assumptions regarding the distribution of the inefficiency term. More recent studies have also examined the potential effect of macroeconomic and institutional factors on the efficiency of banking systems.

Dietsch and Vivas (1996) examined whether environmental factors were important in explaining efficiency differences of French and Spanish banks using annual data covering the period 1988 to 1992 for commercial and savings banks by introducing these variables in the cost frontier estimations for these institutions. Three categories of environmental variables were taken into account: the main macroeconomic factors, the structure and regulation of the banking industry and the accessibility of banking services. The results of the study showed that specific environmental conditions of each country are important factors in the explanation of efficiency differences between the French and Spanish banks. The results suggest that, on average, French banks appeared to be more efficient than the Spanish banks. Additionally, the higher numbers of branches as well as the higher intermediation ratio in Spain compared to France are some of the factors explaining the higher bank costs and lower efficiency levels in Spain. Another explanation is related to the lower density of demand, which could have created a cost disadvantage for Spanish banks.

Yildirim (2002), investigated the efficiency of the Turkish banking sector between 1988 and 1999, a period characterized by strong macroeconomic volatility. Technical efficiency, which involves producing a given set of outputs using the smallest possible amount of inputs, and scale efficiencies of Turkish commercial banks was measured using the DEA approach. Furthermore, the relationship between profitability, asset quality size and the two definitions of efficiency was considered. The results showed that efficient banks exhibit stronger profitability and technical and scale efficiency are positively related to size. In addition, macroeconomic conditions had a profound influence on efficiency measures over the period examined.

Drake et. al (2005), examined the impact macroeconomic and regulatory factors on bank efficiency for Hong Kong’s banking sector. These factors were incorporated in the efficiency analysis using a Tobit regression approach advocated by Fried et al. (1999) as well as a DEA specification. The results indicate high levels of technical inefficiency for many institutions, considerable variations in efficiency levels and trends across size groups and bank sub-sectors. Both approaches indicated that banks in Hong Kong may have been affected by a range of macroeconomic and regulatory factors outside the control of the institutions’ management. Moreover, one of the key findings of the paper is that failure to account for the impact of external factors can have a marked impact on relative efficiency scores and on trends in efficiency levels over time, both across the sector as a whole and across different size and institutional groupings.

Using Barbadian data, Craigwell et.al (2005) estimated efficiency scores for Barbadian commercial banks for the period 1979 to 1999 using DEA analysis as well as estimating a cost function using the stochastic frontier methodology. The study also assessed the determinants of efficiency, including the impact of financial innovation on bank efficiency. The computed efficiency scores suggest that the average bank in Barbados is relatively efficient when compared to the results of similar studies, while the panel regression findings show that financial innovation is a significant determinant of bank efficiency, along with bank size, the loan to asset ratio and national income growth.

The efficiency of the Greek banking industry and its determinants was examined in a study by Delis (2008) et. al for the period 1996 to 2006. Efficiency estimates were derived by applying the DEA technique primarily to profit and loss data. In addition, in the context of the DEA method, similar to many studies, the paper investigated the impact of capital adequacy, profitability, liquidity risk, market power, credit risk and the regulatory framework and macroeconomic environment on bank efficiency. Furthermore, in addition to total efficiency, the study also examined its components, i.e. technical and allocative efficiency where the latter involves the extent to which resources are being allocated to the use with the highest expected value. The findings showed an improvement in overall efficiency, attributable mainly to an increase in allocative efficiency. Also, it was found that there is a positive relationship between efficiency and determinants such as bank capital, profitability and loan portfolio quality. Finally, in this study, the macroeconomic environment appeared to have no statistically significant effect on bank efficiency.

Garcia (2012) analysed developments and the main determinants of bank efficiency in the Mexican banking industry for the period 2001–2009. The DEA methodology is applied to obtain efficiency estimates and then a Tobit model is run to find its main determinants. Findings show that the main determinants of increased bank efficiency are loan intensity, Gross Domestic Product (GDP) growth and foreign ownership.

3. Methodology & Data

3.1 Measures of Efficiency

In the international literature, bank efficiency is measured using indices, or by applying parametric or nonparametric methods. Each of these methodological approaches has its specific advantages and disadvantages. The study of simple indices offers the advantage that the necessary calculations are easy but its main weakness is that it confines the analysis to the use of only one input and one output, which is restrictive in the case of the banking sector, which is characterized by multiple inputs and outputs that are interrelated. This disadvantage of using indices is overcome by applying parametric and/or nonparametric methods, which can include more than one inputs and/or outputs. Parametric methods, among which include the stochastic frontier approach, which is applied in this study, and involves banks' costs diverging from an efficiency frontier due to either random effects or inefficiency. In addition, the DEA technique is a non-parametric approach where no hypothesis is required regarding the distribution of the inefficiency term.

3.1.1 Technical Efficiency

Technical efficiency or X-efficiency is a measure of how effectively banks utilize inputs to produce a given level of output. The bank's effectiveness in achieving the optimal mix of cost-minimizing inputs can be specified by an efficient cost frontier. Given the likelihood of bank-by-bank deviations in the efficient cost frontier, it is necessary to specify a stochastic cost function. As such, this paper employs the stochastic cost frontier proposed by Aigner et al. (1977), where deviations from the efficient cost frontier are captured by a random noise, v_i, and an inefficiency component, u_i.[4]

The cost function is represented as:

$$\ln tc = f(y_i, p_i) + \varepsilon_i \tag{1}$$

where $\varepsilon_i = u_i + v_i$, y_i, is the output i of each bank, p_i, is the cost of input i and, v_i, is statistical noise distributed normal $(0, \sigma_2)$.[5] U_i is a an inefficiency measure which can follow a truncated or half-normal distribution and measures the individual firm's deviation from the efficient cost frontier, due to non-optimal employment of the quantity or mix of inputs given their prices as a result of management errors. This variable is referred to as 'technical inefficiency'. However, it relates to both technical inefficiencies from using too much of the inputs to produce the same output and allocative inefficiencies from failing to react optimally to the relative prices of inputs. The variable v_i is an exogenous component which is due to data or measurement error or unexpected and uncontrollable factors such as labour strikes and war that are not under the influence of management. Estimates of u_i or technical inefficiency are derived from the stochastic frontier for each bank.

The log-likelihood function for equation (1) is specified as:

$$\ln L = \frac{N}{2} \ln \frac{2}{\pi} - N \ln \sigma - \frac{1}{2\sigma^2} \sum_{i=1}^{N} \in_i^2 + \sum_{i=1}^{N} \ln \left[\psi \left(\frac{\in_i \lambda}{\sigma} \right) \right] \tag{2}$$

[4] Aigner et al. utilized the approach to investigate cost efficiencies.
[5] Maximum likelihood estimation techniques are utilized in estimating the coefficients.

with N denoting number of banks and ψ is the standard normal cumulative distribution. Equation (8) shows that the ratio of variability, σ, can be used to measure a firm's mean inefficiency by:

$$E(u_i / \in) = \left[\frac{\sigma\lambda}{1+\lambda^2}\right]\left[\frac{\phi(\in_i \lambda / \sigma)}{\psi(\in_i \lambda / \sigma)} + \frac{\in_i \lambda}{\sigma}\right] \tag{3}$$

where $\sigma^2 = \left[\sigma_u{}^2 + \sigma_v{}^2\right]$, $\lambda = \sigma_u / \sigma_v$, and $\phi(\cdot)$ is the standard normal density function.

This paper employs a variations of the model specified in equation (1), in estimating a cost frontier for banks in Jamaica. A translog cost function is considered because of its flexibility in allowing for input substitutability (see equation (4).

$$\begin{aligned} \ln tc = \alpha_0 + \sum_{i-1}^{2}\alpha_i \ln(y_i) + \sum_{j=1}^{3}\beta_j \ln(p_j) + 1/2\sum_{i=1}^{2}\sum_{k=1}^{2}\alpha_{ik}\ln(y_i)\ln(y_k) + 1/2\sum_{j=1}^{3}\sum_{h=1}^{3}\beta_{jh}\ln(p_j)\ln(p_h) \\ + \sum_{i=1}^{2}\sum_{j=1}^{3}\delta_{ij}\ln(y_i)\ln(p_j) + \in \end{aligned} \tag{4}$$

Additionally, TC represents total operating and interest costs. Two outputs are employed in the model; loans, which is the primary output, y_1, and all other earning assets, y_2, is included as a secondary output. There are three inputs, with prices defined as the price of labour, p_1, price of fixed capital, p_2, and borrowed funds, p_3. P_1 is defined as personnel expenses divided by total assets, P_2 is defined as capital and occupancy expenses divided by fixed assets, and P_3 is defined as total interest expenses divided by interest bearing liabilities. Consistent with linear homogeneity conditions, TC and the prices of all inputs are normalized by the price of labour ($p1$). Therefore, the transformed variables are denoted as TC*, $p_2{}^*$ and $p_3{}^*$.

The cost function defined by equation (4) and is estimated using FRONTIER®, an econometric software package designed to provide maximum likelihood estimates of a variety of stochastic frontiers.[6] FRONTIER follows a three-step estimation procedure. First, ordinary least squares (OLS) estimates of the function are obtained as starting values and then a two-phase grid search is conducted to refine these starting values. [7] Final estimates are obtained iteratively using the Davidson, Fletcher, and Powell Quasi-Newton Method. Cost efficiency estimates derived from the model range over the interval $[1, \infty]$, with a score of one indicating full efficiency, which means that the firm is operating on its efficient cost frontier. The amount by which the score deviates from 1 is a measure of technical inefficiency.

3.1.2 Data

The model utilizes quarterly commercial banking system data covering the period March 2000 to June 2012. Average inefficiency measures are derived for the sector for each quarter over the sample period. The economic factors included in the study include bank specific and macroeconomic variables[8]. An OLS framework was employed to assess the relationship between economic factors and efficiency for large and small banks. These factors are utilized in a VEC model, which is outlined below, in analysing whether there is a long run relationship between these economic factors and bank efficiency.[9]

More specifically, this study includes economic variables such as capital adequacy, the non-performing loans to total loans ratio, which is a measure of loan quality, growth in GDP, inflation, interest rate spread, where the spread between loan and deposit rates is utilized and also the Herfindahl-Hirshman Index (HHI), which is a measure of concentration.[10] Regarding a priori expectations, it is anticipated that there will be a negative relationship between the capital to assets ratio and cost inefficiency, as banks with a strong capital base are more able to expand their activities safely, avoiding excessive risks and to face potential adverse developments. As it relates to the HHI, the relationship between this variable and cost inefficiency may be ambiguous and can be further explained by the SCP hypothesis and the efficient structure hypothesis. Regarding the efficient structure hypothesis, banks with large market shares may operate more

[6] See Coelli (1996) for a complete discussion of FRONTIER.
[7] These estimates (except for the intercept) are unbiased.
[8] See Table 2 in Appendix for the summary statistics of the variables.
[9] Dummy variables are used to capture the global crisis period and also the JDX and post-JDX period.
[10] It was calculated as the sum of the squares of bank size measured as market shares. These market shares were calculated as the ratio of assets of individual banks to total industry assets.

efficiently because of better management of inputs, offer of differentiated outputs, technological superiority and these institutions taking advantage of synergies related to exploitation of scale economies. As it relates to the SCP hypothesis, greater concentration may be associated with greater profitability and increased inefficiencies due to market players have the capacity to raise prices and increase market share through monopolistic conduct. The inflation rate is a measure of macroeconomic stability and banks' ability to manage their risks under inflationary pressures can affect their cost structure and resource allocation decisions as it relates to input choices. Further, higher levels of inflation may be associated with greater cost inefficiency. The positive sign of inflation is also in line with our expectation as the higher inflation, the higher costs it may incur since the inflation may increase the input prices involved in the banking production process. For instance, employees may demand higher payment and savers may ask for higher deposits rate, etc.

As it relates credit risk, this is a major risk banks face, and therefore the sound management of credit risk is expected to be positively related to bank efficiency. Increases in the ratio of non-performing loans to total loans may be due to less efficient functioning of lending procedures. Banks may incur increased costs related to the granting, monitoring and managing of its loans and thus may appear less cost efficient. Furthermore, banks with a loan portfolio of relatively high risk may seem less efficient and may reflect the impact of better provisioning by these institutions. On the other hand, banks may not increase costs related to these different aspects of credit risk management and thus may appear relatively cost efficient at least in the short run, whereas in the long run its credit risk may be increasing.

The overall rate at which the economy grows may positively impact cost efficiency by resulting in more optimal decision choices related to the type and mix of inputs banks employed. In addition, stronger GDP growth may positively impact bank profits and is expected to be positively related to efficiency. Higher profitability may stimulate increased efficiency by facilitating greater investment in skilled personnel, improvements in technology and stronger cost savings and output gains. Increased GDP growth may also lead to greater demand for bank services, higher profitability and by extension more opportunities for banks to improve efficiency.

The interest rate spread variable, as measured by the spread between the average weighted loan and deposit rates, is a proxy for the interest rate environment and is expected to affect interest rate risk decisions in banks. Increases in this variable may be reflective of a higher interest rate environment and may either be reflected in fair value losses for institutions depending on the nature of their gap positions or may be reflected in increased provisions, as increases in this variable may also result in increased credit risk, both impact efficiency in a negative way.

3.1.3 VEC Modelling Framework:

VEC models can be utilized where non-stationary variables may move together in the long run. In this instance, the variables are possibly driven by a common stochastic trend and as such are co integrated. In this context, there exists a linear combination of the *I(d)* variables which is stationary.

Equation (5) outlines a p-dimensional vector autoregressive model with Gaussian errors, where Y_t is a *k*-vector of I(1) variables, X_t is a *d*-vector of deterministic variables, A_i s are matrices of coefficients to be estimated, the matrix *B* contains exogenous variables that are excluded from the co-integration space and et is a *k*-vector of Gaussian errors.

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + BX_t + \varepsilon_t, \qquad (5)$$

Following Johansen (1991, 1995), equation (5) can be reformulated into a vector-error-correction form as:

$$\Delta Y_t = \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \Gamma_2 Y_{t-2} ..... + \Gamma_p \Delta Y_{t-p+1} + BX_t + \varepsilon_t, \qquad (6)$$

OR

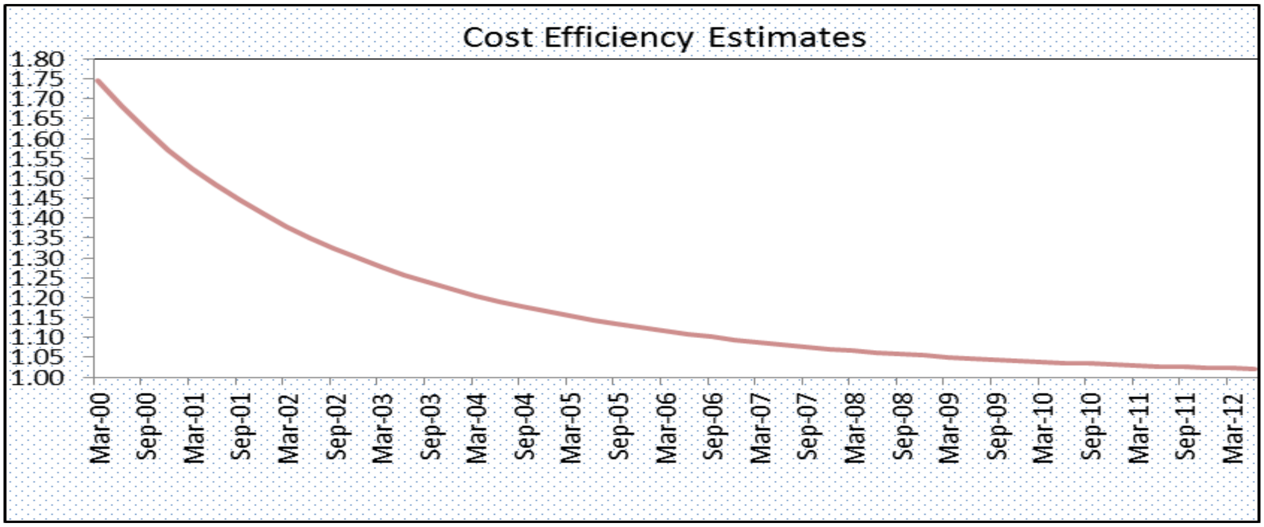
$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + Bx_t + \varepsilon_t \qquad (7)$$

where:

Y_t is the vector of endogenous variables and the parameter matrices α and β are contained in the Π matrix. In addition, α and β specify the long run component of the model with β containing the co-integrating relation while α represents the speed of adjustment coefficients.

4.0 Trends in Efficiency: 2000 – 2012

Figure 1

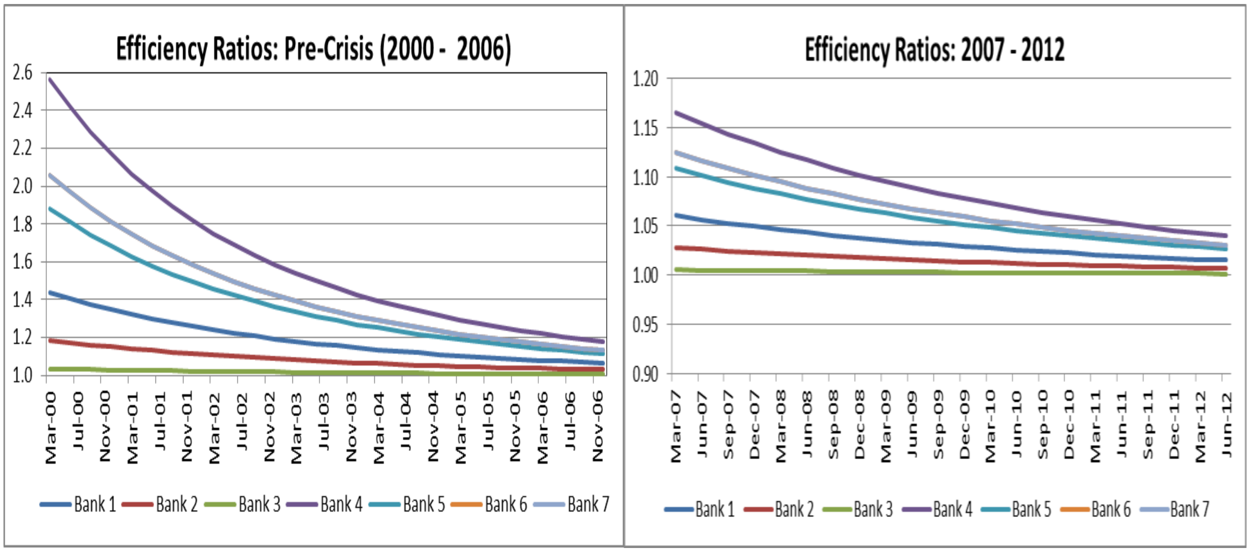


There have been strong improvements in efficiency for the banking sector for the period March 2000 to June 2012, with the strongest declines in scores during the global crisis period (see Figure 1). Efficiency scores for banks ranged from 0.3 per cent of total costs to 7.8 per cent of total cost for all banks.

This performance is reflective of banks' efforts to better manage and also optimally react to variations in the user cost of their inputs based on input choices and also consolidate operations to increase efficiency and maintain profit margins in the context of a challenging economic environment.[11]

[11] These values are consistent with findings for many developed economies.

Figure 2

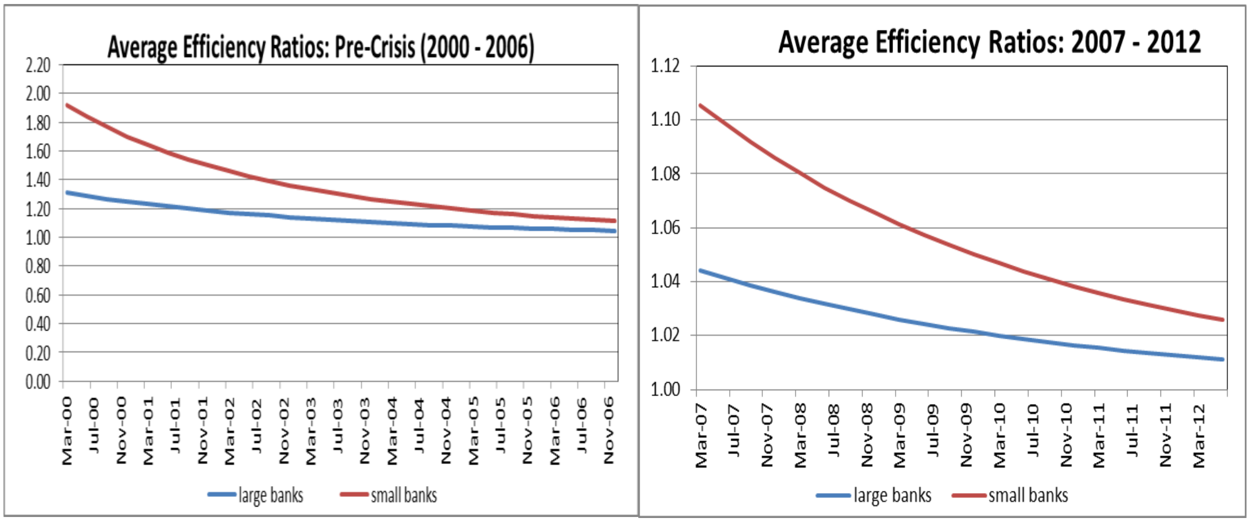


Moreover, there was stronger improvement in scores to less than 5.0 per cent during the post-JDX period, as banks adjusted to this economic change which substantially impacted the investment profile and net earnings performance of these institutions as well as resource allocation decisions relating to input choices (see Figure 2).

Additionally, average efficiency scores for the 2 largest banks averaged 1.1 during the roughly 12 and a half year period, while scores for the remaining banks was higher, averaging 1.2 over the same period (see Figure 3). The higher scores for the 2 largest banks over the sample period can be partly explained by the fact that large banks have greater economies of scope and lower unit cost of providing services relative to smaller banks. Moreover, the divergence between the efficiency scores of large and small banks strongly narrowed during the global crisis and post-JDX period.

Furthermore, efficiency scores for foreign-owned banks remained broadly in line with scores of domestically-owned banks during the review period, except for the divergence in performance at the start of the sample period.

Figure 3



Results:

Ordinary Least Squares *(OLS) Model*

Based on the divergence in inefficiency scores highlighted in Figure 2, an OLS regression was estimated to determine the impact of economic variables on inefficiency in large and small banks. Average inefficiency estimates were calculated for the large and small banks based on the grouping described in the previous section. All macroeconomic and bank specific variables examined were found to significantly affect the level of inefficiency in both small and large banks.

The findings were generally consistent for the large and small banks. Regarding bank specific variables, changes in non-performing loans to total loans had the most impact on inefficiency levels followed by changes in the capital to assets ratio. More specifically, banks with stronger capital buffers will be better able to avoid taking excessive risks as well as implement technological improvements in order to reduce costs. However, deterioration in loan quality leads to deterioration in efficiency and is indicative of increased expenditure by banks to improve the loan monitoring and risk mitigation process. Additionally, changes in industry concentration had the least impact on inefficiency levels. The results found were in line with *a priori* expectations in terms of the direction of the impact on inefficiency. Overall, significant variables explained 37.4 per cent and 44.7 per cent of the variation in inefficiency levels for small and large commercial banks respectively. Dummy variables were included in the model for the JDX programme and the global financial crisis and were significant for both models. Regarding the impact of the macroeconomic variables, the findings indicate that greater stability or improvement in these variables have a favourable impact on bank efficiency. [12]

The OLS model used was subject to several robustness checks to ensure efficient and precise estimates were found. The models were weak in explaining the variation in inefficiency levels but by adding lagged effects and correcting for heteroskedasticity and serial correlation there were some improvements.[13]

Results:

VEC Model

In general, before estimating a time series model, several properties have to be satisfied. One such property is that of stationarity in order to avoid spurious regression results. Time plots of the series were constructed to view the movement of the variables over time (see Figure 3). All data series were then tested with the Augmented Dickey Fuller (ADF) test. The null hypothesis for this test assumes no unit root is present in the series. Table 5 shows the results of the unit root test for the efficiency variable as well as the economic factors employed. The results indicate that all variables are integrated of order one. [14]

In keeping with the VECM methodology, the next step was to perform cointegration testing on the variables. Prior to this though, the model was run in levels under a VAR framework in order to obtain the optimal lag length. This was to ensure the proper fitting of the model and ensure model parameters are efficiently estimated. The optimal lag length as suggested by the several test was 2 lags (see Table 6). Additionally, tests were conducted in order to determine the proper model for the deterministic components of the system. Based on the Akaike Information Criterion, the model selected was the one which included an intercept and trend in the

[12] See Table 3 and Table 4 in the Appendix

[13] Newey-West Heteroscedasticity and Autocorrelation Consistent (HAC) robust standard errors were used in order to relax the OLS assumtions about the error term. Newey and West (1987) developed a variance-covariance estimator that is consistent in the presence of both heteroscedasticity and autocorrelation.

[14] The first differences of the series are stationary.

cointegrating equation and no trend in the VAR. It was also found that one cointegrated relationship existed within the model framework (see Table 7).

The Lagrange Multiplier (LM) Test for autocorrelation was applied in order to ensure that the model was correctly specified. The null hypothesis for this test is that no serial correlation exists at lag order h. The results indicate that the model suffers from no autocorrelation in the residuals using 12 lags since all p-values are greater than the 0.05 level of significance. Table 8 shows the results of this test.

The VEC model was primarily used to generate impulse response functions to show how shocks to the variables would affect the level of inefficiency. Generalized impulse response function (GIRF) analysis was used as it is invariant to the ordering of the variables in the VECM, allowing a unique solution to be achieved. Impulse response functions were estimated for 12 quarters ahead. Prior to this though, an examination of the characteristic autoregressive polynomial of the VEC system showed that the system satisfied stationarity conditions and was therefore stable.[15]

The impulse response functions show that there is an initial worsening of inefficiency in response to a shock in the HHI, while there were improvements in later periods. The improvement provides evidence in support of the efficient market hypothesis, in a context where, as commercial banks increase market share this may lead to greater efficiency in the sector.

A shock to GDP growth showed a similar response. Despite the initial deterioration in efficiency, improvements in this variable may have occurred in a context where GDP growth positively impact bank profits as well as institutions' ability to improve technology, skilled labour and output gains.

A shock to capital adequacy is expected to improve efficiency in the commercial banking system. The results show that shocks to this variable resulted in a general improvement in cost efficiency levels. This finding is consistent with a priori expectations, in that banks with stronger capital bases will be better able to avoid taking excessive risks, face adverse developments as well as implement technological improvements in order to reduce costs. A shock to the loan quality ratio results in improvements in efficiency, and is indicative of stronger credit risk

[15] See Figure 4 in the Appendix.

management by banks in allocating expenditure which may be needed to improve the loan monitoring and risk mitigation process. Furthermore, this could lead to continued deterioration in loan quality. On the other hand, also consistent with a priori expectations, an innovation in interest rates is likely to cause an immediate worsening in inefficiency estimates for the sector. With respect to the shock to inflation, despite an initial deterioration in efficiency, there were sustained improvements for subsequent periods. The initial deterioration in efficiency may have been influenced by increases in input prices involved in the delivery of bank services. The results of the impulse response functions can be seen in Figure 4 in the Appendix.

6.0 Conclusion:

The issue of efficiency is important and is widely discussed in banking. Higher efficiency generally influences greater profitability and performance in the banking sector. By using a Translog cost function, this study examined the performance in efficiency of Jamaican commercial banks over the period 2000 to 2012. Efficiency estimates showed improvements across all banks over the period with the strongest convergence in scores during the global crisis period to values of less than 15.0 per cent of total costs across all banks. Concerning the impact of economic variables on bank efficiency, OLS findings showed similar results for large and small banks, with small banks showing much greater responsiveness to the factors considered. Overall findings for the commercial bank sector based on the VEC model employed showed that, consistent with a priori expectations, lower interest rate spreads, declines in inflation and increases in GDP growth largely lead to improvements in cost efficiency. These findings suggest that improved performance in these variables is supportive of stronger cost efficiency in the commercial banking sector. Against this background, the results of the study are useful in informing policymakers of the potential impact of the macroeconomic policy environment on the performance of banking institutions.

Concerning the impact of bank specific variables on efficiency, the model showed that banks with higher capital to asset ratios exhibit improvements in efficiency. The findings are useful for regulators and provide evidence which promotes the adoption of capital adequacy standards, as banks with stronger capital base are better able to expand their activities safely, avoid excessive risk taking and also face adverse developments.

Additionally, the findings show that a lower loan quality ratio has a significant positive impact on the efficiency of the banks. This may signal stronger credit management by banks in the long run, in a context where institutions may have, in the short run, increased expenditures related to the loan monitoring and risk mitigation process. These findings provide evidence in support of the continued monitoring of these ratios as well as other financial stability indicators by regulators in order to promote the performance and stability of the sector. Regarding the HHI, the results shows that greater concentration leads to improvements in efficiency, and may be related to better management of inputs by larger banks in the sector.

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Appendix:

Figure 3: Time Plots of the Variables

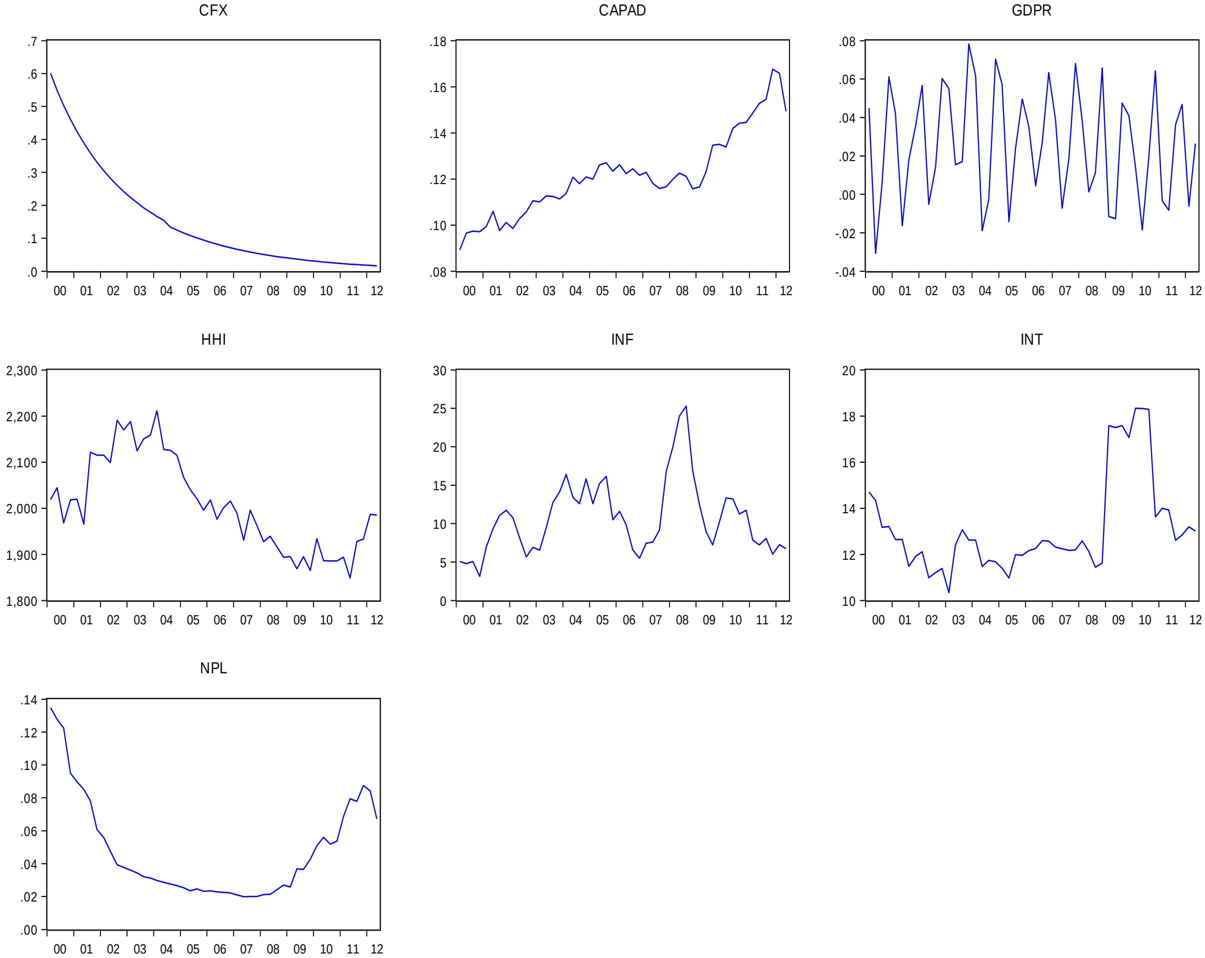

Figure 4: Stability Test for the Estimated VEC Model

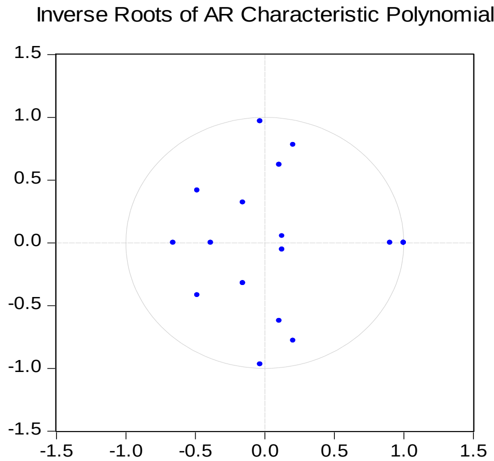

Figure 4: Impulse Response Graphs

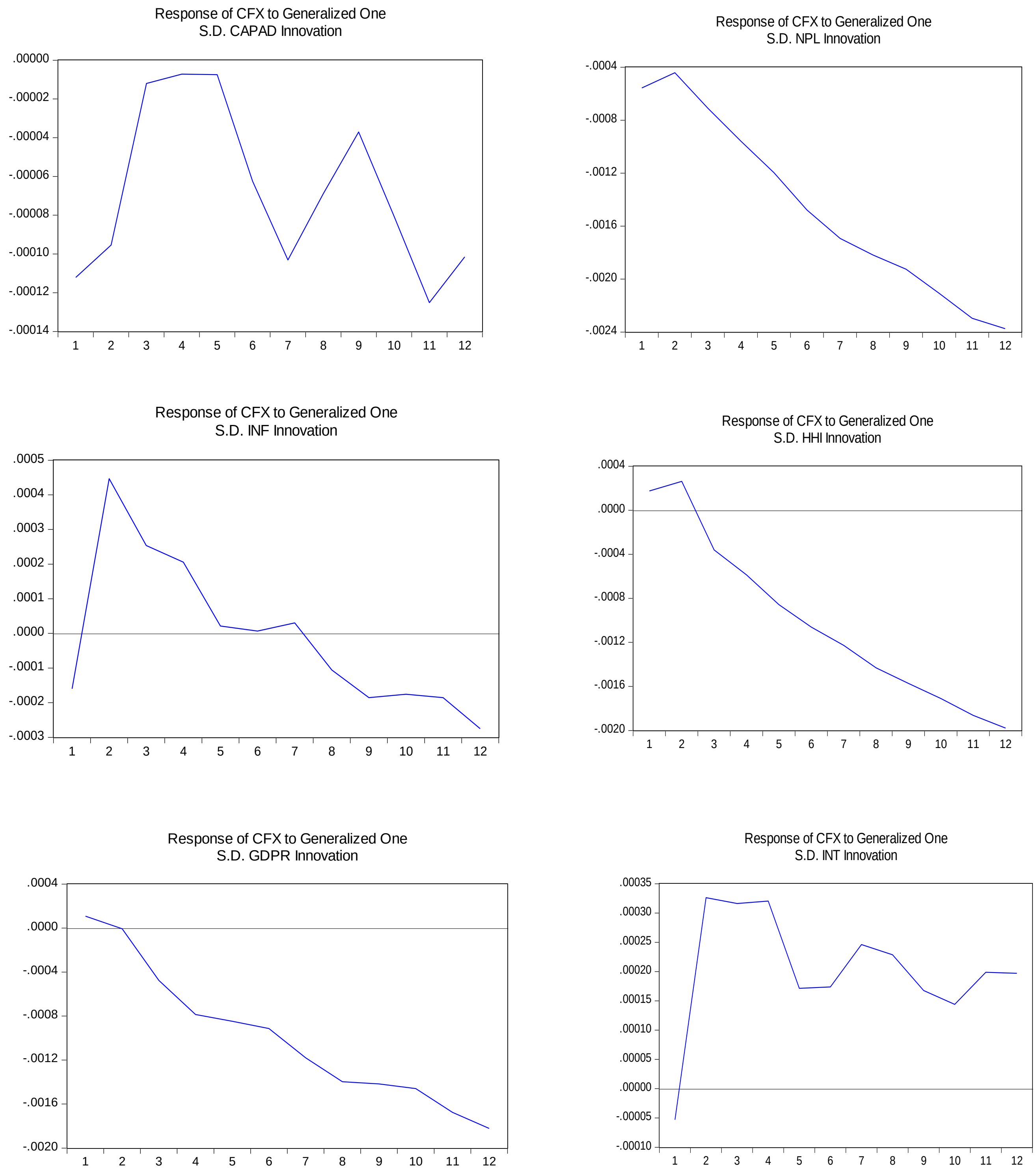

Table 1: Model parameters of the stochastic cost function specified in Equation 1

Variables	Coefficient	t-ratio
Dependent variable: ln (cost)		
constant	1.79	1.51
ln(Y1)	0.22	1.08
ln(Y2)	*0.68	2.58
ln(P2*)	0.18	0.61
ln(P3*)	-0.3	-0.97
ln(Y1)ln(Y1)	*0.20	10.58
ln(Y1)ln(Y2)	*-0.38	-9.01
ln(Y2)ln(Y2)	*0.18	5.95
ln(P2*)ln(P2*)	-0.02	-0.48
ln(P3*)ln(P2*)	-0.02	-0.49
ln(P3*)ln(P3*)	*0.20	9.06
ln(Y1)ln(P2*)	*0.04	2.08
ln(Y1)ln(P3*)	*-0.05	-4.18
ln(Y2)ln(P2*)	-0.03	-1.48
ln(Y2)ln(P3*)	*0.08	3.73
log likelihood function value	223.22	

"*" Significance at 10% level

Table 2: Summary Statistics of the Variables

	CFX	CAPAD	GDPR	HHI	INF	INT	NPL
Mean	0.1523	0.1215	0.0255	2008.5180	10.7234	13.1222	0.0480
Median	0.0847	0.1204	0.0250	1995.6580	10.0133	12.5750	0.0363
Maximum	0.6010	0.1676	0.0782	2211.7640	25.3025	18.3300	0.1347
Minimum	0.0164	0.0893	-0.0307	1848.8200	3.1224	10.3400	0.0198
Std. Dev.	0.1556	0.0181	0.0293	100.3181	4.7488	2.0992	0.0304
Skewness	1.3289	0.6445	-0.0410	0.3382	1.0339	1.4592	1.2342
Kurtosis	3.7817	3.0592	1.8180	2.0053	4.0907	4.0430	3.7145
Jarque-Bera	15.9902	3.4692	2.9249	3.0141	11.3866	20.0102	13.7583
Probability	0.0003	0.1765	0.2317	0.2216	0.0034	0.0000	0.0010
Observations	50	50	50	50	50	50	50

Note: CFX – Cost Inefficiency Estimates, CAPAD – Capital to Total Assets, GDPR – Growth Rate of GDP, HHI – Concentration Ratio, INF – Inflation Rate, INT – Interest Rate Spread, NPL – Non-Performing Loan to Total Loan Ratio

Table 3: OLS Results for Small Commercial Banks

Variable	Coefficient	Std. Error#	t-Statistic	P-Value
ΔCAPAD	-0.36855**	0.14184	-2.59835	0.01330
ΔGDPR (1)	-0.03831*	0.02047	-1.87176	0.06900
ΔINT (2)	0.00425***	0.00131	3.25781	0.00240
ΔNPL	0.39244***	0.07995	4.90867	0.00000
ΔHHI	-0.00007**	0.00003	-2.68748	0.01060
ΔINF (2)	0.00029**	0.00012	2.39772	0.02150
JDX	0.01865***	0.00526	3.54490	0.00110
GCRIS	0.00846***	0.00303	2.79247	0.00810
C	-0.01964***	0.00414	-4.74679	0.00000

Notes: Dependent Variable Cost Inefficiency (ΔCFX)
- shows Heteroskedasticity and Autocorrelation Consistent (HAC, Newey-West) Standard Errors;
Adj. R^2 = 0.3743; Δ represents the first difference of a variable; Numbers in parentheses represent the number of lags;
*, **, *** indicate the 1%, 5% and 10 % level of significance respectively

Table 4: OLS Results for Large Commercial Banks

Variable	Coefficient	Std. Error#	t-Statistic	P-Value.
ΔCAPAD	-0.11243***	0.01416	-7.93939	0.00000
ΔGDPR (1)	-0.00644***	0.00220	-2.93055	0.00580
ΔINT (2)	0.00030**	0.00015	2.04252	0.04830
ΔNPL	0.38361***	0.08636	4.44226	0.00010
ΔHHI	-0.00002***	0.00000	-7.49451	0.00000
ΔINF (3)	-0.00015***	0.00004	-3.70654	0.00070
JDX	0.00484**	0.00233	2.08119	0.04440
GCRIS	0.00389*	0.00195	1.99330	0.05360
C	-0.00619***	0.00203	-3.04463	0.00430

Notes: Dependent Variable Cost Inefficiency (ΔCFX)
- shows Heteroskedasticity and Autocorrelation Consistent (HAC, Newey-West) Standard Errors;
Adj. R^2 = 0.4466; Δ represents the first difference of a variable; Numbers in parentheses represent the number of lags;
*, **, *** indicate the 1%, 5% and 10 % level of significance respectively

Table 5: Augmented Dickey-Fuller Stationarity Test for Unit Roots

2000Q1-2012Q2	Level		First Difference		Order of Integration
	T-Statistic	P-Value	T-Statistic	P-Value	
CFX	-29.1606	0.0000	-4.0834	0.0124	I(1)
GDPR	-2.4795	0.1270	-13.6785	0.0000	I(1)
INT	-2.2038	0.2076	-7.1802	0.0000	I(1)
INF	-1.9914	0.2895	-6.2366	0.0000	I(1)
NPL	-2.9077	0.1691	-5.1776	0.0006	I(1)
HHI	-1.0445	0.7298	-10.2794	0.0000	I(1)
CAPAD	-2.2948	0.4287	-6.0495	0.0000	I(1)

Table 6: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	22.15642	NA	2.25e-09	-0.049209	0.777452	0.261869
1	330.0258	484.7304	3.87e-14	-11.06493	-8.309387*	-10.028
2	409.8831	101.9456*	1.26e-14*	-12.37801*	-7.69359	-10.61523*
3	454.7545	43.91668	2.48e-14	-12.20232	-5.589027	-9.713694

Note: * Indicates lag order selected by the criterion; LR - sequential modified LR test statistic (each test at 5% level); FPE - Final prediction error; AIC - Akaike information criterion; SC - Schwarz information criterion; HQ - Hannan-Quinn information criterion

Table 7: Trace and Maximum-Eigen Value Tests for Cointegration

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.743333	170.8953	150.5585	0.0021
At most 1	0.539995	106.9764	117.7082	0.1956
At most 2	0.412252	70.48001	88.80380	0.4884
At most 3	0.305012	45.50153	63.87610	0.6237
At most 4	0.275799	28.40009	42.91525	0.5981
At most 5	0.186500	13.23386	25.87211	0.7198
At most 6	0.072407	3.532619	12.51798	0.8081

Notes: Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.743333	63.91891	50.59985	0.0013
At most 1	0.539995	36.49634	44.49720	0.2831
At most 2	0.412252	24.97848	38.33101	0.6732
At most 3	0.305012	17.10143	32.11832	0.8559
At most 4	0.275799	15.16623	25.82321	0.6195
At most 5	0.186500	9.701240	19.38704	0.6508
At most 6	0.072407	3.532619	12.51798	0.8081

Notes: Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 8: Autocorrelation LM Test

Lags	LM-Stat	Prob
1	35.11841	0.9323
2	33.19180	0.9592
3	40.93852	0.7868
4	48.42137	0.4965
5	66.71447	0.0469
6	41.71963	0.7602
7	57.91575	0.1794
8	34.66009	0.9396
9	43.65690	0.6889
10	41.77004	0.7585
11	52.46184	0.3413
12	45.34064	0.6223

Notes: Probs from chi-square with 49 df.