Credit Risk and the Macroeconomy: Evidence from Jamaican Data

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Abstract

This paper employs a panel OLS model to investigate the relationship between Jamaica's macroeconomic environment and banking sector loan quality based on monthly data over the period January 2000 to May 2012. Findings show that the unemployment rate, exchange rate and spread between loan and deposit rates are important determinants of loan quality. Value-at-Risk (VaR) estimates based on the OLS model show that NPL exposures as share of capital was in excess of 100.0 per cent for most banks as at end-May 2012 based on both a baseline and stressed scenario. The paper also investigates the presence of procyclicality in loan quality and based on the GMM technique this is confirmed for the tourism, professional services, agriculture and electricity sectors. These results suggest that policymakers will need to continue to carefully monitor credit quality in these sectors given the potential adverse implications for macro-financial stability.

Key Words: Nonperforming loans, Stress tests, Credit risk, Value-at-Risk (VAR)

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1. Introduction

Given the many banking crises over the past decades, banks and other financial institutions have experienced unprecedented levels of scrutiny from regulators and policymakers. In this regard, prudent credit risk management has remained a key area of emphasis for regulators, particularly in a context where the role of banks remains fundamental in financing and facilitating economic activity. Studies have shown that weakness in loan quality has the potential to compromise the effectiveness of the transmission mechanism and by extension, monetary policy. Furthermore, if weakness in credit quality is procyclical or results in amplifying business cycle fluctuations, this can feed through to macroeconomic instabilities and lead to further deterioration in financial system soundness.

In a recent study on Jamaica, Tracey (2006) examined the impact of the country's macroeconomic environment on banking sector loan quality. Specifically, the paper employed a VAR framework to investigate the causal relationships between economic variables and credit quality by tracing out the loan quality time paths in response to macroeconomic innovations. In addition, sensitivity and scenario-based stress testing was applied to examine the impact of these variables on the loan portfolio quality of banks. The results suggest that both monetary and structural influences play a role in accumulating non-performing loans. Stress testing results also revealed that increases in prices and real interest rates are relatively good early warning signals of loan quality depletion.

This paper employs an OLS model to investigate the relationship between Jamaica's macroeconomic environment and banking sector loan quality based on data over the period January 2000 to May 2012. The model was also utilized to compare the performance in loan quality using a baseline and stressed-scenario for the macro economic variables employed. These coefficient estimates were also utilized in a credit Value-at-Risk (VaR) framework, which evaluates banks' credit losses using NPLs as a proxy for default, to produce baseline and stressed VaR estimates.[2] Auxiliary results of the study show that exchange rate growth, loan-deposit interest rate spread and unemployment are important determinants of the performance in banking sector loan quality.

The paper also adds to the existing literature for Jamaica by investigating whether there is evidence of procyclicality of banking system loan quality for different economic sectors. Against this background, the study applies the GMM technique to banking system panel data for the period January 2000 to March 2012 primarily to estimate the sensitivity of banking system non-performing loans (NPLs) ratio to GDP growth across different economic sectors.[3,4] Findings from the panel GMM framework confirm the presence of strong procyclicality of credit behavior and show a negative relationship between NPLs

[2] The paper employs a similar approach to that used by Vasquez et. al (2010). VaR refers to the maximum loss not exceeded with a given probability (confidence interval), over a given period of time.
[3] Loan quality is defined as the ratio of non-performing loans to total loans in a bank's lending portfolio.
[4] The data is retrieved from the Bank of Jamaica which is the regulator of banks in Jamaica.

and GDP growth for the agriculture, electricity and manufacturing sectors. The results from the baseline VaR show loan quality estimates in a range of 27.0 per cent to 39.0 per cent while stressed VaR estimates are in a range of 28.0 per cent to 40.0 per cent and these findings are based on data for the period January 2000 to May 2012. In addition, VaR exposures as a share of capital show that these ratios would be in excess of 100.0 per cent for all banks at end-May 2012.

The paper is organized as follows. Section 2 presents the review of existing literature on the relationship between credit quality and the macroeconomy while section 3 provides an empirical framework with a description of the data and methodology to be used in the model. Section 4 presents and discusses the results of the model and section 5 concludes the paper and provides policy implications and recommendations.

2. Literature Review

A large body of research exists which empirically investigates the dynamic relationship between macroeconomic factors and the quality of loan portfolios. In a recent study of non-performing loans and bank stability in the Barbados banking sector, Guy and Lowe (2011) used a series of bank idiosyncratic variables and macroeconomic factors to explain non-performing loans. They used panel data techniques to examine the relationship at the aggregate as well as the individual bank level. The findings of the stress testing of bank stability and NPL forecasts suggested that both macro and micro variables are critical to understanding the behaviour of NPLs. Moreover, while loan delinquency is expected to remain relatively high in the near future, the banking system remains resilient to significant shocks in the real economy.

Using quarterly bank level data of disaggregated loans for business and consumer credit, Vasquez et al. (2010) proposed a model to conduct macro stress tests of credit risk for the Brazilian banking system based on scenario analysis.[5] They found strong procyclical behaviour of credit quality with a lag response up to three quarters. The stress test framework presented in their paper comprised three components that were integrated in sequence. First, a macroeconomic model was used to simulate distressed, internally consistent, macroeconomic scenarios projected over two years. Then a microeconomic model was employed to assess the sensitivity of loan quality to macroeconomic conditions with the help of dynamic panel econometrics. Finally, the resulting distributions of the NPLs for each bank and credit type as a proxy for the distribution of distressed PDs are combined with data on the credit exposures of individual banks to compute a credit VaR using the Credit Risk+ approach with programs developed by Avensani et al. [2006]. The results showed differences in the persistence of NPLs across credit types and in their sensitivity to economic activity.[6] Notably, the Brazilian banking system appeared to be well equipped to absorb the credit losses associated with the scenarios analyzed without threatening financial stability.

[5] Scenario analysis commonly focuses on estimating what a portfolio's value would decrease by if an unfavorable event, or the "worst-case scenario", were realized

[6] See Vasquez et al (2010).

Podlich et al. (2010) explored stress testing methodology for the Kazakh banking system using four Kazakh institutions.[7] They applied different methodologies for developing stress testing tools : "bottom-up" and "top-down" approaches. The bottom-up approach involves the distribution of questionnaires to Kazakh banks asking them to calculate their own risk positions under stress. The results from this approach showed that banks tend to underestimate the decline in real estate prices and to overestimate currency devaluation. The top-down approach applied methodologies for portfolio and macro stress tests to raw data collected by the Financial Services Authority and estimated the impact of the external macroeconomic shocks on the expected losses of the financial institutions. From the portfolio stress test, the change in the expected losses under stress ranged between 34.0 and 86.0 per cent relative to the unconditional expected losses. The macro stress test found an average change of 26.0 per cent in the ratio of bad loans to total loans under stress scenario one and an average change of 80.0 per cent under scenario two relative to the baseline scenario.[8] Wong et al. (2008) developed a framework for stress-testing the credit exposures of Hong Kong's retail banks to macroeconomic shocks. This was done to assess the vulnerability of banks' overall loan portfolios and mortgage exposures in a financial system that could lead to systemic problems. They introduced a variety of shocks individually into the framework for the tests and the results showed that even for the value-at-risk (VaR) at the confidence level of 90.0 per cent banks would continue to

[7] These participating Kazakh institutions are the National Bank of Kazakhstan (NBRK), Financial Supervisory Agency (FSA), the National Analytical centre of the Government and the National Bank of Kazakhstan.

[8] The baseline analysis uses actual data for the period 1994 to 2007. Scenario 1 is based on a decline in GDP and falling gas and oil prices as experienced during 2008 and assuming a constant ratio of credit to GDP and constant real house prices. Scenario 2 is also based on the 2008 period but uses a 1 standard deviation shock to the values of the variables during this period.

make a profit in most of the stressed scenarios. This suggests that the credit risk of the Hong Kong banking sector was moderate for the review period.

Zeman and Jurča (2008) used a vector error correction (VEC) model to project the impact of a simulated slowdown in the Slovak economy on the Slovak banking sector, i.e. on credit, interest rate and exchange rate risk exposures. The VEC allowed them to estimate the aggregated impact of the credit risk, interest rate risk and the exchange rate risk. Their results showed that significant slowdown of the GDP growth would not considerably threaten the Slovak banking sector provided that there is adequate response of the monetary policy.

Using data on industry-specific corporate sector bankruptcies over the time period from 1986 to 2003, Virolainen (2004) estimated a macroeconomic credit risk model for the Finnish corporate sector. The sample period includes a severe recession with significantly higher-than-average default rates in the early 1990s. The results imply that there was a significant relationship between corporate sector default rates and key macroeconomic factors including GDP, interest rates and corporate indebtedness. The estimated model was used to analyze corporate credit risks conditional on current macroeconomic conditions. The paper also presented some examples of applying the model to macro stress testing and the results of the stress tests suggested that Finnish corporate sector credit risks were fairly limited in the current macroeconomic environment.

3. Data & Empirical Framework

3.1 Data

This paper employs monthly bank-specific and macroeconomic data over the period January 2000 to May 2012. Bank-specific data include the overall loan quality ratio, which is measured as non-performing loans (NPLs) as a share of total loans, as well as the loan quality ratio by economic sector for each bank.[9] This data was captured for 13 banks and covered institutions in the commercial banking and building societies sector as well as FIA Licensees. An unbalanced panel was used since some institutions either went out of operation or were merged during the sample period. Observation of sectoral level loan quality data for the sample period showed that the highest average rates of growth in NPLs were associated with the construction, distribution and tourism sectors as well as personal loans. In general, there was deterioration in loan quality over the last four years of the estimation period. This deterioration in credit quality was fuelled by the impact of the global financial crisis on the macroeconomic and financial environment.

The macroeconomic variables included in the model are real GDP growth, inflation rate, exchange rate, the spread between weighted average loan and deposit rates and the unemployment rate for the estimation period.[10] In addition, given that GDP and

[9] NPLs is defined as principal and interest payments outstanding 3 months and over.
[10] The ratio of non- performing loans to total loans for the different sectors is weighted using the fraction of the total assets in the entire banking system (depository institutions) that each sector holds.

unemployment data are only available on a quarterly basis these values were interpolated using the quadratic match approach to obtain monthly values for the estimation period.

3.2 Empirical Framework

The framework employed to evaluate the relationship loan quality and selected macro-economic variables is based on the linear form of the general model by Vasquez et al. (2010). The model is outlined in equation (1):

$$NPLs_{it} = k_{it} + \beta' Y'_{it} + \alpha x_{it} + \varepsilon_{it} \tag{1}$$

where i = 1…, N, where i represents the individual banks; t = 1…., T, where t represents the time dimensions.

k = a constant

β' = (1x5) matrix of estimated coefficients

$$Y' = \begin{bmatrix} \text{int} \\ \text{inf} \\ \ln(ex) \\ \Delta \ln(rGDP) \\ unem \end{bmatrix}$$

α = coefficient of the dummy variable for unemployment

x = dummy values for unemployment

int = interest rate spread for the system of DTIs (by sectors)

inf = inflation rate

ex = exchange rate

rGDP = real gross domestic product

unem = unemployment rate

ε = error term reflecting other factors that affect Y

Similar to Greenidge and Grosvenor (2010), *a priori* expectations point to an inverse relationship between loan quality and real GDP growth, while a positive relationship is expected between loan quality and the spread between loan and deposit rates. This is expected as increases in economic growth is anticipated to lead to improvements in borrowers' ability to repay loans while higher interest rate spreads restricts individuals' ability to make their contractual payments. Additionally, the sensitivity of nonperforming loans to the rate of unemployment is anticipated to be positive given that as more persons become unemployed this is expected to adversely impact these individuals' capacity to repay their debt. Based on the literature, *a priori* expectations as it relates to the impact of rising prices and exchange rates on loan quality may be ambiguous.

The model is estimated using panel OLS. A diagnostic check is carried out on each variable employed to observe the trend in each series over the sample period. The real GDP series was de-seasonalized and log-linearized and then first differenced to achieve stationarity. The exchange rate series was stationary but these values were logged to further compress the series. The inflation rate and interest rate spread series for the banking system also proved to be mean reverting sequences and therefore stationary.[11]

[11] Appendix 1 shows trends in the NPLs ratio was well as the selected macroeconomic variables. Of note is that for the unemployment data there was an upward trend as at late 2008 however there were also obvious breaks in the series particularly in period 2003. Additionally, the ratio of NPLs for the banking sectors and by extension the entire system

The unemployment series illustrates uneven structural breaks which were treated with the use of dummy variables using one to represent the period of the break and zero otherwise. The tables presented in the appendix show the descriptive statistics of these macroeconomic variables and the ratio of NPL to loans for the banking sub-sectors as well as the system of DTIs for the sample period.[12]

The model was also re-estimated, to create stressed coefficient estimates, after simulating the performance in each variable during the May 2008 – May 2009 global crisis period for the final year of the sample, specifically over the May 2011 – May 2012 period. Coefficient estimates from the models above served as inputs in producing baseline and stressed VaR estimates based on data for the period January 2000 to May 2012.

3.2.1 The Credit Value at Risk (VaR) Model

The historical VaR approach was used to compute baseline and stressed credit VaR estimates for the entire banking system as well as the individual banks. This is accomplished by utilizing the regression results from the baseline and stressed models estimated above to produce the distribution of NPLs for each bank. The credit VaR model produces the worst expected loss in terms of NPLs over a specified time period, at a given confidence level, under normal market economic conditions. A 95.0 per cent confidence interval was applied using monthly data over a 149 month period.

of DTIs exhibited a general U-shape implying that the NPLs were high between 2000 and 2001 but fell and started deteriorating again as at approximately 2008 until present.

[12] See Tables A and B

3.2.2 GMM estimation

The model specified in Equation (1) was also re-estimated using GMM estimation technique in order to investigate the degree of procyclicality for bank-by-bank loan quality of different economic sectors. This method of estimation was employed partly as a robustness check for the original model and also because it is useful in obtaining efficient and unbiased estimates in dynamic models of this nature.

One main advantage of this method is that it aids in obtaining consistent estimates for the parameters of interest when the persistence of the dependent variable needs to be explicitly modeled without requiring strong hypotheses about the exogeneity of the regressors (see Bochina, 2008). It is possible to obtain consistent and efficient estimates by using all available lagged values of the dependent variable plus lagged values of the exogenous variables as instruments.

4. Empirical Results

4.1 Panel Results

Table 1: OLS Panel Results for Baseline Estimation

	All Banks			
Y=NPLs	OLS	std error	t-stat	P-Value
INT(-1)	0.0116**	0.000054	2.133438	0.033
INF	0.0168	0.000262	0.641634	0.5212
LNEX(-1)	0.00347***	0.000936	3.704908	0.0002
DLNRGDP(-4)	-0.012148	0.021517	-0.564569	0.5724
UNEM(-1)	0.0677*	0.000379	1.786659	0.0742
DUMM_UNEM	5.09E-06	0.000969	0.005255	0.9958
NPLS(-1)	0.958855***	0.004873	196.783	0.0000

*, **, *** Significant at the 10%, 5% and 1% respectively

Observations	1937
R-squared	0.96
Durbin-Watson	2.06

The estimation results show that the model has good explanatory power with an overall R-squared of 0.96 (see ***Table 1***). One key finding of the model is the positive and significant relationship between the loan quality ratio and the interest rate spread variable with a one month lag. This finding is consistent with *a priori* expectation that increases in the interest rate spread should lead to deterioration in loan quality. The results also show that the inflation rate is not important in explaining movement in the loan quality ratio. The coefficient on real GDP growth is insignificant indicating that GDP is not an important determinant in explaining the performance in credit quality. Furthermore, the findings show a positive and significant relationship between the loan quality ratio and the exchange rate. This result indicates that depreciation in the exchange is expected to contribute to deterioration in loan quality and may reflect increasing difficulty of borrowers in foreign currency to service debt obligations, particularly those debtors which are non-foreign currency earners. Finally, consistent with *a priori* expectations, the unemployment rate is positively related to the loan quality ratio, albeit weakly significant at the 10.0 per cent level with a one month lag.

Results from the VaR model, using the above baseline model, reflect estimates in a range of 27.0 per cent to 39.0 per cent for the loan quality ratio at end-May 2012 for the 13 banks examined (see ***Figure 1***). In addition, results for the commercial banks and building societies sector show higher VaR estimates, reflecting greater sensitivity of these institutions to the macroeconomic environment (see ***Table D in Appendix***).[13]

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[13] Table D presented in appendix shows results for all 13 institutions in the different sectors.

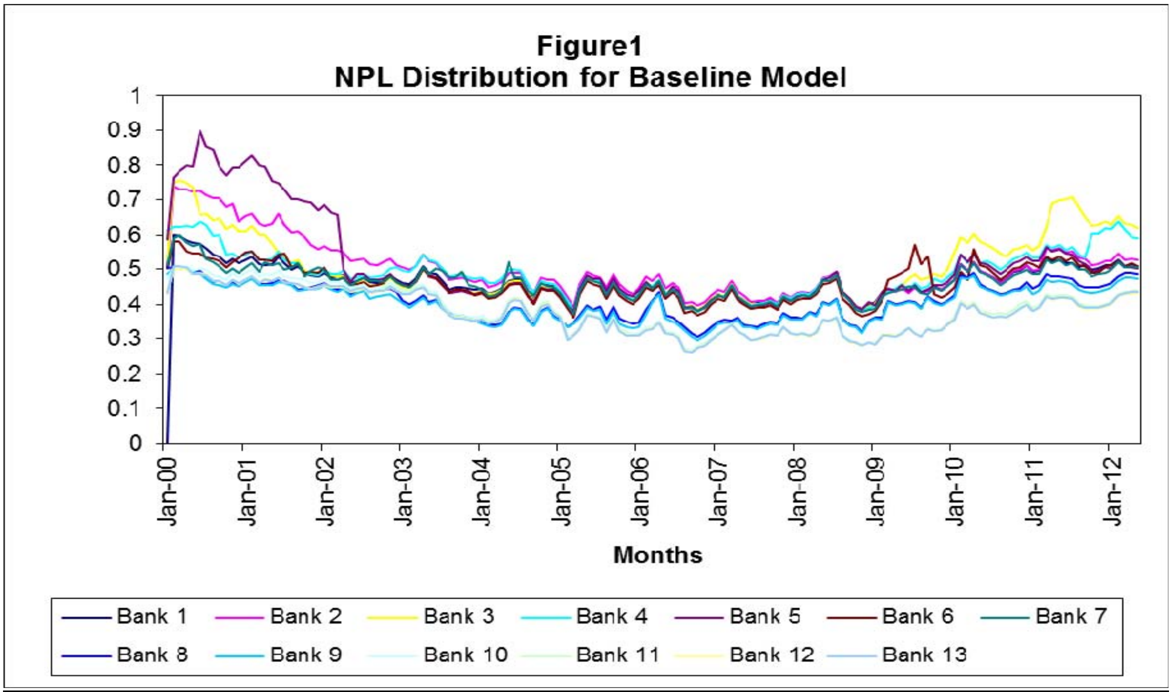

Figure1
NPL Distribution for Baseline Model

4.1.2 Stress Test Results

Table 2: OLS Panel Results for Distressed Scenario Estimation				
	All Banks			
Y=NPLs	OLS	std error	t-stat	P-Value
INT(-1)	0.0125**	0.000059	2.124740	0.033700
INF(-1)	-0.0038	0.000297	-0.127704	0.898400
LNEX(-1)	0.004335***	0.001049	4.131665	0.000000
DLNRGDP(-1)	-0.028666	0.023770	-1.205979	0.228000
UNEM(-1)	0.0739*	0.000443	1.669590	0.095200
NPL(-1)	0.974235***	0.004920	198.035300	0.000000
DUMM_UNEM	-0.000030	0.001049	-0.028943	0.976900

*, **, *** Significant at the 10%, 5% and 1% respectively
Observations 1937
R-squared 0.95
Durbin-Watson 2.23

The R-squared for the stressed model is 0.95 and is generally consistent with the value for the baseline model. In addition, the findings of the stressed model as it relates to the sign and significance of the variables is also consistent with the baseline scenario. Nonetheless, there is an increase in the coefficients of most variables under the stressed scenario, with the exception of the real GDP and inflation variables (see ***Table 2***). The results of the stressed historical VaR show higher estimates in a range of 28.0 per cent to 40.0 per cent for the loan quality ratio for the banks examined (see ***Figure 2***).

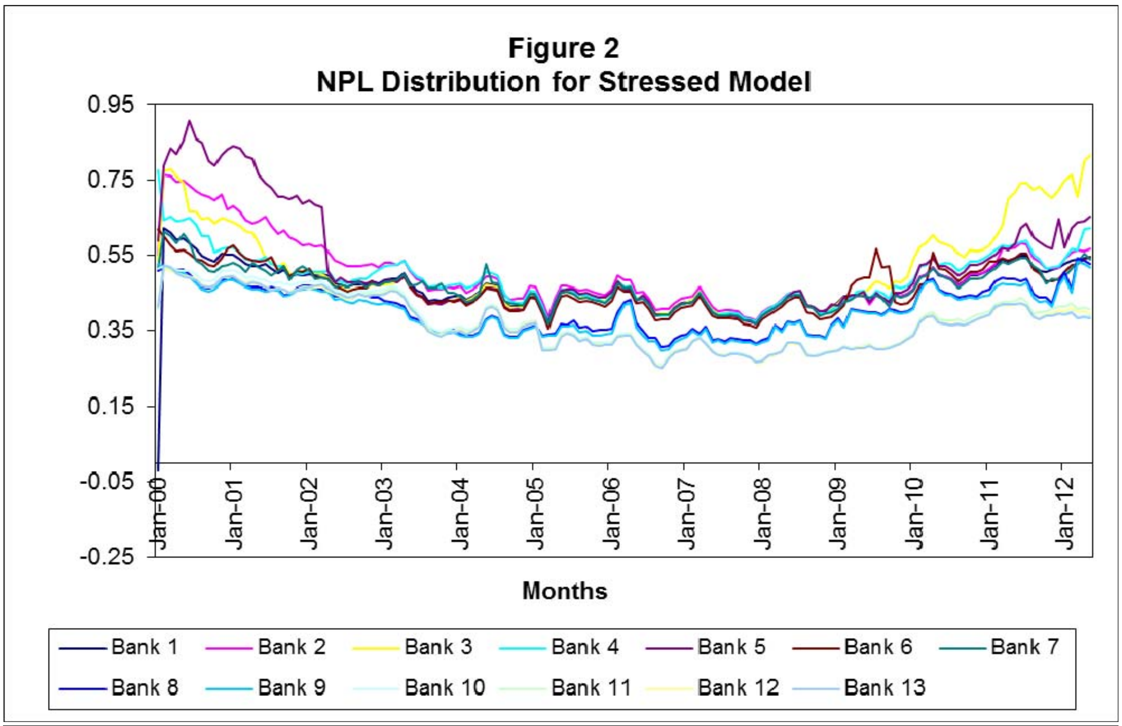

Figure 2
NPL Distribution for Stressed Model

4.1.3 GMM Results:

Table 3 : GMM Estimation Results of Microeconomic Model												
	Economic Sectors											
	Agriculture		Electricity		Personal		Professional		Tourism		Transportation	
NPLs (Y)	GMM	std error	GMM	std error	GMM	std error	GMM	std error	GMM	std error	GMM	std error
LNEX(1 to 6)	0.001	0.009	-0.003	0.003	-0.211***	0.067	-1.549***	0.466	-0.32	0.024	-0.006	0.002
INFL(1 to2)	0.018***	0.004	0.000	0.000	-0.052***	0.013	-0.677***	0.251	0.055	0.097	-0.001***	0.000
LNRGDP(1 to 8)	-0.288***	0.056	-0.015*	0.009	0.088***	0.017	-37.975*	21.928	-5.276***	2.111	0.065***	0.021
INT(0 to1)	0.000	0.001	0.001***	0.000	-0.001	0.023	-0.087*	0.050	-0.083	0.190	0.000***	0.000
DUNEM(1 to 2)	0.059***	0.024	0.010***	0.002	-0.197	0.288	-1.681	1.351	1.166	1.455	0.021***	0.006
Y(-1)	0.752***	0.015	0.823***	0.035	0.945***	0.010	0.840***	0.013	0.932***	21.468	1.000***	0.025
Effects Specification												
R-Squared	0.58		0.80		0.93		0.74		0.93		0.83	
Sargan Stat	0.75		0.79		0.83		0.81		0.53		0.89	
Instrument rank	11		8		10		11		8		10	

Results from the GMM model show the relationship between banks' credit quality ratio by economic sector and the selected macroeconomic variables (see ***Table 3***). The key variable of interest is the relationship between loan quality and real GDP growth, which will indicate whether there is evidence of procyclicality. The instrumental variables used in this model were lagged values of the dependent and independent variables as well as period instruments. The J-test rejects the alternative hypothesis at the 0.95 quantile of the $\chi^2_{L-\ell}$ distribution for the listed sectors and therefore implies that each model is valid and the data comes close to meeting its restrictions. Of the sectors examined, four showed a significant inverse relationship as it relates to loan quality and real GDP growth. These are the agriculture, electricity, water and gas, professional services and tourism sectors. These results constitute evidence that these sectors are procyclical or, more specifically, that deterioration in the loan quality of these sectors will result in amplifying business cycle fluctuations or reinforce the state of an economic cycle. These sectors are strong contributors to GDP and hence have important implications for macro-financial stability. Results also show a positive and significant relationship between loan quality and real GDP growth for personal loans and loans to the transportation sector.

5. Conclusion and Implications

The key objective of the paper is to determine the implications of the macroeconomic environment for credit risk management in the Jamaican banking sector. Results from both the baseline and stressed panel OLS models show that the spread between loan and deposit rates, the unemployment rate and the exchange rate are important determinants of credit quality.

The paper also investigated the presence of pro cyclicality in banking system loan quality ratios for different economic sectors using the GMM technique. The estimated model provided evidence of procyclicality for agriculture, electricity, water & gas, professional services and tourism sectors. One implication of this is that banks with more exposure to these sectors are likely to experience greater credit losses under scenarios of distress. Another implication of this finding is that given that these sectors are strong contributors to GDP, deterioration in loan quality in these sectors may worsen the existing state of an economic cycle, which may present challenges to policymakers in maintaining macro-financial stability. Against this background, it will be important for policymakers to continue to carefully monitor credit quality in these sectors.

The results from the baseline VaR show loan quality estimates in a range of 27.0 per cent to 39.0 per cent, while stressed VaR estimates are in a range of 28.0 per cent to 40.0 per cent as at end-May 2012 and based on data for the period January 2000 to May 2012. VaR results also show that NPLs as a share capital for most banks is in excess of 100.0 per cent as at end-May 2012. Further work could also be done to determine the VaR estimates for the different economic sectors under normal and stress conditions.

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Appendix 1

Table A: Descriptive Statistics of the ratio of non-performing loans to total loans by banking sector and the overall system of DTIs.

	NPL_BS	NPL_CB	NPL_MB	NPL_DTIs
Mean	0.011	0.037	0.004	0.052
Median	0.010	0.027	0.003	0.040
Maximum	0.017	0.112	0.014	0.130
Minimum	0.005	0.014	0.002	0.020
Std. Dev.	0.004	0.025	0.003	0.030
Skewness	0.129	1.358	2.151	0.995
Kurtosis	1.414	4.022	6.046	2.937
Jarque-Bera	16.027	52.272	172.456	24.586
Probability	0.000	0.000	0.000	0.000
Sum	1.574	5.533	0.637	7.800
Sum Sq. Dev.	0.002	0.095	0.001	0.133
Observations	*149*	*149*	*149*	*149*

Table B: Table showing the Descriptive statistics of the macroeconomic variables

	INT	INF	EX	RGDP	UNEM
Mean	9.681621	0.840981	66.65176	60686.47	4.094034
Median	9.940000	0.761182	65.49510	61081.68	3.998765
Maximum	16.22000	3.272976	89.75000	64746.31	5.477778
Minimum	1.470000	-0.68525	42.09000	55231.63	2.920988
Std. Dev.	3.517808	0.713463	15.42510	2392.872	0.641021
Skewness	-0.38279	0.889342	0.072850	-0.37016	0.227778
Kurtosis	2.218663	4.198142	1.784483	2.316623	1.973131
Jarque-Bera	96.57737	371.1985	120.9585	81.92603	101.8531
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	18753.30	1628.980	129104.5	1.18E+08	7930.144
Sum Sq. Dev.	23957.95	985.4813	460639.5	1.11E+10	795.5180
Observations	*1937*	*1937*	*1937*	*1937*	*1937*

Table C:Panel Unit Root Results

Variables	**Levin, Lin& Chu**	**Breitung**	**Im, Pesaran and Shin**	**ADF-Fisher**	**PP-Fisher**
Nonperforming Loans (NPL)	-3.02225***	3.96996	-1.33823*	43.0658**	66.5937***
Inflation Rate	-15.0748***	-9.84277***	-9.81568***	141.95***	421.464***
Interest Rate	2.22285	1.46875	-0.39228	24.9874	67.0137***
Real GDP Growth	-19.8719***	-11.8915***	-26.926***	562.924***	308.446***
Exchange Rate	-0.66387	0.33809***	-1.90362**	31.1091	8.22335
Unemployment Rate	-0.05784	2.93008	3.28771	4.11366	1.26303

N.B: *, **, and *** denote significance at 1%, 5% and 10% respectively.

Table D: Table showing the VaR values for the individual DTIs in the banking system.

Institutions	**Baseline VaR**	**NPL/Capital(%)**	**Stressed VaR**	**NPL/Capital(%)**
Bank 1	37.9%	219.25	39.3%	227.22
Bank 2	38.7%	164.93	40.1%	170.88
Bank 3	37.9%	198.10	39.5%	206.27
Bank 4	37.8%	147.93	39.4%	154.04
Bank 5	37.6%	100.29	39.0%	104.02
Bank 6	36.3%	32.84	38.0%	34.34
Bank 7	37.4%	80.42	39.0%	83.83
Bank 8	31.8%	97.46	32.6%	100.01
Bank 9	31.5%	131.96	32.0%	133.97
Bank 10	27.5%	100.23	28.5%	104.08
Bank 11	27.3%	107.40	28.3%	111.27
Bank 12	27.3%	128.78	28.2%	133.18
Bank 13	27.3%	167.97	28.3%	174.20

Charts:

Time Graphs Plotting Selected Macroeconomic Variables and Ratio of Nonperforming Loans to Total Loans (2000M1 – 2012M5)

Figure 1: Real GDP Growth and Total DTIs NPL Ratio

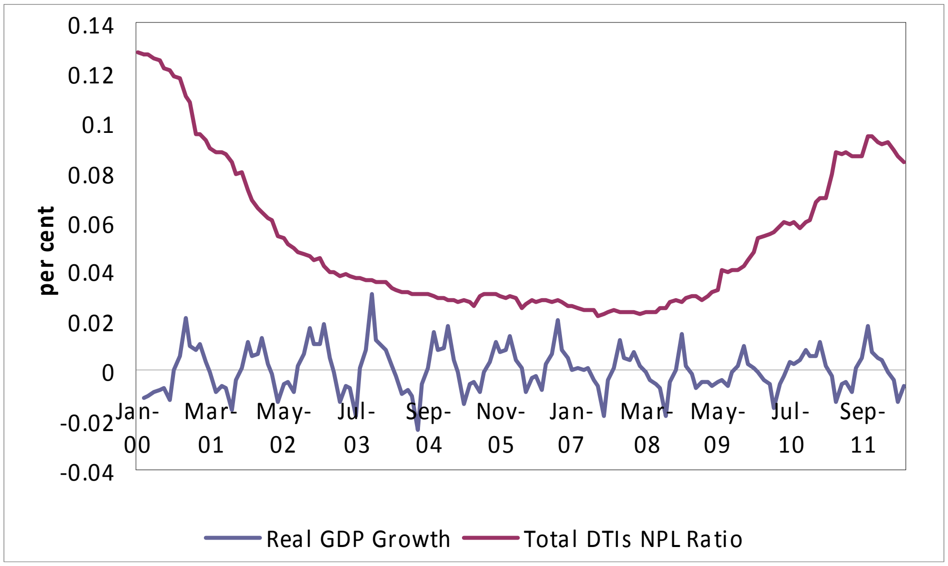

Figure 2: NPL Ratios for Individual Banking Sectors

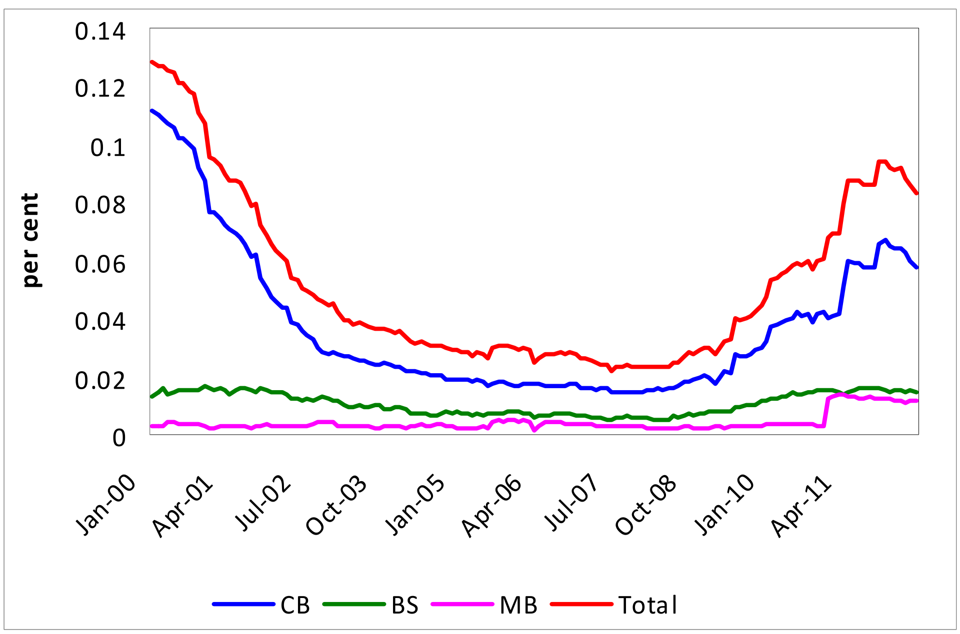

Figure 3: Interest Rate Spread for system of DTIs and the Individual Banking Sectors

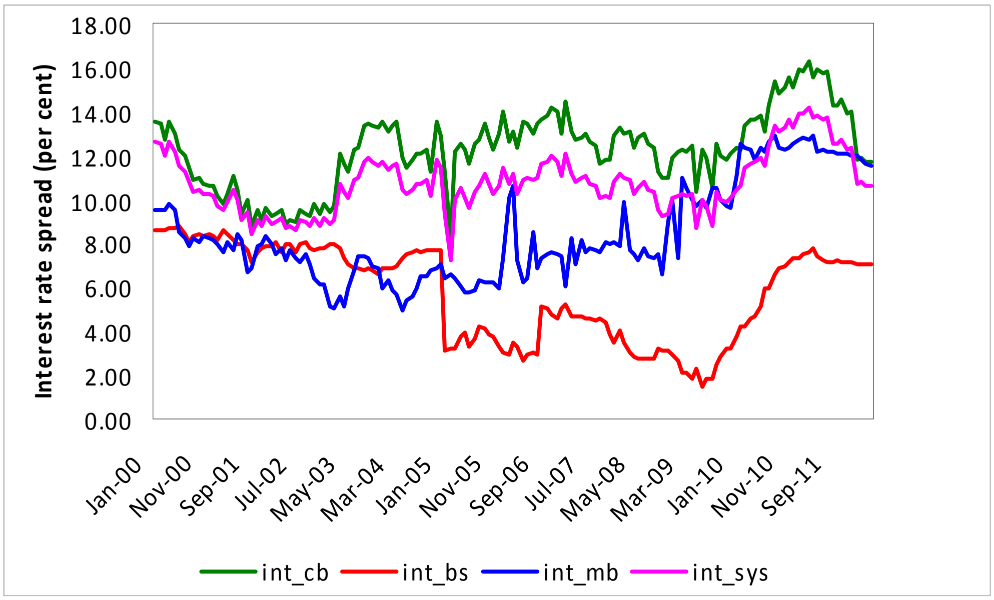

Figure 4: Exchange Rate

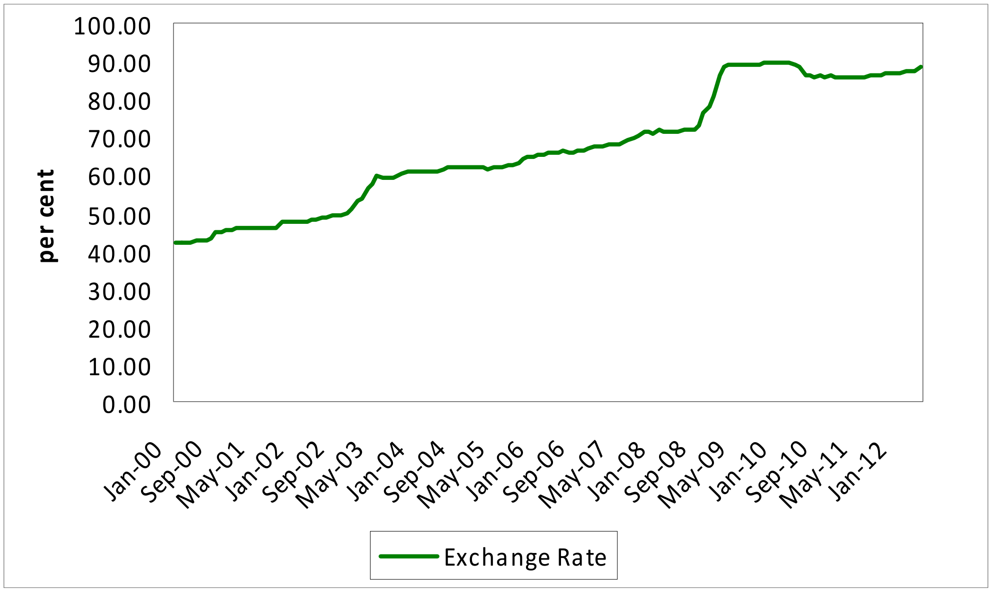

Figure 5: Unemployment Rate

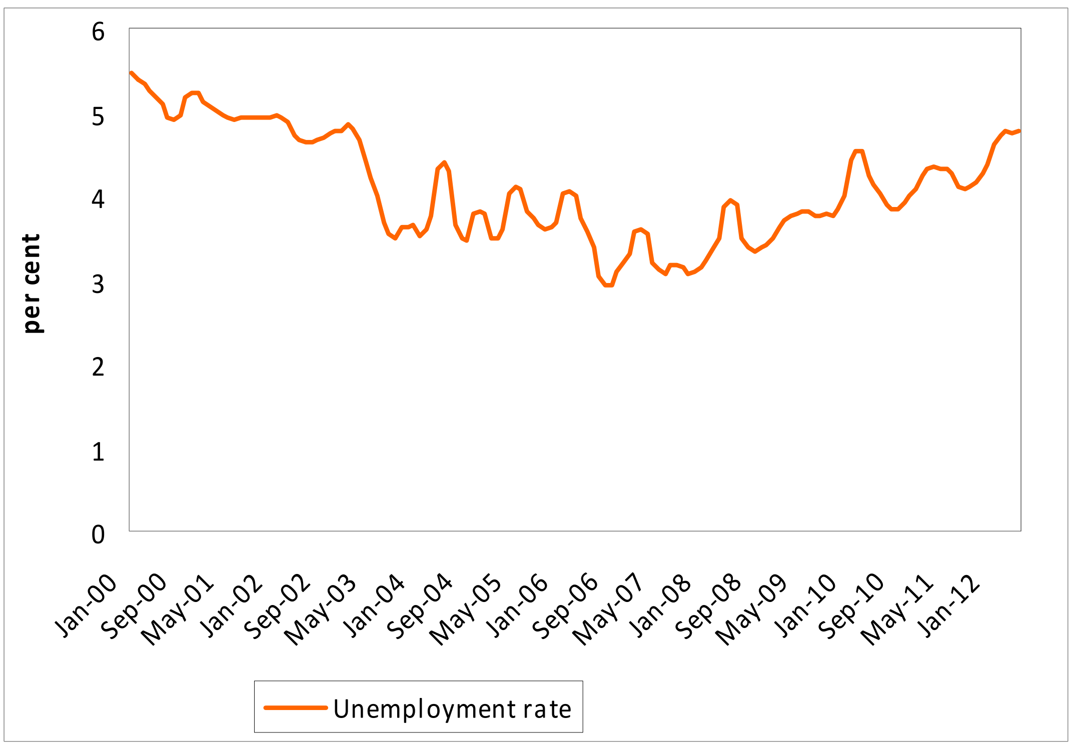

Figure 6: Percentage Change in CPI (Inflation Rate)