Predicting Bank Failures in Jamaica: A Logistic Regression Approach

Chevano Baker[†]
Financial Stability Department
Bank of Jamaica

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Abstract

The global banking and financial crisis of 2007-2008 has reignited efforts to develop early warning models which can aid in predicting bank failures. The primary objective of this study is to identify the main determinants of bank failures in Jamaica by analyzing the predictive power of financial ratios motivated by the CAMELS framework. Additionally, the resulting scoring model has been useful in identifying known periods of fragility and can be used as a tool going forward to assess potential risks to financial stability. This study also applies the logistic regression methodology to a panel of deposit taking institutions using quarterly data over the period March 2008 and December 2017. Results from the analysis demonstrate that non-performing loans to total loans and regulatory capital to risk-weighted assets are significantly and positively related to the probability of default of Jamaican deposit taking institutions. The finding for the regulatory capital to risk-weighted assets ratio is consistent with expectations that higher capital requirements may increase fragility as banks may be incentivized to take on additional risk.

Keywords: Bank Failures, Bankruptcy prediction, CAMELS, Financial Stability, Logistic Regression

JEL classification: G01, G28, G32, G33

[†]The views expressed in this paper are those of the author and do not necessarily reflect the views of the Bank of Jamaica. Author's email: Chevano.Baker@boj.org.jm

1.0 Introduction

The financial sector has been under even greater scrutiny following the US financial crisis in 2007-2008 that spiraled into a global economic crisis. To this end, numerous changes have been made to the regulatory framework in order to strengthen the overall prudential and supervisory environment in which financial institutions operate. Many regulators have developed early warning systems in an attempt to identify the factors causing the failure of firms in the financial system as well as to monitor financial institutions' performances overtime. In general, early warning systems are integral in the prudential (micro and macro) monitoring, supervision and evaluation of financial institutions, and the stability of the financial sector is of paramount importance to sustainable economic growth and development.

In the context of Jamaica, the financial sector is one of the fastest growing sectors and is considered an integral part of the economy. As such, a number of studies have focused on developing early warning systems (EWS) tools that can be used for identifying financial stress in Jamaican banks. Langrin (2002) developed an early warning system framework to monitor a comprehensive set of aggregated microprudential and macroprudential variables based on a non-parametric signals approach. Lewis (2006) utilized an informational-based approach known as the Generalized Maximum Entropy (GME) to estimate the probability of the banking sector transitioning into crises. This semi-parametric technique used in the study considered bank specific variables, changing financial market conditions and bank exogenous macroeconomics effects in the estimation of bank fragility probabilities. A study by Lewis (2010) calibrates a computable general equilibrium (CGE) model which incorporates heterogeneous banks and capital requirements with incomplete markets in order to evaluate the fragility of the banking sector in Jamaica. Lewis (2012) also used a contingent claims approach based on the Black-Scholes-Merton's option pricing theory to compute probability of default and distance to default measures for the sovereign and publicly listed financial institutions in Jamaica. Finally, Samuels (2016) developed composite indices in an effort to identify and analyse financial risks and vulnerabilities in other key sectors of the Jamaican economy.

This paper contributes to the literature on early warning systems for Jamaica by examining the financial soundness of deposit taking institutions (DTIs) in Jamaica. The results indicate that

the non-performing loans to total loans and regulatory capital to risk-weighted assets ratios have significant power to predict the level of bank fragility in the system. The study also attempts to identify the characteristics distinguishing healthy firms from failing ones. The logistic regression methodology is used to construct a new index based on the financial ratios obtained from the balance sheets and income statements of DTIs over the period March 2008 to December 2017. The scoring model complements some of the other composite indices calibrated by the Bank of Jamaica. While the Banking Stability Index (BSI), the Aggregate Financial Stability Index and the Z-score model focus on partial indicators from an accounting based perspective, the scoring model attempts to measure financial soundness using all categories under the CAMELS[1] framework. Moreover, the inclusion of management quality indicators in the analysis adds value to the suite of indices since little attention has been given to this area in previous studies on the Jamaican banking system. The model serves as a macro-prudential tool which policymakers and regulators can use to supervise the level of stability within the financial system.

The remainder of the paper is structured as follows. Section 2 provides a detailed review of literature relating to the development of bankruptcy prediction models. Section 3 outlines the data and methodology used in the analysis. Section 4 presents the empirical results. Finally, the concluding remarks and policy implications are outlined in Section 5.

2.0   Literature Review

Several studies have explored bankruptcy prediction models and their approaches have varied over time. Earlier models used univariate and multivariate discriminant analysis (MDA) whilst models in recent years have employed logistic regression and artificial intelligence frameworks. Although the literature discusses these models and various financial ratios, this paper will primarily focus on the logistic regression model using financial ratios motivated by the CAMELS framework.

One of the earliest models of bankruptcy prediction was developed by Beaver (1966). He paved the way for the development of models to predict bank failure by examining the predictive

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[1] The CAMELS rating system is a quantitative framework that is used to rank banks based on their performances in six components of bank safety and soundness: **C**apital Adequacy, **A**sset Quality, **M**anagement Quality, **E**arnings Ability, **L**iquidity and **S**ensitivity to Market Risk. For more details see, for example, Aspal and Dhawan (2016) and Rostami (2015) who provide a theoretical review of the CAMELS rating model and its application to the banking industry respectively.

ability of individual financial ratios. Though Beaver's univariate model provides a single ratio that serves as the best predictor, it does not consider the ability of multiple ratios to predict bankruptcy simultaneously. However, following this, Altman (1968) studied the ability of multiple financial ratios to predict corporate bankruptcy simultaneously. In the study, a multivariate discriminant analysis (MDA) on twenty-two financial ratios and a Z-score model which comprised of five ratios are used to predict the bankruptcy of US manufacturing firms with a 95 per cent degree of accuracy. In addition, Zavgren (1983) contended that a single prediction measure is unable to capture all the complexity of financial failure since a firm's financial status is multidimensional.

As it relates to the MDA approach, this is a statistical technique used to categorize an observation into one of many groups or clusters based on the measured characteristics (Altman and Hotchkiss, 2006). In order to determine the classification of the observations, the discriminant coefficients are computed and appropriate weights are selected. The weights, which are also referred to as the cut-off scores, separate the average values of each group whilst minimizing the statistical distance of each observation and its own group mean (Altman, cited in Chung *et al.*, 2008). Subsequently, a firm is classified into either bankrupt or non-bankrupt by using the Z-score model and the cut-off score from the MDA model (Chung *et al.*, 2008). Despite the fact that MDA has a better predictive ability than the traditional univariate models, there are some statistical drawbacks that make it difficult for discriminant analysis to be widely applied (Eisenbeis, 1978). For instance, the model requires that variables are independent and normally distributed and the variance-covariance matrices of the predictors are the same for the clusters (bankrupt and healthy firms) examined. These distributional properties of the predictors restrict the use of independent dummy variables and the ability to conduct traditional econometric analysis and tests for statistical significance (Olson, 1980).

Following the use of MDA in literature, several authors have explored the logit regression methodology and its application to various sectors of the economy. A study by Olson (1980) finds that the use of conditional logit analysis essentially circumvents all the problems associated with MDA. Zavgren (1985) applied logit models in order to distinguish American industrial failing firms from healthy firms for up to five years prior to failure. A study by Lakshan and Wijekoon (2013) which predicts corporate failure of listed companies in Sri Lanka one year prior to failure finds that the logistic model has a prediction accuracy of 77.86 per cent. Similarly, Jakubik and

Teply (2011) developed a JT index using the logit methodology to predict failure within the corporate sector of the Czech Republic. Given the predictive ability of the JT index, the Czech National Bank uses the model as an auxiliary tool to assess the risks inherent in financial failures within the corporate sector. Hjelseth and Raknerud (2016) took a slightly different approach to the application of the logit regression methodology by developing an econometric model which include economic indicators at the industry level as well as standard financial ratios and actual credit rating information. Further, individual models were generated for each industry and a risk weight was assigned to each firm.

In the context of the banking sector, studies which attempt to predict bankruptcy and measure the financial performance of banks usually have analyses grounded in the CAMELS rating system. Using logit regression, Thomson (1991) modeled bank failures of all sizes in the United States over the 1984-1989 period. Results of this study demonstrated that the variables under the CAMELS framework are significantly related to the probability of banks failing as much as four years prior to failure. Likewise, Zaghdoudi (2013) noted that financial ratios which focus on bank profitability and leverage are the most suitable microeconomic indicators of Tunisian bank failures. Chokuda *et al.* (2017) constructed a corporate governance based logistic model for predicting bank failure in Zimbabwe. The study revealed that the management aspect of the CAMELS framework, which is mostly overlooked by researchers, contributes significantly to bank failures experienced in Zimbabwe between 2003 and 2004. As such, indicators which capture information relating to corporate board structure, concentrated ownership and shareholder concentration should be taken into consideration when measuring the probability of bank failure. From a sample of forty-two commercial banks in Turkey during 1997-1999 period, Erdogan (2008) showed that a logit regression bankruptcy prediction model with financial ratios provides good results in predicting 80 per cent of failed banks two years *a priori*.

Some authors believe that financial ratios in general are good indicators of the potential vulnerabilities banks may encounter. Maricica and Georgeta (2012) argue that financial ratios are good early warning signals of business failure and they have been proven to accurately discriminate between failed and non-failed firms. In addition, applying statistical techniques to the analysis of financial statements (profit and loss accounts and balance sheets) serves as a good measure for risk management in the banking industry (Martin, 1977). In contrast, many authors

question the utility or predictive power of some financial indicators. Mears (1966) (cited in Maricica and Georgeta, 2012) warns that ratios do not possess the ability to predict bankruptcy absolutely and their predictive ability depends on the ratios utilized as well as the ability to interpret these indicators. Lakshan and Wijekoon (2013) reason that the accrual accounting financial ratios which are considered in most studies are subject to manipulation and cannot reflect the ability of the firm to manage its cash flow. They conclude that cash flow, which is used to measure the liquidity of a firm, is an important determinant of financial failure. Notably, Zeitun *et al.* (2007) evidenced that there is a negative relationship between cash flow and corporate failure. They also find that free cash flow (i.e., the remaining cash after paying for operating expenses and capital expenditures) increases the probability of default of Jordanian companies. Chung *et al.* (2008) suggest that macroeconomic variables such as the rate of inflation, the annual growth in real GDP and the unemployment rate should be incorporated in the prediction model since these variables are known to impact corporate insolvency. They also argue that the construction of an optimal multivariate predictive model requires the identification of those ratios which best detect potential failures and the distribution of appropriate weights for each.

In recent years, alternative models have become more prevalent in the prediction of bankruptcy since they tend to be more useful in practice *inter alia*. For instance, artificial neural networks (ANN) eliminate the need to identify appropriate ratios before the construction of a model (Chung *et al.* 2008). Further, ANN models have the propensity to be more useful in practice since they do rely on assumptions regarding the statistical distribution or properties of financial data (Demyanyk and Hasan, 2010). Other non-parametric models include hazard models, fuzzy models, genetic algorithms and hybrid models.[2]

In conclusion, the study, which is motivated by the works of Zaghdoudi (2013), Jakubik and Teply (2011) and Kibritcioglu (2002), will analyse the riskiness of DTIs in Jamaica using the logistic regression method. The study contributes to the literature of bankruptcy research and incorporating the regressing of analysis of financial ratios based on the CAMELS framework and the classification of banks using a banking fragility index. Though authors like Jakubik and Teply (2011) acknowledge the drawback of the logit methodology, which rests on the assumption that

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[2] Such methods go beyond the scope of this paper. For more details see, for instance, Fejér-Király (2015) and Balcaen and Ooghe (2004) who provide extensive reviews on alternative models used to predict corporate bankruptcy.

the cumulative distribution of the error term is logistic which does not always hold in practice, others such as Audrino *et al.*, 2018 believe that it still serves as a benchmark model for the prediction of bank failure.

3.0   Data and Methodology

3.1   Data

The sample being analysed in this study consists of fourteen deposit taking institutions, some of which have ceased or merged operations between the sample period March 2008 and December 2017. The unbalanced quarterly panel used was obtained from the Bank of Jamaica's Financial Stability Database which contains the detailed financial statements (profit and loss accounts and balance sheets) of the deposit taking institutions.

3.2   Selection of variables

3.2.1   The dependent variable

The econometric analysis involves the use of the logistic regression method to estimate a qualitative response which differentiates a bank with low fragility from one that is highly fragile. The model works with a binary dependent variable Y, which takes the value 0 for a bank with low fragility and assigns the value 1 if a bank is highly fragile.

To set up the binary response of the dependent variable, an index of banking fragility was used to classify each bank. The index BF_t, motivated by the works of Zaghdoudi (2013) and Kibritcioglu (2002), is constructed through three indicators: banking deposits, total loans and the net open position (NOP).[3] Essentially, the fluctuations in these variables can be used to capture the economic risks related to banks' balance sheets.[4] Of importance is that banking sector crises are usually caused by massive bank withdrawals, significant increases in total loans and shocks to foreign liabilities particularly due to an actual or potential depreciation in the domestic currency.

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[3] See Table 1 in the Appendix for the definition of the NOP.
[4] The three economic variables used in the BF_t index are different from the financial (accounting) ratios estimated in the logit model and as such there would not be statistical measurement problem embedded in the model. Moreover, the resulting model fits well statistically.

The index is defined by:

$$BF_t = \frac{\left(\frac{DEP_t - \mu_{dep}}{\sigma_{dep}}\right) + \left(\frac{TL_t - \mu_{tl}}{\sigma_{tl}}\right) + \left(\frac{NOP_t - \mu_{nop}}{\sigma_{nop}}\right)}{3} \tag{1}$$

where $DEP_t = \left(\frac{LDEP_t - LDEP_{t-12}}{LDEP_{t-12}}\right)$, $TL_t = \left(\frac{LTL_t - LTL_{t-12}}{LTL_{t-12}}\right)$ and $NOP_t = \left(\frac{LNOP_t - LNOP_{t-12}}{LNOP_{t-12}}\right)$ are the annual[5] variations in the volume of banking deposits, total loans and net open positions[6] respectively. And, μ and σ represent the arithmetic average and standard deviation of the three variables, respectively. In addition, Figure A1, seen in the appendix below shows how the statistical characteristics of the three variables evolved over the sample period.

Substantial falls in all three indicators typically lead to a lower value of BF. Though this may be seen as a trend towards greater fragility, every fall in the index should not be interpreted as a tendency towards a deep systemic crisis. Hence, the level of fragility is determined by the following expression:

$$\begin{cases} 0 > BF > -0.5, & low\ fragility \\ -0.5 \geq BF, & high\ fragility \end{cases} \tag{2}$$

That is, there is low fragility if the value of BF index lies between 0 and -0.5 and high fragility when the index is equal to or lower than -0.5.[7] The dependent variable used in the model is derived using the following transformation:

$$\begin{cases} 0 > BF > -0.5, & low\ fragility, & Y\ take\ 0 \\ -0.5 \geq BF, & high\ fragility, & Y\ take\ 1 \end{cases} \tag{3}$$

So, Y becomes 0 if there is low fragility and Y takes the value 1 when there is high fragility.

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[5] The index incorporates 12-month changes in the quarterly data instead of quarterly changes in order to minimize the risk of providing misleading interpretations via incorporating any seasonality in the data.

[6] For the four quarters in 2008, the index was calculated as follows: $BF_t = \frac{\left(\frac{DEP_t - \mu_{dep}}{\sigma_{dep}}\right) + \left(\frac{TL_t - \mu_{tl}}{\sigma_{tl}}\right)}{2}$ given that NOP data was only available from March 2008 and annual variations for those quarters could not be calculated.

[7] The threshold of 0.5 used for classifying banks is usually chosen in literature (see, for example, Zaghdoudi (2013) Erdogan (2008) and Kibritcioglu (2002)). Though Erdogan (2008) suggests that a threshold of 0.8 may be used for developing countries, transforming the results of the index using 0.8 proved to be immaterial.

3.2.2   The explanatory variables

Various authors examined a wide array of ratios in order to ascertain their ability to provide signals about the evolution of DTIs' financial health and soundness. The number and type of ratios used to create models vary across studies and there is little or no consensus on the selection of predictor variables.[8] This study analyse the financial soundness of the fourteen DTIs which operated in Jamaica between March 2008 and December 2017. This is accomplished using thirteen ratios based on the six categories of the **CAMELS** rating system which cover capital adequacy, asset quality, management quality, earnings and profitability and liquidity indicators. CAMELS is used by regulators for monitoring the financial and operational condition within the banking system.

Capital adequacy is one of the most crucial indicators for assessing the financial strength of the banking sector. The ratios under this category measure the banking sector's ability to absorb unexpected losses generated by the manifestation of certain vulnerabilities or substantial macroeconomic imbalances. **A**sset quality indicators measure the strength of a bank to respond to potential risks which threaten the value of assets by considering the quality and diversity of its loans portfolio. Banks with low quality loans are more risky and are more likely to be in financial distress. **M**anagement quality indicators are occasionally measured in banking literature since it is qualitative in nature and is difficult to quantify. Nevertheless, some authors have attempted to quantify the quality of management by considering ratios which deal with cost efficiency. Well-managed banks are better able to utilize resources more efficiently than poorly managed banks. **E**arnings and profitability indicators measure how profitable bank assets are in generating revenue as well as the ability to absorb losses without any impact on capital. More profitable banks are less likely to fail than those with lower levels of earnings. **L**iquidity indicators measure the operational performance of a bank by evaluating a bank's resilience to cash flow shocks including its short term obligations to depositors and the ability to meet its credit demand. Banks with relatively illiquid assets are more likely to default than those with liquid assets. **S**ensitivity to market risk indicators measure how macroeconomic variables such as interest rates, the exchange rates and equity prices influence the earnings and capital of banks. A bank whose earnings or capital is less

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[8]A table of ratios used by several researchers can be found, for example, in Rostami (2015).

likely to be affected adversely by changes in market conditions has a lower degree of market risks than one with greater sensitivity.

The thirteen financial ratios used and the method by which they are computed are presented in Table A1. In situations where the denominators of certain ratios were zero and could not be calculated, the results were replaced by zero so that the length of the data series remains unaffected. Each financial indicator was transformed using the Z-score normalization technique to ensure that the model is robust to outliers.[9] Descriptive statistics of the variables used in this study are outlined in Table A2 of the Appendix.

3.3   Methodology

Logit modelling has been used widely in studies on predictive analysis. The method enables predicting the probability of a discrete outcome from a group of variables that may be continuous, discrete, or dichotomous. In other words, logit regression is an appropriate statistical method for analysing data when the dependent variable is a categorical variable whereas the predictor variables can be either quantitative or qualitative. The logit model is derived from the simple linear regression model which takes the form:

$$y_i = b_0 + \sum_{i=1}^{N} b_i x_i + u_i \tag{4}$$

where y_i represents the probability of default of the bank, x_i denotes the financial ratios of the bank, b_i represents the coefficients of the relevant scoring functions indicators, and u_i is the error term. The possibility of y_i to take values outside the interval <0, 1> coupled with the assumption of homoscedasticity (that is often violated in practice) make it difficult for the linear regression method outlined in equation (4) to represent a probability function which is bounded. Using the logit model, this linearity problem can be solved by applying an exponential transformation as follows:

$$y_i = f(w_i) = \frac{1}{1+e^{-w}} \tag{5}$$

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[9] As per the standardisation technique, $z = \frac{x-\mu}{\delta}$, where z is the normalized value of a member of the set of observed values of x and, μ and δ are the average and standard deviation values in x given its range.

where y_i represents the probability of default of the bank and $w_i = b_0 + \sum_{i=1}^{N} b_i x_i$ is the linear function of the financial ratios in equation 4. Performing further computations give:

$$ln\frac{s}{1-s} = b_0 + \sum_{i=1}^{N} b_i x_i \tag{6}$$

where s represents the probability of default of the bank at the one year forecast horizon, x_i denotes the financial ratios of the bank, b_i represents the coefficients of the relevant scoring functions indicators. The implicit interpretation of equation (6) is that the natural logarithm of the default rate is linearly related to the explanatory variables multiplied by their coefficients. Subsequently, the relationship for the probability of default is derived and expressed using the following logit curve:

$$s = \frac{1}{1+e^{-b_0 \sum_{i=1}^{N} b_i x_i}} \tag{7}$$

For the best model selection, it is necessary to choose the best performing explanatory variables to predict banking defect. To achieve this, the backward stepwise regression procedure was performed. [10] This method involves regressing all the explanatory variables in the model, iteratively removing the least contributing predictors, and stopping at the model where all the predictors are statistically significant. To test for statistical significance, the Akaike Information Criterion (AIC) was calculated for each model and the one with the weakest AIC was selected.[11]

4.0   Empirical Results

Table A3 shows the Pearson correlations between pairs of the explanatory variables used in the study.[12] The highest correlation occurs between two asset quality indicators, aq_1 and aq_3 (0.82). Other pairs which show moderately high correlations are: ep_1 and ep_2 (0.56), ep_3 and ep_4 (0.63), aq_2 and li_1 (-0.52), aq_2 and sr_1 (-0.59). Though it may seem necessary to eliminate variables

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[10] Both forward and backward regressions were considered. However, backward selection was preferred to forward selection since it avoids the problem that occurs when the addition of a new variable may result in classifying one or more of the already selected variables non-significant.

[11] The AIC is defined as follows

$$AIC = 2\ln(L) + 2p$$

Where L is the maximum likelihood of the fitted model and p is the number of estimated parameters.

[12] See Table A1 regarding the definition of the explanatory variables used in the study.

which show high correlations from the model, caution must be exercised since correlations only indicate the relationship between two variables, instead of a single variable and the remaining variables. Likewise, a low Pearson correlation coefficient does not necessarily mean that no relationship exists between the variables. Additionally, correlation is inappropriate when determining whether a relationship is casual.

From the stepwise regression analysis conducted, the model which showed the best statistical properties includes the best six statistically significant variables, of the thirteen variables considered. The estimates of the panel logistic regression with fixed effects are shown in Table 1. The results show that ca_1 and aq_1 are statistically significant at a level of 5% meanwhile mq_1 is significant at the 10% level. For completeness, the ratios that are insignificant are still included in the model since they do not materially change the overall coefficients or significance of the model. It is also observed from the test statistics reported in Table 1, that the model as a whole has a likelihood ratio chi-square of 15.84 and fits well significantly at the 5% level.

Table 1: Logistic regression of financial indicators on bank fragility

Explanatory variables	Coefficient	Standard error	z	Significance	
constant	-1.822746	0.329553	-5.53	0.000	*
ca_1	0.5386405	0.2188663	2.46	0.014	*
aq_1	0.4041522	0.1399515	2.89	0.004	*
mq_1	0.4103595	0.2331206	1.76	0.078	**
mq_2	-0.0949235	0.1912533	-0.50	0.620	
ep_1	-0.0837945	0.1452154	-0.58	0.564	
sr_1	0.3403188	0.2293432	1.48	0.138	
Likelihood ratio chi-square	15.84		Significance	0.0095	

Note: * represents a p-value less than 0.05
      ** represents a p-value less than 0.10

The sign of the coefficients as seen in Table 1 confirmed most of the a priori expectations regarding the impact of the individual ratios on bank fragility. More specifically, the positive and significant sign on the coefficient of aq_1 (non-performing loans to total loans) is consistent with expectations and is supported by literature such as Kingu *et al.* (2018) and Ugoani (2016). Banks with huge portfolios of non-performing loans are more risky and are more likely to be in financial distress. Furthermore, the low quality loans endangers the value of assets and has to potential to eventually erode the ability of banks to make profits. The variable$s$ mq_1 and sr_1 also positively influence the fragility of banks while ep_1 is negatively related to the fragility of banks. These results suggest that banks with poor management quality, high sensitivity to market risks and low profitability levels as indicated by operating expense to total assets, NOP to capital and return on assets are likely to be classified as highly fragile.

The coefficient of deposit interest expenses to total deposits (mq_2) is negative. This may imply that Jamaican banks tend to be less risky as the deposit interest expenses to total deposits ratio increases. Using customer deposits as a proxy for stable funding, increases in interest expenses would mean that banks would have relatively larger customer deposit bases, stronger balance sheets and greater capacity to lend. As supported by Altunbas et al. (2011) and Mohamudally-Boolaky and Auhammud (2011), customer deposits provide one of the cheapest and stable source of funding for banks and reduces the probability of bank failure. Further, they contend that customer deposits generally impact banking performance positively.

The negative coefficient on regulatory capital to risk weighted assets (ca_1) suggests that as the ratio increases the level of fragility in the banking system increases. Authors such as Bandt *et al.* (2014) and Anguren and Jiménez (2017) argue that higher capital requirements may increase the vulnerability of bank performance as well as incentivize banks to take on more risk. In the context of Jamaican banks, it is possible that the cost of financing may increase significantly as a result of holding more capital. Moreover, higher voluntary capital (in excess of regulatory capital) encourages banks to extend higher-risked loans since they would not need to justify the capital required. The increased risk appetite by DTIs can also be explained by the high and positive instantaneous correlation between regulatory capital and trading income. It is observed that the correlation is relatively low and negative when a two quarter lag of total loans and capital is

considered, suggesting that exposure may fall over time due to greater provisioning for non-performing loans (see Table A4)[13].

The odds ratios of the variables, which provide useful information for further analysis, are given in Table 2 below. The absolute size of the coefficients reflects the importance of the ratios in the scoring model. Notably, ca_1 and aq_1 record very high odds ratios which are largely superior to 1. This means that the odds of bank failure increase by a factor of 1.71 and 1.50 for one unit increases in the non-performing loans to total loans and the regulatory capital to risk-weighted assets ratio. Overall, the results show that the two most significant variables, ca_1 and aq_1 record high odds ratios and are therefore the two variables which strongly explain bank fragility in Jamaica.

Table 2: Odds Ratio

Explanatory variables	Odds ratio	Confidence interval		
constant	0.1615815	0.0846985	0.3082532	*
ca_1	1.713675	1.11591	2.631649	*
aq_1	1.498032	1.13866	1.970825	*
mq_1	1.50736	0.9545183	2.380398	**
mq_2	0.9094425	0.6251441	1.323032	
ep_1	0.9196202	0.6918325	1.222408	
sr_1	1.405396	0.896564	2.203007	

Note: * represents a p-value less than 0.05
       ** represents a p-value less than 0.10

4.1   Usefulness of the model for identifying periods of financial stress

The resulting model contains one capital adequacy indicator (ca_1), one asset quality indicator (aq_1), two management quality indicators (mq_1 and mq_2), one earning and profitability indicators (ep_1) and one sensitivity to market risk indicator (sr_1) and is captured in equation 8.

$$S = \frac{1}{1+e^{-(b_0+ b_1ca_1 + b_2aq_1 + b_3mq_1+ b_4mq_2+ b_5ep_1+ b_6sr_1)}} \qquad (8)$$

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[13] Table A4 shows the correlation between capital, total loans and trading income.

The value of s, which ranges from 0 to 1, expresses the aggregate view of the riskiness of the banking sector. The larger s is, the greater is the probability of bank failure. Put differently, values of s closer to 1 suggest higher levels of bank fragility while values closer to 0 indicate that the banking system is in a stable position. From this viewpoint, the scoring model confirmed our expectations regarding the impact of financial ratios on bank failure given that a score of 1 was never obtained from the model over the observed period. This results corresponds with the constant output of 0 attained from the banking fragility index, BF_t over time, implying that the banking system would not have failed. Notwithstanding the predictive power of the absolute value of the score, its evolution over time is more important when assessing the potential risks to financial system stability.

The scoring model identified three known periods of financial stress in Jamaica (see Figure 1 below). First, the increasing evolution of the probability of default from September 2008 to its peak in September 2009 captured the lagged effect of the 2007-2008 global financial crisis on the local banking sector. The global financial crisis and the subsequent recession fueled the high levels of non-performing loans and increased foreign exchange risk exposures as a result of the depreciation of the Jamaican dollar. The two other periods of financial stress captured by the model are: March 2010 to June 2010 and December 2012 to March 2013 which are associated with the Jamaica Debt Exchange (JDX) and the National Debt Exchange (NDX) respectively. Both the JDX and NDX were implemented in an attempt to improve the Government of Jamaica's debt sustainability via facilitating the exchange of existing bonds for new bonds of the same principal value but which have lower interest rates and longer maturity. As it relates to the impact on the banking system, the debt exchanges contributed to the reductions in the net interest income, total loans as well as the increased volume of non-performing loans of banks. Overall, the score has a decreasing trend from June 2014 onwards, largely driven by the continued improvement in the non-performing loans to total loans ratio. The dynamics of the index from March 2008 to December 2017 suggests that the vulnerability of the banking sector has shown steady improvements.

Figure 1: S-score for the Jamaican Banking Sector, 2008 – 2017
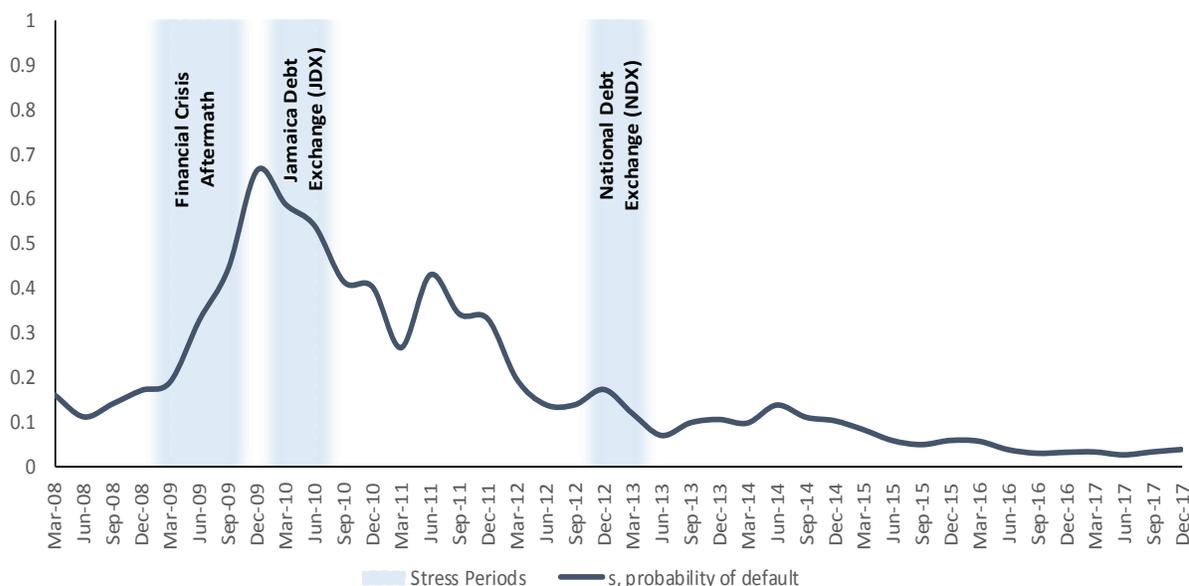
5.0   Conclusions

The global banking and financial crisis of 2007-2008, which has affected many countries, has prompted many academics and regulators to pay greater attention to the level of risks in the banking system. These developments have led to the development of early warning models in an attempt to safeguard the banking and the wider financial system from potential financial crises.

This paper investigated the usefulness of financial ratios, covered under the CAMELS framework, in predicting bank failures in Jamaica. Against this background, the study focused on estimating logistic regressions on financial ratios for deposit taking institutions operating over the period March 2008 and December 2017. The resulting S-score model which comprised of the six best predictors – one capital adequacy indicator, one asset quality indicator, two management quality indicators, one profitability indicator and one sensitivity to market risk indicator produced meaningful results. Most importantly, non-performing loans to total loans and regulatory capital to risk –weighted assets had the greatest impact on the probability of default of Jamaican deposit taking institutions. In particular, both ratios are significantly positively related to bank failure.

The significance of NPLs to total loans ratio in the scoring model highlights the importance of monitoring the quality of the non-performing loans portfolio since high levels of NPLs may erode the profitability of banks and heighten financial stability risks. Though the positive sign on the coefficient of regulatory capital to risk–weighted assets was unexpected, it was supported by literature amidst the ongoing debate on the effect of capital requirements on bank performance. Specifically, banks may be incentivize to take on additional risk as a result of the positive effect of higher capital requirements on vulnerability of bank performance. Results also lead to the conclusion that operating expense to total loans and net open position to capital positively impacts bank fragility while deposit interest expenses to deposits and return on assets are negatively related to the level of financial risks. Although these ratios were not significant, they were included in the model given their inclusion did not affect the overall fit of the model materially.

The S-score model is a useful early warning tool for detecting high levels of bank fragility. It was constructed using the aggregate financial data of DTIs and thereby expressed the scores of the DTI sector as a whole corresponding to its level of risk over the examined period. The resulting S-score model which was constructed using the aggregate financial data of DTIs expresses the scores of the DTI sector as a whole corresponding to its level of risk over the examined period. The model identified three known periods of financial stress in Jamaica including the global crisis of 2007-2008 and the JDX and NDX during 2010 and 2013 respectively. The model also gives an aggregate view of the riskiness of the DTI sector and highlights the steady improvements made over the years to improve financial stability within the sector. As such, it can be employed by policymakers to identify signs of distress in the banking sector which can aid in the use of preventative measures in an effort to safeguard financial system stability. Future work should consider the use of ANN and other non-parametric models in assessing the vulnerabilities of DTIs in Jamaica. In addition, the study should be extended to include the non-DTI financial sector in an attempt to examine the risks within the entire financial system. Based on the usefulness of the scoring model developed, supervisors of financial institutions (DTIs and non-DTIs) in Jamaica and the region can use the framework to aid in the prudential surveillance of individual financial institutions.

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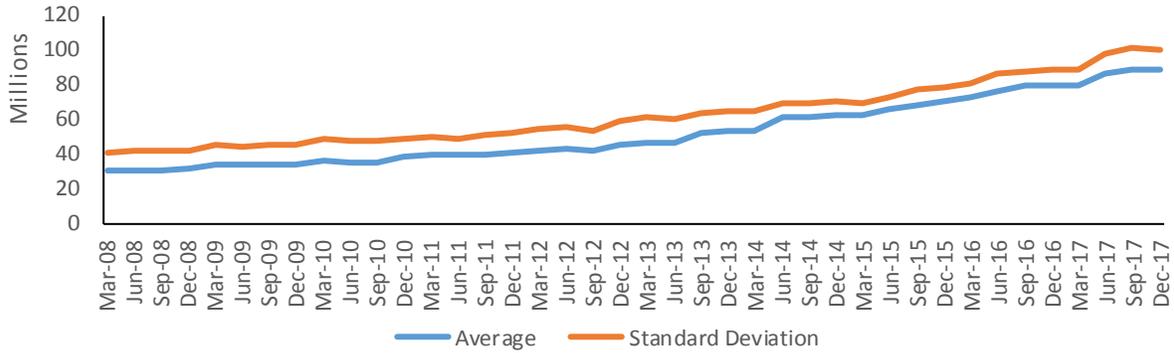
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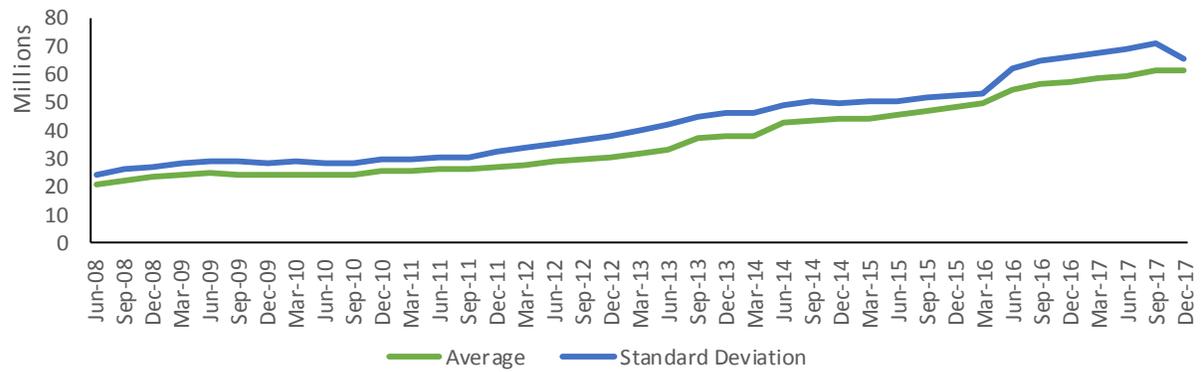Zeitun, R., Tian, G. and Keen, K., 2007. Default probability for the Jordanian companies: A test of cash flow theory.

Appendix

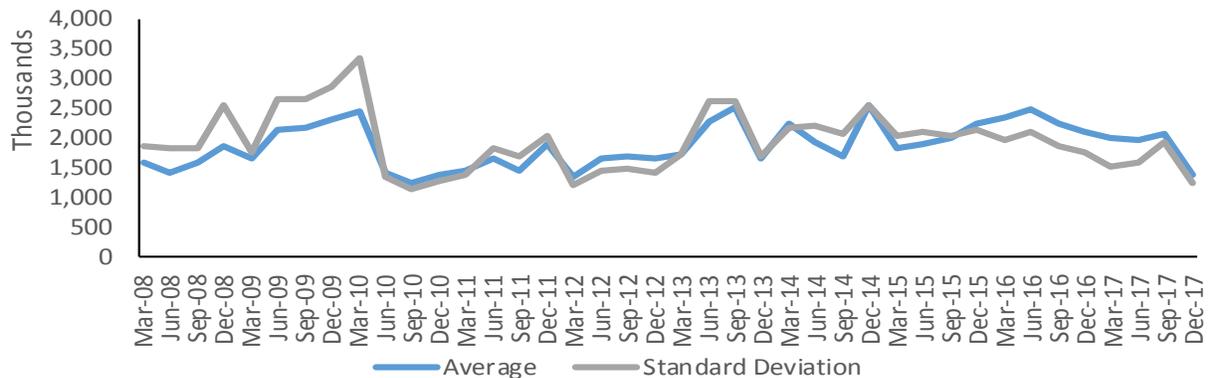**Figure A1: Variables used in Banking Fragility Index, March 2008 – December 2007**

A. Deposits

B. Total Loans

C. Net Open Position (NOP)

Source: Author's calculations

Table A1: Definition of Financial Indicators

CAMELS Component	Ratio	Calculation Method	Notation	Expected impact
Capital Adequacy	Regulatory capital to risk-weighted assets	$$\frac{Total\ regulatory\ capital}{(Risk-weighted\ assets\ +\ foreign\ exposure\ )}$$	ca_1	-
	Loan loss provisions to non-performing loans	$$\frac{Loan\ loss\ provisions\ capital}{(Non-performing\ loans\ )}$$	ca_2	-
Asset Quality	Non-performing loans to total loans	$$\frac{Non-performing\ loans}{Total\ loans}$$	aq_1	+
	Total loans to Total assets	$$\frac{Total\ loans}{Total\ assets}$$	aq_2	+/-
	Coverage of NPLs	$$\frac{Loans\ loss\ provisions}{Net\ interest\ income}$$	aq_3	-
Management Quality	Operating expense to total assets	$$\frac{Operating\ expenses}{Total\ assets}$$	mq_1	+
	Deposit interest expenses to total deposits	$$\frac{Interest\ expenses}{Total\ deposits}$$	mq_2	+
Earnings and Profitability	Return on assets	$$\frac{Net\ income\ before\ taxes}{(Total\ assets_{t-1}+total\ assets_t)/2}$$	ep_1	-
	Return on equity	$$\frac{Net\ income\ before\ taxes}{(Capital\ \&\ reserves_{t-1}+capital\ \&\ reserves_t)/2}$$	ep_2	-
	Interest margin to income	$$\frac{Net\ interest\ income}{Gross\ income}$$	ep_3	-
	Non-interest expenses to income	$$\frac{Non-interest\ income}{Gross\ income}$$	ep_4	+
Liquidity	Liquid assets to total assets	$$\frac{Liquid\ assets}{Total\ assets}$$	li_1	-
Sensitivity to Market Risk	Net open position to capital	$$\frac{Net\ open\ position\ in\ foreign}{Total\ regulatory\ capital}$$	sr_1	+

Source: Author

Table A2: Descriptive Statistics

	Mean	Std. Dev.	Minimum	Maximum
ca_1	19.63	8.49	10.29	72.72
ca_2	97.33	212.57	0	4310.78
aq_1	5.28	7.07	0	55.41
aq_2	47.76	18.57	3.29	96.46
aq_3	223.56	288.46	2.09	2502.77
mq_1	2.43	1.34	0.64	7.80
mq_2	1.33	1.56	0.10	14.76
ep_1	0.53	0.80	-3.56	6.21
ep_2	2.68	9.20	-134.62	35.54
ep_3	43.06	37.92	-699.18	122.59
ep_4	23.36	18.20	-231.92	88.86
li_1	23.69	20.28	0	281.88
sr_1	0.43	0.68	0	3.49

Source: Author's calculations.

Table A3: Correlation Coefficients between explanatory variables

	ca_1	ca_2	aq_1	aq_2	aq_3	mq_1	mq_2	ep_1	ep_2	ep_3	ep_4	li_1	sr_1
ca_1	1												
ca_2	-0.08	1											
aq_1	-0.05	-0.06	1										
aq_2	0.40	-0.15	-0.06	1									
aq_3	0.07	-0.04	0.82*	0.17	1								
mq_1	-0.32	-0.11	-0.12	-0.13	-0.27	1							
mq_2	0.17	-0.07	0.15	0.25	0.10	-0.02	1						
ep_1	0.24	-0.07	-0.19	0.21	-0.07	-0.27	0.00	1					
ep_2	-0.04	0.00	-0.07	0.03	-0.04	-0.09	0.00	0.56*	1				
ep_3	-0.16	-0.05	-0.06	0.02	-0.17	0.26	-0.04	0.14	0.14	1			
ep_4	-0.33	0.09	0.13	-0.29	0.02	0.05	-0.33	-0.18	-0.19	0.63*	1		
li_1	-0.26	0.12	-0.23	-0.52*	-0.30	0.18	-0.29	0.02	0.03	0.04	0.12	1	
sr_1	-0.24	0.3	0.1	-0.59*	0.03	-0.10	-0.07	-0.06	-0.03	-0.06	0.21	0.40	1

Note: * represents high correlation with a probability < 5% i.e. the pair is highly correlated and coefficient is significant at the 5% level. For example, aq1 and aq3 are significantly and positively correlated.

Table A4: Correlation Coefficients between capital, total loans and trading income

	Regulatory capital	Total loans	Trading Income		Regulatory capital	Total Loans(-2)	Trading Income(-2)
Regulatory capital	1			Regulatory capital	1		
Total loans	0.9905*	1		Total loans(-2)	-0.0424	1	
Trading income	0.5016*	0.4928*	1	Trading income(-2)	-0.0033	0.1278	1

Note: * represents high correlation with a probability < 5% i.e. the pair is highly correlated and coefficient is significant at the 5% level. (-2) represents a two-quarter lag of the variable.