Estimating & Forecasting Default Risk: Evidence from Jamaica

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December 2016

Abstract

This paper employs the GMM estimation technique to evaluate the impact of macroeconomic factors on bank default risk for listed Jamaican banks and securities dealers (SDs) over the period December 2004 to June 2016. Default risk is captured by a distance-to-default measure which is computed using a Merton type, option-based model. This indicator accurately tracks the default experience of listed Jamaican banks and SDs over important dates throughout the sample period. The estimation results of the model revealed that GDP growth, inflation, the unemployment rate, growth in domestic private sector credit as well as the REER have a statistically significant impact on the performance of the distance to default measure. As such, the econometric findings validate the sensitivity of the fragility measure to the variability of key macroeconomic variables. The model was also utilized to forecast the distance to default measure six-quarters ahead, as this will aid in the formulation of policy to mitigate systemic risks in the financial sector. The forecast results showed less volatility and lower overall default risk for Jamaican banks and securities dealers due to the projected improvement in various macroeconomic indicators.

JEL Classification Numbers: E17; F4
Keywords: Default risk; forecasting; macroeconomic factors

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[1] The views expressed are those of the authors and do not necessarily reflect those of The Bank of Jamaica.

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1.0 Introduction

With more frequent instances of widespread distress during the last few decades, financial stability has become an increasingly important objective for policymakers. Episodes of profound banking system distress have occurred not only in emerging and developing economies but also in advanced industrialised countries, such as the U.S. and Japan. In many cases, banking sector calamities have resulted in large losses of wealth and led to disturbances in the supply of credit within the economy. Furthermore, resolving these crises has frequently imposed a large burden on public funds. These serious consequences underscore the value of indicators that signal a rising probability of banking sector problems before such problems actually occur and therefore represent an important aspect of effective banking supervision and financial market surveillance.

The approach to the development of measures of financial system distress has changed over the years and the locus of concern has largely emphasis has shifted from examining solely micro-prudential indicators to also incorporating macro-prudential dimensions of stability. Against this background, there has been increasing emphasis on early warning and forward looking measures which can signal the risk of default of individual institutions as well as the system. These measures are useful in identifying the build-up of risks and potential vulnerabilities and would facilitate and enable a more timely reaction by the relevant authorities to any financial sector weaknesses which may arise. The distance to default is one such quantitative measure of financial stability which has been increasingly used by a number of central banks and international financial institutions. It is a widely used indicator of default risk and is a market-based risk measures for banks and nonfinancial corporates and captures the probability that the market value of a firm's assets falls below the value of its debt.[2] Market-based risk measures aim at supplementing more traditional analyses based on financial statements and income account statements with the added advantage of using the forward-looking information incorporated into security prices. Empirical studies have shown that the distance-to-default predicts well ratings downgrades of banks in developed countries and in emerging market countries. There is

[2] See Tudela and Young (2003) and Chan-Lau (2006).

also empirical support for using the distance-to-default for financial institutions as a forecasting tool of bank distress.

Regarding Jamaica, based on a study by Lewis (2010), distance-to-default and the probability of default estimates were computed for the sovereign and for publicly listed financial institutions in the bank and non-bank sector in Jamaica for the period 2005 and 2010. The results underscored that these estimates serve as an early warning indicator of macro-financial vulnerabilities during known periods of distress. Mingione (2011), also utilized principal component analysis (PCA) to forecast indices of financial vulnerability for the Jamaican banking sector. He found that the PCA model leads to more accurate predictions over the out-of-sample period using an aggregate index of vulnerability. Based on the literature, forecast of these measures are useful in enabling policy makers and financial system participants to better monitor the degree of stability of the financial system as well as anticipate the sources and causes of financial stress to the system.

This paper builds on prior work for Jamaica by investigating the macroeconomic factors which impact Banks' distance to default measures. The paper also provides a six-quarter ahead forecast of these institutions' distance to default using the GMM estimation technique in order to gauge the degree of solvency and systemic risks within the banking sector. The paper is organized as follows: Section 2 provides an overview of the literature on the impact of macroeconomic factors on institutions' distance to default. In section 3, there is a summary of the distance to default methodology as well as trends in the measure for financial institutions listed on the Jamaica Stock Exchange. Section 4 provides a brief outline of the data used in the study as well as the estimation technique employed, while section 5 presents the findings of the model. The conclusion and policy implications are presented in section 6.

2.0 Literature Review

Bernoth and Pick (2010) forecasted systemic risk taking into account linkages within the financial sector irrespective of whether they are caused by direct financial linkages or common shocks to the financial system. The study combined the use of unobserved common factors and observed variables for forecasting in a panel data set spanning 211 banks and 120 insurance companies in 21 countries. More specifically, it examined the importance of a number of macroeconomic variables and unobserved factors on the performance of banks and insurances. Against this background, there was an investigation of the forecast performance of macroeconomic and factor augmented models of the fragility of banks and insurance companies. In addition, given that the performance of firms in two industries and in geographically distinct regions was analysed, there was an examination of the importance of regional, industry-specific or worldwide factors in forecasting financial fragility.

Furthermore, the study utilized distance-to-default as the measure of the performance of banks and insurance companies. It is based on the theoretical option pricing model of Merton (1974). An advantage of the distance-to-default is that it combines information about stock returns with leverage and volatility information and is therefore a more efficient indicator of default risk than simple equity price based indicators.[3]

The explanatory variables included in the model are the growth rate of the 10-year bond yield, industrial production, inflation, domestic credit, equity returns, real effective exchange rate, unemployment rate, price earnings ratio and the Chicago board of exchange volatility index. The results indicated that unobserved common factors play an important role, in particular taking unobserved factors into account leads up to 11 per cent reduction in the root mean squared framework error (RMSFE) of the forecasts of individual firms' distance-to-default. Systemic risk can also be better forecasted as the aggregate RMSFE is reduced by 29 per cent in one-quarter ahead forecasts and by 23 per cent in four-quarter ahead forecasts.

Laurin and Martynenko (2009), quantitatively examined the relationship between corporate default probability and macroeconomic information using panel data analysis. They also performed a quantitative comparison of default probability and macroeconomic

[3] See Vassalou and Xing (2004)

information between different Swedish stock indexes based on market capitalization. The firms were segmented based on market capitalization. More specifically, a large-capitalization index was used which consisted of firms with market capitalization of one billion Euros, a mid-capitalization index included firms with market capitalization over 150 million Euros but less than one billion Euros and a small-capitalization index comprising firms with capitalization up to 150 million Euros. The explanatory variables used were the domestic industrial production index (IPI), consumer price index (CPI), nominal domestic three-month rate for Treasury bills (R3M), GDP-growth, unemployment rate, exchange rate, equity price index and a measure of equity volatility. An autoregressive model with one-year lagged distance to default is also estimated. [4]

The panel regression results for the large-capitalization and the mid & small-capitalization firms appeared to be similar. It was found that the one year lagged Industrial Production Index and the one year lagged exchange rate exhibited a large negative effect on the probability of default. The interest rate and the one year lagged interest rate were found to have a positive impact on the probability of default. The autoregressive model, with an autoregressive lagged term, showed a decreasing distance to default over time.

In concluding, macroeconomic factors such as the one year lagged industrial production index, the one year lagged exchange rate, and the one year lagged interest rate explained 75.0 per cent of the changes in the probability of default for the large capitalization firms (68.0 per cent in the model for the mid & small capitalization firms, respectively). The autoregressive model indicates a weak explanatory power and an increasing probability of default overtime.

Hamerle, Liebig and Scheule (2004), forecasted credit default risk in loan portfolios using a Merton-style threshold-value model for the default probability which treats the asset value of a firm as unknown and where default correlations are also modeled. The empirical

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[4] Autoregressive models are often used in studies of time series data where the behaviour of a dependent variable is determined by its previous estimations. Åsberg and Shahnazarian (2008) presented an estimation model for predicting the distance to default. The model is based on the hypothesis that the best forecast for future distance to default is provided by the recent outcomes for the variable in question.

analysis is based on a large data set of German firms provided by Deutsche Bundesbank for the period 1987 to 2000. The data was collected by Deutsche Bundesbank's branch offices in order to evaluate the credit quality of firms for refinancing purposes.

Of importance, the inclusion of variables which are correlated with the business cycle improved the forecasts of default probabilities. Further, the better the point-in-time calibration of the estimated default probabilities, the smaller the estimated correlations, as such, correlations and default probabilities should always be estimated simultaneously. The macroeconomic variables included in the model were the business climate index, unemployment rate and systematic growth in new orders of the construction industry. The model allowed default probabilities to be forecasted for individual borrowers and estimated correlations between those borrowers simultaneously.

3.0 Methodology

3.1 Distance to Default Framework

The distance-to-default measure captures the probability that the market value of a firm's assets falls below the value of its debt. More specifically, the face value of debt is typically computed from balance sheet data and is assumed equal to the sum of the short-term liabilities plus half the long-term liabilities. The distance-to-default is then derived using the market value of the firm as well as the implied equity price volatility.

Distance-to-default is based on the structural model of corporate debt first introduced by Black and Scholes (1973) and Merton (1974). Furthermore, the framework is premised on the relationship between the value of the firm, V_A, (or the value of its assets) which should be equal to the sum of the values of its debt, X, and equity, V_E. In addition, typically the firm's assets are first used to pay debtholders while whatever is left is distributed to shareholders. In particular, the value of equity is shown in equation 1:

$$V_E = \max(0, V_A - X) \quad (1)$$

Also, compensation to equity holders is equivalent to a call option on the value of the firm with a strike price equal to the face value of debt. The strike price is also known as the default barrier is set equal to the level of the firm's short-term liabilities and half its long-term liabilities. Information on the value of the firm, the debt owed by the firm and the market value of equity is enough to derive the remaining unknown variable.

According to the Black-Scholes (1973) model, the market value of the firm's underlying assets is due to the following stochastic process:

$$dV_A = \mu V_A dt + \sigma_A V_A dz \tag{2}$$

where

V_A , dV_A are the firm's asset value and change in asset value,

μ, σ_A are the firm's asset value drift rate and volatility, and

dz is a Wiener process

Furthermore, the Black and Scholes (1973) and Merton (1974) option pricing theory, the equity call option written by debt holders to shareholders may be valued by solving the following second-order linear partial differential equation (PDE):

$$\frac{\partial V_E}{\partial t} = rV_E - rV_A \frac{\partial V_E}{\partial V_A} - \frac{1}{2}\sigma^2 V_A^2 \frac{\partial^2 V_E}{\partial V_A^2}$$

subject to the boundary conditions:

$$V_E\,(V_A, t) = \max\,(0, V_A - X), \quad V_A \geq X$$
$$= 0, V_A < X$$

The unique solution to this PDE is the celebrated Black-Scholes-Merton option pricing formula:

$$V_E = V_A N(d1) - e^{-rT} X N(d2) \tag{3}$$

where V_E is the market value of the firm's equity, N (d) is the cumulative normal density function and r is the risk free interest rate. Solving equation 3 for d1 and d2 yields the following expressions:

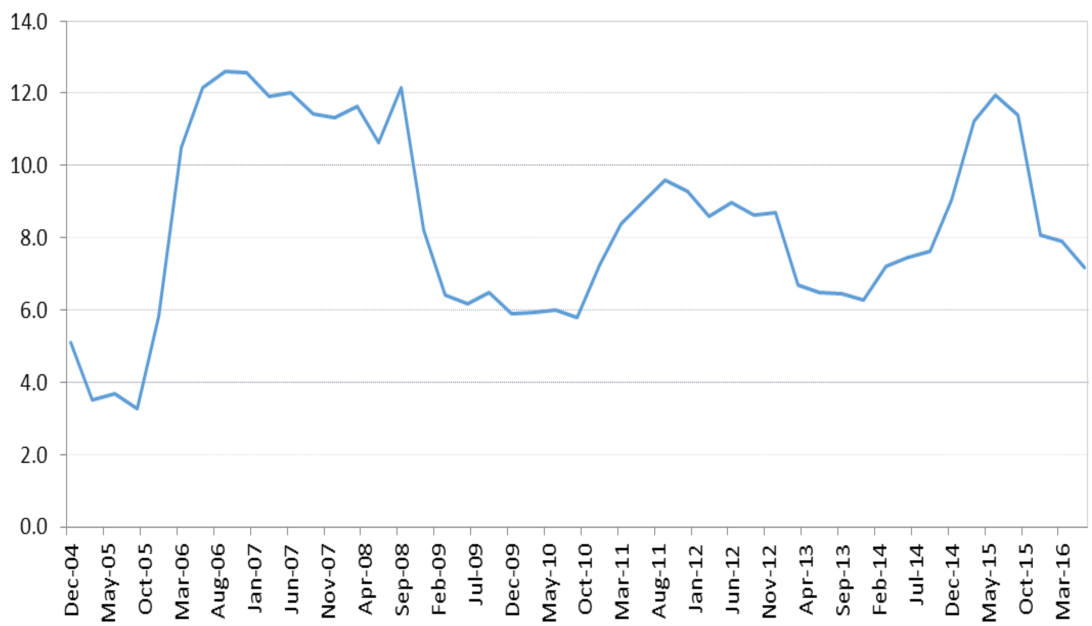
$$d1 = \frac{ln\left({V_A}/{X}\right)+\left(r+\frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \tag{4}$$

$$d2 = \frac{ln\left({V_A}/{X}\right)+\left(r-\frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} = d1 - \sigma_A\sqrt{T} \tag{5}$$

Of note, d2 shown in equation 5 represents the distance-to-default, where (V_A/X) captures the firm value relative to the default threshold, which over time is impacted by the interest rate and asset value volatility. This distance to default expression is then standardized by the volatility of the firm's assets.

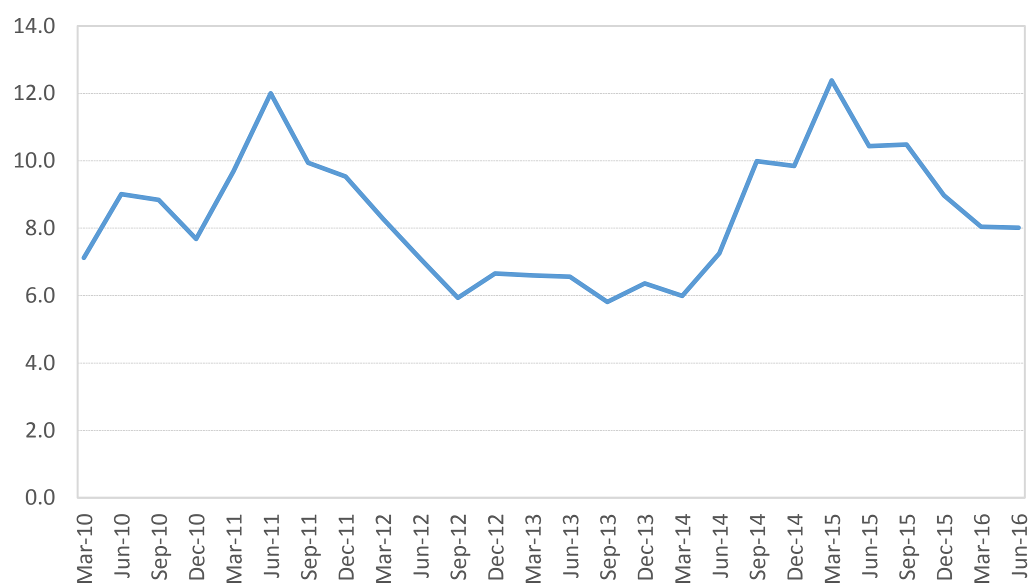
3.2 Trends in Distance to default for Financial Institutions Listed on the Jamaica Stock Exchange

Figure 1: Distance to Default: DTIs Listed on the Jamaica Stock Exchange



The distance-to-default was successful in tracking the default experience of listed banks during periods of vulnerability throughout the sample period (see **Figure 1**). The measure declined during the global crisis period, indicating that there was deterioration in the default measure of these institutions during this period. This occurred in a context where the crisis would have contributed to declines in the value of the asset holdings of these institutions. In addition, the measure also fell during the two debt exchange periods in Jamaica, which occurred in 2010 and 2013 and which involved the extension of maturity and reduction of coupon rates on local currency denominated Government of Jamaica bonds.[5] The distance to default measure was adversely impacted by weaker profitability performance of the listed banks due to the lower revenue performance on these investments.

Figure 2: Distance to Default: Securities Dealers Listed on the Jamaica Stock Exchange



The distance to default for the securities dealers declined or remained low throughout periods of vulnerability, such as during the two debt exchanges which occurred during

[5] The Jamaica Debt Exchange occurred in the March 2010 quarter and the National Debt Exchange took place during the March 2013 quarter.

2010 and 2013 (see **Figure 2**). The measure was adversely impacted by weaker profitability performance of the listed securities dealers due to the lower revenue performance on domestic currency Government of Jamaica investments. Securities dealers have also been impacted by the continued phasing down of the retail repurchase business of the sector since 2015.[6] This has coincided with weaker profitability and lower distance to default values for these institutions during this period.

4.0 Empirical Analysis

4.1 Data & GMM Estimation Technique

The paper employs quarterly distance-to-default data for banks and securities dealers listed on the Jamaica Stock Exchange as well as information on selected macroeconomic variables over the period December 2004 to September 2016. Macroeconomic variables utilized in the study included nominal GDP growth, growth in the inflation and unemployment rates, growth in the real effective exchange rate (REER), changes in the 10-year GOJ global bond yields, growth in private sector credit and the spread between loan and time deposit rates.

Panel data estimation was used as it facilitates the inclusion of time series data across several variables. Panel data analysis also makes it possible to predict the behavior of the individual variables more precisely than other techniques as it utilizes time series data and therefore captures the past experiences of each variable. More specifically, the Generalized Methods of Moments estimation technique (GMM) was employed to estimate the relationship between distance-to-default and macroeconomic variables for both banks and securities dealers.[7] The technique was chosen as it uses assumptions about specific

[6] Securities dealers' fund the purchase of securities through repurchase agreements ("repos"). The risks embedded in these repos emanate from SDs' reliance on borrowing very short-term funds from retail clients and institutional investors to take proprietary positions in primarily long-term government securities. To address the systemic risks from these broker-dealer activities, the GOJ committed to reform the broker-dealer industry, which included the phasedown of the "retail repo" business model. Legislation was enacted to allow for the establishment of the CIS which facilitates the transfer of market, interest rate and liquidity risk to individual investors and off the balance sheet of broker dealers. As a result, since 2013, the SDs' sector embarked on a process of reform which entailed the phasedown of the "retail repo" business model.

[7] Of importance is that the bond yield variable was only included in the model for the securities dealers.

moments of the random variables instead of assumptions about the entire distribution. The GMM method is also useful in providing unbiased and efficient estimates in dynamic models which have lagged endogenous variables as regressors. Based on work by Boucinha and Ribeiro (2007), the methodology can be utilized to obtain consistent estimates of the parameters of interest when the persistence of the dependent variable needs to be modelled explicitly. Furthermore, the model does not require strong hypotheses about the exogeneity of the regressors. Arellano and Bond (1991) suggest that consistent and efficient estimates can be obtained by using lagged values of the dependent variable and lagged values of the exogenous variables as instruments. Baltagi (2001), also highlighted that the GMM methodology accounts for the possibility of correlations between the independent variables, making it an advantageous technique.

More specifically, the GMM estimation technique shows how a variable in period t, for example, y_{it}, could be explained through the value of the same variable in period t-1, $y_{i,t-1}$, along with other different explanatory elements, x'_{it}, and a random error term, η_{it}. This relationship is outlined in equation (6):

$$y_{it} = \alpha + \delta y_{i,t-1} + x'_{it}\beta + \eta_{it} \tag{6}$$

Where y_{it} is the dependent variable, α is the intercept, δ is a scalar, β is the $kx1$ vector of explanatory variables' parameters, x_{it} is the $1xk$ vector of explanatory variables, with equation (7) explaining the random error term, η_{it} which includes individual unobserved effects, μ_i, and the genuine random error term, ε_{it}

$$\eta_{it} = \mu_i + \varepsilon_{it} \tag{7}$$

where $\mu_i \sim \mathrm{IID}(0,\ \sigma_\mu^2)$ and $\varepsilon_{it} \sim (0,\ \sigma_\mu^2)$ are independent of each other and themselves.

Furthermore, concerning the matter of autocorrelation as it relates to the GMM framework, Arellano and Bond (1991) utilized internal instruments that are lagged values of the levels of the variables which appear on the right-hand side of equation (6) in addressing this issue. These instrumental variables should not be correlated with the first difference of the error term, but should be correlated with the variable to be estimated. The idea behind this technique is to estimate the model by combining several instruments around a single vector of parameters, in order to obtain the minimum correlations between the error term and the relevant instruments. In particular, this technique considers as suitable instruments of the second- and higher-order lags of the regressors in the event of no serial correlation in the time-varying component of the disturbance term.

5.0 Results

5.1 *GMM Model*

Panel unit root tests were done on the residuals of the GMM model for each sector. More specifically, the unit root tests applied were the Levin, Lin and Chu test, Im, Peasaran and Shin test, ADF – Fisher Chi-square test and PP – Fisher Chi-square test. All the tests showed that the residuals for both models are stationary, reflecting a non-spurious regression (see **Tables A.3** and **A.6**). Additionally, the Sargan test of orthogonality between the instruments and the residuals, which tests the validity of instruments used in the regression through a comparison between the estimated moments and the sample moments was used to evaluate the results. The Sargan test results showed that there was no evidence to reject the null that 'over-identifying restrictions are valid', which suggests that the instruments used in the models are valid.

DTI Results

The results of the GMM model were consistent with expectations. All macroeconomic variables included in the model, with the exception of the growth in the REER index, have a statistically significant impact on the distance to default measure. In particular, the findings showed a positive relationship between GDP growth and the distance to default. Stronger performance in GDP growth is expected to contribute to stronger bank performance, for instance through increased deposit growth and investments, which will ultimately lead to improvements in these institutions' distance to default. There is also a positive relationship between the loan rate and time rate deposit spread and the distance to default. An increase in this spread typically contributes to improvement in the revenue performance of banks and should lead to increases in the distance to default.

An increase in the growth of the unemployment rate resulted in deterioration in the distance to default. This is anticipated given that worsening in the unemployment rate is expected to increase non-performing loans of banks and worsen performance. Based on the literature, the relationship between growth in domestic credit to the private sector and financial institution performance is ambiguous. Some studies, such as Hagen and Ho (2004) and Goldstein (1998), indicate that there is a negative relationship between credit growth and distance-to-default, as banking distress is typically preceded by credit booms.[8] The findings of this study also show an inverse relationship between growth in private sector credit and distance to default. Furthermore stronger growth in inflation was also found to negatively impact distance-to-default, as deterioration in inflation performance can tend to erode the profitability of banking institutions. Additionally, the lagged dependent variable was positive and statistically significant and is indicative of the persistence of the dependent variable in explaining itself.

The model has a high R-squared of 76.1 per cent and a Durbin Watson statistics of close to 2. Furthermore, period dummies for the global crisis period and the NDX period were found to be significant.

Forecast Performance & Forecast Evaluation Results

The results of the GMM model in section 3.1, was used to generate both in-sample and out-sample forecasts of the distance to default measure. The in-sample estimates were generated over the entire sample period, March 2004 to June 2016, while the out-of-sample estimates were generated for the period, December 2014 to June 2016. The summary statistics for these estimations are reported in Table A.1 and Table A.2

The forecasting ability of the GMM model was evaluated using common measures such as the Theil Inequality Coefficient (Theil U) statistic and the root mean square error (RSME). The Theil U statistic is useful is determining a model's prediction performance relative to a naïve model, which is a benchmark used for evaluating forecast accuracy where the forecast assumes that the value in the next period is the same as the value in this period. Furthermore, the Theil U coefficient lies between 0 and 1, with values closer to zero,

[8] Work by Bernoth and Pick (2010), showed a positive relationship between credit growth and distance to default, indicative of stronger credit growth improving the profitability of banking institutions.

indicative of greater accuracy of the prediction model. Additionally, the root mean squared error is calculated based on the square root of the squared difference between predicted and observed values, where lower values are indicative of better forecasting ability of the model.

The prediction performance of the model was assessed using in-sample and out-of-sample forecasts. In-sample performance statistics based on the Theil U and RSME were 0.2 and 3.3, respectively, while the respective values for the out-of-sample forecast were 2.7 and 0.1. These results confirm that the model utilized has strong predictive power.

Given the strong predictive power of the model, which relied on projections of specific macroeconomic variables, the model was used to project the distance of default of listed DTIs up to December 2017. For the banking sector, the findings showed that growth in the inflation rate, growth in private sector credit, bank spreads, growth in the unemployment rate and GDP had a statistically significant impact on the distance to default of these institutions. Of note, the unemployment rate, growth in private sector credit and growth in inflation have an inverse relationship with DTIs' distance to default. The forecast for the distance to default of the banking sector was generally low and also reflected much lower volatility. This forecasted performance is largely due to the projected orderly movements of the statistically significant macroeconomic variables, in particular, credit growth and the unemployment rate.

Securities Dealers Results

Consistent with expectations, the finding showed a significant inverse relationship between the distance-to-default and growth in the inflation rate. Similar to the DTIs, deterioration in this predictive variable is expected to have an adverse impact on the distance-to-default as deterioration in inflation performance can lead to higher expenses for the financial institutions and weaken profitability. The results also indicate a significant inverse relationship between the distance to default and growth in private sector credit, as it is often the case that financial system fragility is sometimes preceded by marked acceleration in credit growth. Unlike for the DTIs, it was found that there is a significant inverse relationship between the distance to default and GDP growth. This performance may occur because stronger performance in GDP growth may lead to higher funding demand, increased interest costs, higher bond yields and lower bond prices, which will ultimately lead to deterioration in these institutions' distance to default. There is also a positive relationship between the loan and time deposit rate spread and the distance to default. An increase in this spread typically contributes to improvement in the revenue performance of banks and should lead to increases in the distance to default.

The results also showed that the growth in the REER index, return on GOJ global bonds and growth in the unemployment rate do not have a statistically significant impact on the distance-to-default. Nonetheless, as in the case of the DTIs, the lagged dependent variable was positive and statistically significant and is also indicative of the persistence of the dependent variable in explaining its own performance.

The R-squared of the model is 62.8 per cent, and suggests that the variables employed have a strong impact in explaining the performance of the distance to default. Additionally, period dummies for the NDX period as well as the dummy capturing the periods of reform as it relates to the securities dealers business model were found to be significant.

Forecast Performance & Forecast Evaluation Results

Based on the GMM model in section 3.1, an in-sample forecast of the distance to default measure was done for the entire sample period, March 2010 to March 2016, while the out-of-sample forecast covered the period, March 2015 to March 2016. The in-sample performance statistics based on the Theil U and RSME were 0.1 and 2.0, respectively, while the respective values for the out-of-sample forecast were 0.08 and 0.8. The results also confirmed the strong predictive power of this model.

This GMM estimation techniques was also used to project the distance of default for the SDs' sector up to December 2017. For the SDs' sector, growth in the inflation rate, private sector credit growth, GDP growth and banks' interest rate spreads had a statistically significant impact on the distance to default of these institutions. Of note, growth in inflation has a negative relationship with SDs' distance to default. The forecast for the distance to default of the SDs' sector also reflected lower volatility. This forecasted performance is largely due to the projected orderly movements of the statistically significant macroeconomic variables, in particular, credit growth and GDP.

6.0 Conclusion & Policy Implications

The distance to default measure utilized in the study was useful in identifying important dates throughout the sample period, where financial institutions would have experienced increased likelihood of insolvency. The periods included the recent global crisis period and the JDX and NDX periods during 2010 and 2013, respectively.

In addition, the GMM estimation technique was also used to determine the impact of macroeconomic factors on the distance to default of DTIs and SDs. For DTIs, the findings showed that growth in the inflation rate, growth in private sector credit, banks spreads, growth in the unemployment rate and GDP had a statistically significant impact distance to default of these institutions. Regarding the securities dealers, similar macroeconomic factors were found to impact default risk. In particular, the growth in the inflation rate, GDP, and the interest rate spread between loan rates and deposit rates had a significant impact on the distance-to-default.

The models were also used to forecast the distance to default, six quarters ahead, for both the DTIs and the SDs. Forecast results will be a useful tool in predicting the likelihood of financial institution distress and incorporates investors' forward-looking expectations. Findings for both DTIs and SDs showed trend improvement for the forecast period as well as significant reduction in volatility for the projected distance-to-default. The performance in the distance to default measure for the DTIs largely reflects the movement in GDP growth rate, inflation rate and the interest rate spread variable. For the SDs, forecast results were also largely underpinned by the performance of the inflation, GDP and interest rate spreads.

The findings re-emphasize the importance of consistency between Jamaica's macroeconomic programme, which includes medium term projections of the real, fiscal, external and monetary sectors, and the solvency of the banking sector. The forecast model is also useful in examining how severe movements in macro variables will impact the likelihood of institution failure. Furthermore, closer attention to market based signals of risk, such as the distance to default, can enable regulators to be more proactive in implementing measures to limit the likelihood of a crisis or minimize its impact.

Distance to default forecasts can also be used as a forward-looking analytical tool to monitor systemic risk in the Jamaican financial system. Information contained in these forecasts can provide guidance for macro-prudential policymakers, by signaling whether there is a build-up of systemic risks. This can fuel an evaluation by the relevant authorities as to the nature these vulnerabilities and whether the implementation of macro-prudential tools are necessary to limit these risks.

Institution by institution findings can be useful in complementing work on systemically important financial institutions (SIFIs) by highlighting which of these institutions have a high degree of vulnerability to default risk. This is critical given that these institutions have a high degree of complexity and close linkages to the rest of the financial system and can pose a high risk to stability. Early signals of distress as it relates to SIFIs can aid in establishing a regulatory framework that can cope with risks arising from systemic linkages.

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Appendix:

Table A.1 Estimation Output for DTI's Distance to Default

Sample (adjusted): 2005Q2 2016Q2		
Periods included: 45		
Cross-sections included: 2		
Total panel (balanced) observations: 90		
Instrument specification: GDPGWTH INFLATGWTH SPREAD @SYSPER		
Constant added to instrument list		
Variable	**Coefficient**	**t-Statistic**
DISTANCE(-1)	0.917959	33.95348
GDPGWTH	12.42028	2.440430
REERGWTH(-2)	4.089674	1.899280
CREDITGWTH	-7.395536	-3.279189
INFLATGWTH	-1.018786	-3.727524
UR	-7.512652	-4.014348
SPREAD	0.075410	5.643401
@ISPERIOD("DECEMBER2008")	-3.912005	-4.593268
@ISPERIOD("DECEMBER2009")	0.146271	0.177412
@ISPERIOD("DECEMBER2012")	0.348913	0.720158
@ISPERIOD("DECEMBER2013")	-1.465139	-4.992281
@ISPERIOD("DECEMBER2014")	0.598372	1.669097
Effects specification		
R-squared		0.761039
J-statistic		29.61345
Durbin-Watson stat		1.669466
Instrument rank		45

Table A.2 Estimation Output for DTI's Distance to Default Out-of-Sample Forecast

Sample (adjusted): 2005Q2 2014Q4		
Periods included: 45		
Cross-sections included: 2		
Total panel (balanced) observations: 78		
Instrument specification: GDPGWTH INFLATGWTH SPREAD @SYSPER		
Constant added to instrument list		
Variable	**Coefficient**	**t-Statistic**
DISTANCE(-1)	0.991793	21.62627
GDPGWTH	18.63147	2.950299
REERGWTH(-2)	2.121872	0.738073
CREDITGWTH	-10.17660	-3.094955
INFLATGWTH	-0.390902	-1.768780
UR	-7.244699	-2.959229
SPREAD	0.044987	1.895589
@ISPERIOD("DECEMBER2008")	-4.057752	-4.755763
@ISPERIOD("DECEMBER2009")	-0.393300	-0.404295
@ISPERIOD("DECEMBER2012")	0.002545	0.005933
@ISPERIOD("DECEMBER2013")	-1.670782	-3.909016
@ISPERIOD("DECEMBER2014")	0.311304	0.767930
Effects specification		
R-squared		0.761056
J-statistic		22.80316
Durbin-Watson stat		1.707767
Instrument rank		39

Table A.3 DTI's Distance to Default Estimation - Unit Root Results for the Residual

Sample: 2004Q1 2017Q4				
Exogenous variables: Individual effects				
Balanced observations for each test				
Method	**Statistic**	**Prob.****	**Cross-sections**	**Obs**
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.73331	0.0000	2	88
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.37522	0.0000	2	88
ADF - Fisher Chi-square	40.7064	0.0000	2	88
PP - Fisher Chi-square	40.1889	0.0000	2	88
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Table A.4 Estimation Output for Securities Dealers' Distance to Default

Sample (adjusted): 2010Q2 2016Q2		
Periods included: 25		
Cross-sections included: 4		
Total panel (balanced) observations: 100		
Instrument specification: @SYSPER GDPGWTH GOJGB SPREAD INFLATGWTH CREDITGWTH		
Constant added to instrument list		
Variable	**Coefficient**	**t-Statistic**
DISTANCE(-1)	0.408153	3.514498
CREDITGWTH	-25.24730	-2.330699
GDPGWTH	-24.39533	-2.026492
INFLATGWTH(-1)	-1.117643	-2.454584
REERGWTH(-1)	-0.312925	-0.028075
GOJGB	-0.203448	-0.800967
SPREAD	0.514586	4.153419
UR	-1.848043	-0.426725
C	-1.162222	-0.501724
@ISPERIOD("DECEMBER2011")	2.091702	2.850433
@ISPERIOD("DECEMBER2013")	1.632662	1.994374
@ISPERIOD("DECEMBER2014")	3.429162	3.756840
@ISPERIOD("DECEMBER2015")	-0.512038	-0.796161
Effects specification		
R-squared		0.627477
J-statistic		16.33019
Durbin-Watson stat		1.332565
Instrument rank		25

Table A.5 Estimation Output for Securities Dealers' Distance to Default Out-of-Sample Forecast

Sample (adjusted): 2010Q2 2015Q4		
Periods included: 23		
Cross-sections included: 4		
Total panel (balanced) observations: 92		
Instrument specification: @SYSPER GDPGWTH GOJGB SPREAD INFLATGWTH CREDITGWTH		
Constant added to instrument list		
Variable	**Coefficient**	**t-Statistic**
DISTANCE(-1)	0.548918	4.969056
CREDITGWTH	-29.87750	-2.543776
GDPGWTH	7.064194	0.479160
INFLATGWTH(-1)	2.198643	1.821364
REERGWTH(-1)	-3.774137	-0.357726
GOJGB	-0.833715	-2.526563
SPREAD	0.346364	2.418892
UR	-2.697641	-0.582113
C	5.287464	1.677455
@ISPERIOD("DECEMBER2011")	0.712883	0.847213
@ISPERIOD("DECEMBER2013")	0.144404	0.152958
@ISPERIOD("DECEMBER2014")	0.691408	0.574013
@ISPERIOD("DECEMBER2015")	-0.436064	-0.591774
Effects specification		
R-squared		0.661071
J-statistic		13.59101
Durbin-Watson stat		1.556667
Instrument rank		23

Table A.6 Securities Dealers Distance to Default Estimation - Unit Root Results for the Residual

Sample: 2010Q1 2017Q4				
Exogenous variables: Individual effects				
Balanced observations for each test				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.65842	0.0001	4	96
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.68516	0.0000	4	96
ADF - Fisher Chi-square	35.2462	0.0000	4	96
PP - Fisher Chi-square	35.4061	0.0000	4	96
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Forecast Performance Results

	In-Sample Forecast	Out-of-Sample Forecast	Projections
Forecast Sample	2005Q2 to 2016Q2	2015Q2 to 2016Q2	2016Q2 to 2017Q4
Root Mean Squared Error	3.33	2.66	1.00
Mean Absolute Error	2.58	2.05	0.82
Theil Inequality Coefficient	0.21	0.14	0.06

Table A.7 GMM estimation of DTIs' Distance of Default

Table A.8 GMM estimation of Securities Dealers' Distance of Default

Forecast Performance Results

	In-Sample Forecast	Out-of-Sample Forecast	Projections
Forecast Sample	2010Q2 to 2016Q2	2015Q2 to 2016Q2	2016Q2 to 2017Q4
Root Mean Squared Error	2.04	0.76	0.95
Mean Absolute Error	1.48	0.58	0.85
Theil Inequality Coefficient	0.14	0.08	0.09

Figure A.1 DTIs' Actual, Fitted, Residual Graph

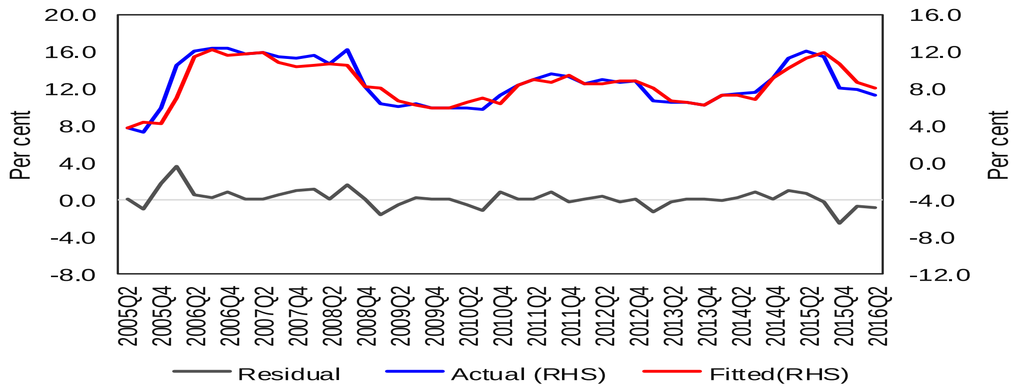

Figure A.2 Securities Dealers' Actual, Fitted, Residual Graph

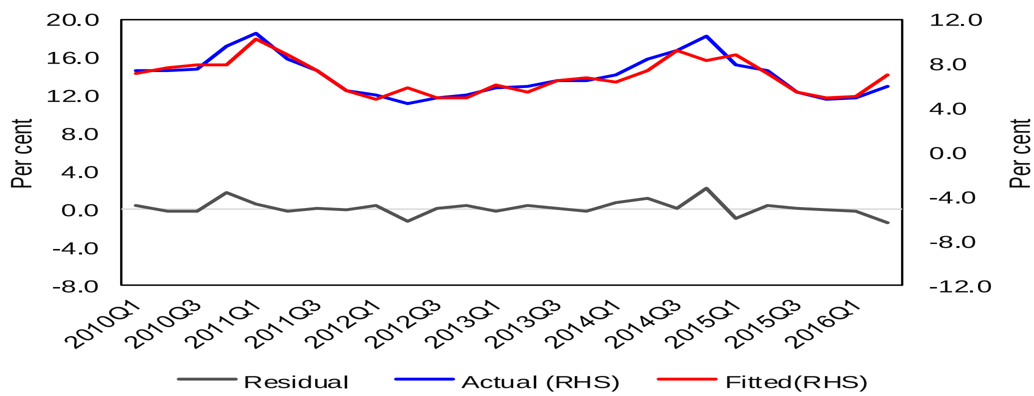

Figure A.3 DTIs' Distance to Default

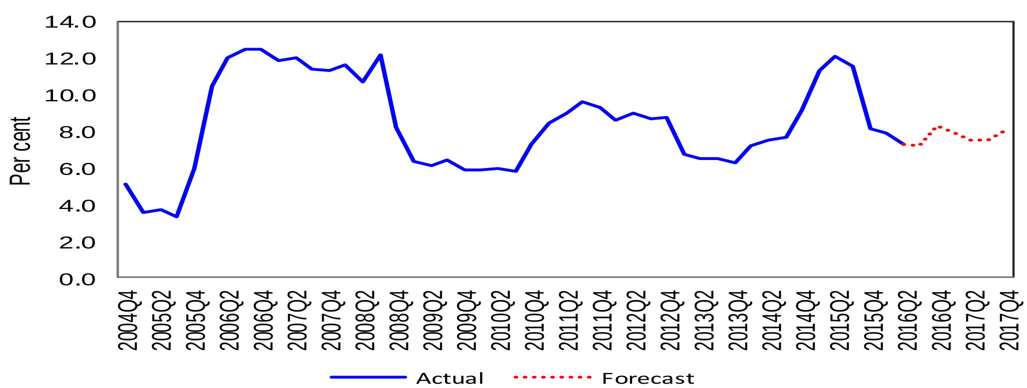

Figure A.4 Securities Dealers' Distance to Default