What Drives Potential Loan Losses in Jamaica?

Katherine Bell
Financial Economist
Bank of Jamaica

September 2022

Abstract

Banks play a central role in a country as they intermediate the flow of credit to the real economy, thereby facilitating long-term economic growth. However, large volumes of bad loans (loan losses) can impair long-term economic growth and lead to greater uncertainty, resulting in elevated financial stability risks. This paper employed the Autoregressive Distributed Lag (ARDL) model to determine the main drivers of loan losses in Jamaica. This was done by assessing the relationship between the non-performing loans ratio for deposit-taking institutions and various bank-specific and macroeconomic variables using quarterly data from 2006 to 2022 quarter one. The results showed that both bank-specific and macroeconomic factors influenced the NPL ratio significantly. In particular, capital adequacy, return on equity, growth in non-interest income, lending interest rates as well as the inflation rate and GDP growth rate all had a significant impact on the NPL ratio. The outcomes of this research emphasize the importance of banks managing risks to their balance sheets and financial performance by monitoring excess capital, profitability levels and continually stress-testing their credit portfolios. In addition, it’s also important for regulators to maintain a healthy macroeconomic environment, develop macroprudential tools to tackle the build-up of future NPLs as well as implement policies that disincentivized banks from taking on excessive risks.

1. Introduction

Credit risk can be considered the dominant source of risk for banks (Pesaran et al, 2006). Therefore, understanding and monitoring the factors that influence the behaviour of loan portfolios is important in minimizing loan losses. This is essential given a portfolio's susceptibility to macro-financial system shocks. The COVID-19 pandemic is one such shock that has caused increasing concern among regulators about future loan losses and their likely effects on systemic risk. Moreover, this is in a context where credit risk has been found to respond to macroeconomic conditions, with strong feedback effects from the real economy to the banking system (Moudud-Ul-Huq, 2020; Pesaran, Schuermann, Treutler & Weiner, 2006). The ability to identify the unique factors that affect a loan portfolio, is therefore important in strengthening the financial system and, by extension, the real economy.

One of the main measures of credit risk or potential loan losses is the ratio of non-performing loan (NPLs) to total loans.[1] Of note, during periods of economic downturns, such as the occurrence of a pandemic, NPLs tend to increase as a result of firms' and households' financial distress (De Lis, Pagés, & Saurina, 2001). For Jamaica, the numerous lockdowns and restrictions which began in March 2020 have led to a contraction of the economy, with real gross domestic product (GDP) projected to have fallen within the range of 10.0 per cent and 12.0 per cent for FY 2020/21 (Bank of Jamaica, 2020). Consequently, Jamaica's NPLs increased by 41.9 percent at end-2020 relative to the previous year, however a major deterioration in the NPL ratio was mitigated by the extension of loan moratoriums from lending institutions.[2] Despite this, the persistence of unfavourable economic conditions and its impact on the financial sector means that movements in the NPL ratio must be closely monitored and well understood because of its susceptibility to further deterioration. Increases in the NPL ratio, especially if widespread and prolonged, can impair long-term economic growth and lead to greater uncertainty resulting in elevated financial stability risks.

The purpose of this research therefore, is to identify the specific variables that have significant associations with the NPL ratio. This was done by using time series data to assess the relationship

[1] A loan is classified as NPLs when the payments of interest and principal are past due by 90 days or more.
[2] The ratio of NPLs to total loans for deposit taking institutions (DTIs), only marginally increased by 0.6 percent to 2.8 percent for 2020 when compared to 2019 (Bank of Jamaica, 2020)

between the NPL ratio for deposit-taking institutions and several macroeconomic and bank-specific variables in Jamaica for the period 2006 to 2022 quarter one.[3]

The ARDL model was chosen because of its robustness in analyzing variables with mixed orders of integration, ability to separate the short-run and long-run dynamics in the data and its efficiency in working with smaller data sets. The remainder of the paper is organized as follows: Literature Review, A brief look at Jamaica's NPL ratio, Data and Methodology, Results and Conclusion and Policy Implications.

2. Literature Review

Several studies have shown that macroeconomic variables as well as bank-specific variables, or a combination of both, are factors that influence loan losses. In particular, the literature highlights that NPLs tend to be higher in times of adverse macroeconomic conditions (Ari, Chen & Ratnovski, 2019). The variables related to these adverse conditions that were, most commonly, found to have a negative impact on NPLs were: decreases in real GDP growth, exchange rate depreciations, increases in interest rates, increases in unemployment and inflation, declines in stock prices, and high levels of debt.[4]In relation to Jamaica, Senior (2015) found that lagged values of GDP growth was significant and negatively related to commercial bank NPLs and that based on projected improvements in GDP, forecasts showed a general decline in commercial banks' NPLs up to March 2018.

A risky loan portfolio is another factor that is generally marked by high NPL levels (Makri et al, 2014); this link was apparent in the literature that identified several bank-specific factors as having influence over NPLs. Notably, De Lis, Pagés, & Saurina (2001) and Keeton & Morris (1987) found in Spain, and the United States (from 1978-1985) respectively, that the variation in loan losses

---

[3] Bank- specific variables are variables that are unique to the banking system. These include variables that deal with aspects of capital adequacy, liquidity, loans, deposits and profitability, among other variables.
[4] See Ari, Chen & Ratnovski, 2019; Beck, Jakubik & Piloiu, 2013; De Bock & Demyanets, 2012; see Espinoza & Prasad, 2010; Jokivuolle, Pesola, & Virén, 2014; Makri, Tsagkanos, & Bellas,2014; Messai & Jouini, 2013; Nkusu, 2011; Zheng et al, 2020).

across banks in the same market was accounted for mainly by the variance in risk appetites across institutions. These risks tended to feed through banks' profitability and capital levels which were most commonly represented by ratios such as return on equity (ROE) or assets (ROA) and capital adequacy ratios (CAR).

In terms of bank profitability and the NPL ratio, Makri, Tsagkanos, & Bellas (2014) and Zheng, Bhowmik & Sarke (2020) found that a significant negative relationship existed between NPLs and return on equity (ROE), suggesting that deteriorated bank profits led to higher NPLs, which supported the theory that poor management leads to riskier activities and weak performance. However, The link between the NPL ratio and measures such as CAR and liquidity are more ambiguous. One argument is that banks with high capital adequacy ratios (CAR) and excess liquidity have incentive to engage in high risk activities, leading to high NPL rates. The relationship between NPLs and CAR is however unclear, since banks with low capital adequacy ratios may respond to moral hazard incentives by increasing the riskiness of their loan portfolio (Berger & DeYoung, 1997; Makri et al, 2014; Zheng et al, 2020).[5]

Many researchers also found significant associations between NPLs and lending interest rates and credit growth (Boudriga, Taktak & Jellouli, 2009; Tracey (2007); Zheng et al, 2020). With regards to credit growth, Boudriga, Taktak & Jellouli (2009) posited that high credit growth is associated with reduced, rather than increased, levels of non-performing loans this being due to the suggestion that banks that concentrate on their credit activity are more likely to effectively evaluate the true credit quality of borrowers. Tracey (2007) also found this to be true for Jamaica, with the implication being that the provision of more credit improves loan quality, provided loans extended are being put to productive uses.

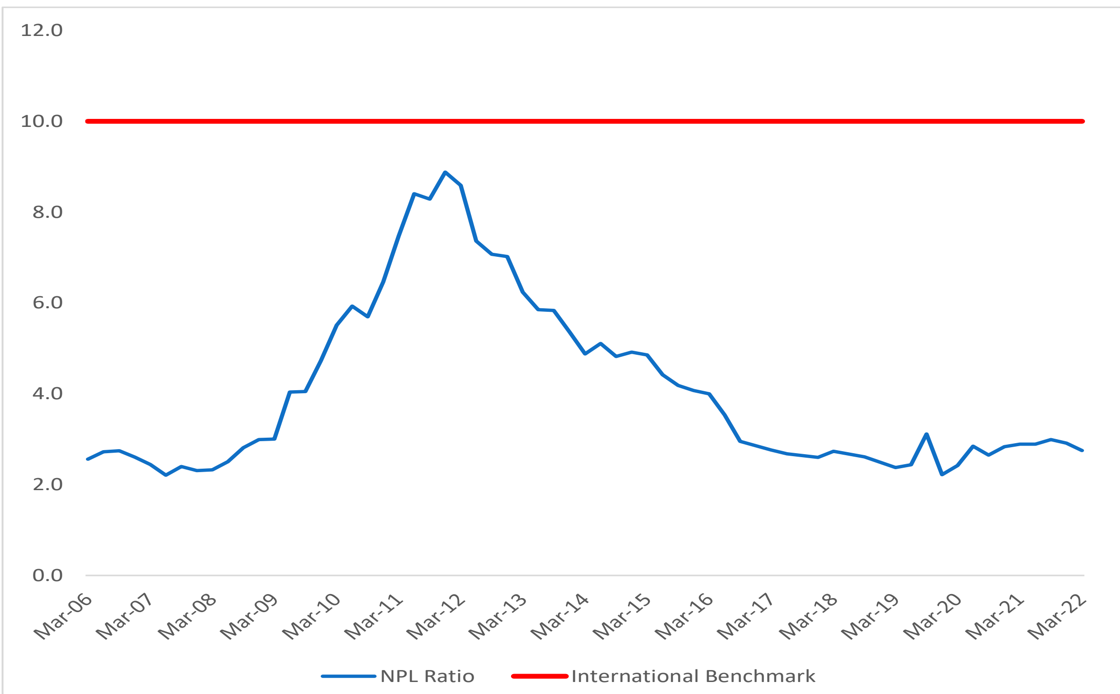
[5] Under the moral hazard hypothesis, when another party is bearing part of the risk and cannot easily prevent risk-taking, banks with relatively low capital may have incentive to take on excessive risk by increasing the riskiness of its loan portfolio, which results in higher nonperforming loans on average in the future. (Berger & DeYoung, 1997)

A vast majority of the methodologies that were used to determine loan losses among the literature included Vector Auto regression (VAR) models, Generalized method of moments (GMM) and the Autoregressive Distributed Lag model (ARDL).[6]

3. Performance in Jamaica's NPL Ratio: 2006 - 2022

During the period 2006 – 2022, the NPL ratio for Jamaica's deposit taking institutions (DTI) remained well below the 10 percent international benchmark. Of note, the ratio trended upwards to a peak of 8.9 per cent at end-2011 and thereafter declined steadily to a low of 2.2 per cent at end-2019 (see Figure 1).

Figure 1: NPL ratio from March 2006 to March 2022



The uptick in the NPL ratio, which began in 2008, reflected the deteriorating macroeconomic and financial sector conditions as a result of the 2007/2008 global financial crisis. Despite this crisis,

[6] References for VAR models : (see Babouček & Jančar, 2005; Espinoza & Prasad, 2010; Nkusu, 2011; Tracey, 2007); GMM: (see Beck, Jakubik & Piloiu, 2013; De Bock & Demyanets, 2012; Espinoza & Prasad, 2010; Makri, 2015; Makri, Tsagkanos & Bellas, 2014); ARDL: (see Greenidge & Grosvenor, 2010; Khalaf & Masih 2018; Zheng et al, 2020) and QR: (Jokivuolle, Pesola, & Virén, 2014; Karadima &Louri, 2020)

loan growth, specifically to the household sector, continued to increase albeit at a slower pace. This development coupled with increased levels of unemployment, reduced remittance inflows and a general slowdown in economic activity led to a deterioration in loan quality.[7]

However, in the years that followed, loan quality began to strengthen as the economic outlook for Jamaica improved. The Bank of Jamaica subsequently adopted an accommodative monetary policy stance, which along with other factors such as the government's continued fiscal consolidation, created an environment for the availability of additional capital for the private sector. This led to strong credit expansion in the adequately capitalized, liquid and profitable DTI sector. Unfortunately, the unexpected COVID-19 pandemic has caused slight increases in the NPL ratio within the context of a contracting domestic economy. Sharp increases in the ratio have, however, been mitigated by moratoria on loan repayments offered by DTIs during the second quarter of 2020 (Bank of Jamaica, 2020). Nevertheless, banks and regulators continue to closely monitor movements in this ratio given the uncertainties surrounding economic recovery in an ever-evolving pandemic.

4. Data and Methodology

4.1 Data

The purpose of this study is to identify the specific variables that have significant associations with the NPL ratio. As such, the NPL ratio was chosen as the dependent variable along with several macroeconomic and bank-specific independent variables (See Table A.1).[8] The sample data consisted of quarterly data spanning the period 2006-2022 quarter one.

The summary of descriptive statistics for the variables used in the empirical analysis are presented in (See Table A.2). Of note, the NPL ratio ranged from 2.21 % to 8.88%, while other bank specific and macroeconomic variables showed large variations. In particular, the ROE, lending interest

---

[7] The inverse U-shape of this graph is akin to the typical shape Ari, Chen and Ratnovski (2019) describe in their observation of NPLs in pre and post crisis periods. They posit that NPLs tend to rise rapidly around the start of the crisis, peak some years afterwards then eventually stabilize and decline.

[8] Studies have used both both aggregate and individual bank data for investigating the factors that affect NPLs, however to avoid individual bank data unavailability aggregate data was exclusively examined in this research.

rate, real GDP growth rate and the inflation rate presented great disparities between maximum and minimum values.

In analyzing the NPL ratio, the histogram (See Figure A.1 in appendix) gives important insight into the distribution of the NPL ratio which is essential in understanding regression results, specifically in the case of the QR method. The significant probability of the Jarque-Bera statistic indicates that the NPL ratio is not normally distributed, with the positive skewness value indicating a right skew, that is, the right tail is long relative to the left. [9] The kurtosis value is slightly above 3, demonstrating that the distribution is leptokurtic. As such, the histogram shows that there is a large concentration of data points with values between 2.0 and 3.0. [10][11]

4.2 Methodology

Autoregressive Distributed Lag

The autoregressive distributed lag (ARDL) approach models the economic relationships between variables using time series data to examine a single equation. In an ARDL model, the dependent variable is expressed by its own lagged value as well as the lagged and current values of independent variables (Ghouse, Khan & Rehman, 2018). The usefulness of this model stems from the fact that cointegration of nonstationary variables is equivalent to an error-correction (EC) process, and that the ARDL model has a reparameterization in EC form (Kripfganz & Schneider, 2016). ARDL models are also known to be relatively more efficient in the case of small and finite data sets and can be applied irrespective of whether the underlying variables are I(0), I(1), or a combination of both (Nkoro & Uko, 2016). The ARDL (p,q) Bounds Test model developed by(Pesaran and Pesaran (1997) and Pesaran et al. (2001) allows us to examine the short-run and long-run dynamics of the model by testing for the presence of cointegration. This is specified as follows:

[9] Skewness is a test of asymmetry. A normal distribution is symmetric, that is the distribution looks the same to the left and right of the centre point, and has a value of 0. Right skewness indicates that the right tail is long relative to the left.
[10] Kurtosis is a measure of whether or not the data is heavy-tailed or light-tailed compared to a normal distribution. High kurtosis values above 3 tend to be heavy tailed and have outliers while low kurtosis below 3 tend to have light tails and a lack of outliers.
[11] When a distribution is leptokurtic (kurtosis > 3.0), it has long tails, indicative of outliers, and is described as being concentrated toward the mean. This gives the distribution a "skinny" appearance as the bulk of the data will appear within a "skinny" vertical range.

$$\Delta Y_t = \delta_0 + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \sum_{i=1}^{q} \alpha_i \Delta X_{t-i} + \delta_1 Y_{t-1} + \delta_2 X_{t-1} + \varepsilon_t \qquad (1)$$

Where p and q are the maximum lags associated with the dependent and independent variables respectively, δ_i are the corresponding long-run multipliers and α_i are the short-run dynamic coefficients of the model.

Cointegration is determined by testing the following hypothesis:
H0: $\delta 1 = \delta 2 = 0$ (No existence of long-run relationship/ no cointegration)
H1: $\delta 1 \neq \delta 2 \neq 0$ (Existence of long-run relationship/ cointegration)

The null hypothesis is tested against the alternative using the F-test with two sets of critical values tabulated by Pesaran et al (2001). The first set assumes that all variables are I (0) while the second set assumes that all variables are I (1). The null hypothesis of no cointegration will be rejected if the calculated F-statistic is greater than the upper bound critical value. If the computed F-statistics is less than the lower bound critical value, then we cannot reject the null of no cointegration (Verma, 2007). If cointegration exists, a short-run ARDL model and an error correction model will be specified to examine the short and long-run relationships respectively. Furthermore, when the long-run component of the ARDL model above is replaced with lagged residuals of the error correction term it is written as follows:

$$\Delta Y_t = \delta_0 + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \sum_{i=1}^{q} \alpha_i \Delta X_{t-i} + \lambda ECT_{t-1} + \varepsilon_t \qquad (2)$$

Where *ECT* is the speed of adjustment parameter.[12]

Following the example of Zheng et al (2020) to avoid a multi-collinearity problem, two different models were estimated, one for macroeconomic variables and the other for bank-specific variables. All variables were log-transformed and a dummy variable was included to account for the volatile economic period from 2010 to 2013[13], with the value 1 being used for the period stated and 0 elsewhere. The equations estimated for this empirical study are specified below:

[12] A negative and significant coefficient of the error correction term is indicative of a long-run causal relationship.
[13]The period 2010Q1 to 2013Q4 was chosen as it represents the period with the largest deviations from the mean NPLs over the review period.

$$\Delta LnNPL_t = \delta_0 + \sum_{i=1}^{p} \alpha_i \Delta LnNPL_{t-1} + \sum_{i=1}^{q} \alpha_{2i} \Delta lnGDP_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta lnUNEMP_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta lnINFL_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta lnDEBT_{t-1} + \sum_{i=1}^{q} \alpha_{7i} \Delta lnDUM_{t-1} + \lambda ECT_{t-1} + \varepsilon_t \quad (3)$$

$$\Delta LnNPL_t = \delta_0 + \sum_{i=1}^{p} \alpha_i \Delta LnNPL_{t-1} + \sum_{i=1}^{q} \alpha_{2i} \Delta lnCAR_{t-1} + \sum_{i=1}^{q} \alpha_{3i} \Delta lnLDR_{t-1} + \sum_{i=1}^{q} \alpha_{4i} \Delta lnLIQ_{t-1} + \sum_{i=1}^{q} \alpha_{5i} \Delta lnROE_{t-1} + + \sum_{i=1}^{q} \alpha_{7i} \Delta lnNONINT + \sum_{i=1}^{q} \alpha_{8i} \Delta lnDUM_{t-1} +_{t-1} \lambda ECT_{t-1} + \varepsilon_t \quad (4)$$

5. Results

Unit Root Tests

The unit root tests (Table 1) revealed that the variables in this research consisted of a combination of those that were integrated of order one (I(1)) and stationary at level (I(0)).

Table 1: Augmented Dickey- Fuller (ADF) and Phillips- Perron (PP) Unit Root Tests

	Variables	ADF				PP				
		At level		First Difference		At level		First Difference		
		T-statistic	P-value	T-statistic	P-value	T-statistic	P-value	T-statistic	P-value	Order of Integration
Macroeconomic	lnNPL	-0.498	0.497	-2.580	0.011	-0.329	0.563	-7.798	0.000	I(1)
	lnGDP	-5.447	0.000	-	-	-5.538	0.000	-	-	I(0)
	lnUNEMP	-1.040	0.930	-7.648	0.000	-1.155	0.911	-7.617	0.000	I(1)
	lnINFL	-2.257	0.450	-9.595	0.000	-2.433	0.360	-9.514	0.000	I(1)
	lnDEBT	-1.031	0.932	-6.931	0.000	-1.343	0.868	-7.179	0.000	I(1)
Bank-Specific	lnCAR	-2.195	0.210	-6.121	0.000	-3.470	0.051	-6.028	0.000	I(1)
	lnNONINT	-12.179	0.000	-	-	-26.650	0.000	-	-	I(0)
	lnLDR	0.165	0.968	-5.779	0.000	0.254	0.974	-5.755	0.000	I(1)
	lnLIQ	-3.904	0.003	-	-	-3.803	0.005	-	-	I(0)
	lnROE	-4.809	0.000	-	-	-4.841	0.000	-	-	I(0)

The absolute values for the t-statistics can be compared to the following test critical values at the 1%,5% and 10% level respectively: -3.536587, -2.90766, -2.591396

The ARDL model

Two equations were estimated, one equation contained macroeconomic variables while the other contained bank-specific variables. The cointegration relationship was tested for each model using the ARDL bounds test, the results of which are displayed in Table 2. The results of the ARDL Bounds test confirmed the existence of a long-run relationship among the variables in both equations at the 5% level, with the F statistic exceeding the upper limit. Accordingly, the long-run association and short-run dynamics were estimated for both models. The Akaike's information criterion (AIC) was selected to choose the optimal lag length for each model. The optimal lags chosen were (1, 0, 4, 0, 1) and (1, 0, 3, 1, 0, 3) for the macroeconomic and bank-specific variables respectively.

Table 2. ARDL (Autoregressive Distributed Lag) Bounds Test

		At 10%		At 5%		At 2.5%		At 1%	
Variable type	**F-statistic**	**Lower Limit**	**Upper Limit**	**Lower Limit**	**Upper Limit**	**Lower Limit**	**Upper Limit**	**Lower Limit**	**Upper Limit**
Macroeconomic Variables	**5.913**	2.450	3.520	2.860	4.010	3.250	4.490	3.740	5.060
Bank Specific Variables	**4.680**	2.080	3.000	2.390	3.380	2.700	3.730	3.060	4.150

Table 3: ARDL Results for Macroeconomic Variables

	Variables	**Coefficeint**	**Standard Error**	**T-statistic**	**P-value**
Long Run Coefficients	lnGDP	-0.36	0.20	-1.76	0.085**
	lnUNEMP	-0.03	0.68	-0.04	0.965
	lnINFL	0.42	0.23	1.86	0.068**
	lnDEBT	0.22	1.68	0.13	0.898
Short Run Coefficients	ΔlnGDP	-0.07	0.03	-2.21	0.032*
	ΔlnUNEMP	-0.01	0.14	-0.04	0.965
	ΔlnINFL	-0.10	0.04	-2.49	0.016*
	ΔlnDEBT	-0.60	0.43	-1.40	0.167
	ECT	-0.21	0.04	-5.65	0.000*

* Significant at the 5% level, ** Significant at the 10% level

From the results for equation 3, the GDP growth rate and the inflation rate were found to have significant relationships with the NPL ratio in the long and short run (Table 3). In line with previous expectations, GDP had a negative relationship with NPL, suggesting that a 1% increase would lead to a 0.07% decrease in the NPL ratio in the short run and a 0.36% decrease in the long run. The inflation rate was found to be negative and significant in the short run but positive and significant in the long run. As outlined in Table A.1, the negative relationship between inflation and NPLs in the short run suggests that high inflation may ease the burden of repayment by reducing the true value of loans. However, the positive relationship with inflation in the long run suggests that rising inflation will eventually put strain on borrowers' ability to repay loans. (Makri, 2015; Babihuga, 2007; Jakubík and Schmieder, 2008; Nkusu, 2011; Castro, 2013). The coefficient on debt, though insignificant is in line with expectations that increases in debt leads to instability in an economy, paving the way for rises in NPLs. The coefficient for the unemployment rate was also insignificant and negative which is in contrast to majority of the literature. This may suggest that increases in unemployment limits households' access to traditional forms of lending, thus decreasing overall NPLs.

The error correction term represented by ECT is both negative and significant with a coefficient of -0.21 which implies that the speed of adjustment of short-run variables to the long-run equilibrium is about 21.0%. More specifically, 21.0% of any movements into disequilibrium are corrected for within one period. The dummy variable for the period 2010 to 2013 was also found to exert a statistically significant and positive impact on NPLs, suggesting that this vulnerable period in Jamaica's economy shifted NPLs upwards.

Table 4: ARDL Results for Bank-Specific Variables

	Variables	Coefficeint	Standard Error	T-statistic	P-value
Long Run Coefficients	lnCAR	3.729	1.883	1.980	0.054**
	lnNONINT	1.677	0.698	2.404	0.020*
	lnLDR	-1.003	0.679	-1.476	0.147
	lnLIQ	0.100	0.934	0.107	0.915
	lnROE	-0.024	0.331	-0.074	0.942
Short run coefficients	ΔlnCAR	0.630	0.208	3.037	0.004*
	ΔlnNONINT	0.284	0.086	3.296	0.002*
	ΔlnLDR	1.778	0.549	3.237	0.002*
	ΔlnLIQ	0.263	0.168	1.564	0.125
	ΔlnROE	-0.069	0.035	-1.977	0.054**
	ECT	-0.169	0.028	-6.076	0.000*

* Significant at the 5% level, ** Significant at the 10% level

Robustness Checks

The overall stability of the model was examined through the diagnostic tests displayed in Table 5 below. Both the macroeconomic and bank specific models showed no evidence of serial correlation or heteroskedasticity and both were normally distributed. Additionally, the CUMSUM of squares showed that both models were generally stable and within the 5% band (Figures A.2 and A.3)

Table 5: ARDL Diagnostic Tests

	Macroeconomic		Bank-Specific	
Test	**P-value**	**Interpretation**	**P-value**	**Interpretation**
Breusch-Godfrey Serial Correlation LM Test	0.864	No Serial Correlation	0.190	No Serial Correlation
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.753	Homoscedastic	0.135	Homoscedastic
Jarque-Bera Test	0.664	Normal	0.954	Normal

6. Conclusion

This research applied the Autoregressive Distributed Lag model to investigate the main determinants of the NPL ratio for the DTI sector in Jamaica using various macroeconomic and bank-specific variables for the period 2006- 2022 quarter one. Based on what was found in the existing literature, this study is unique, as it explores the impact of not only macroeconomic variables but also bank specific variables on the NPL ratio using the ARDL model in the Jamaican context.

The ARDL model was, robust and long-run convergences showed that higher levels of capital may incentivize banks to engage in risky lending, which could lead to increases in NPLs. In addition, increased profits may have the effect of lowering banks' risk appetite and leading to decreased NPLs, higher lending rates impair borrowers' ability to repay loans leading to higher NPLs while banks that engage in activities outside their core business of lending the NPL ratio may rise. Adverse economic conditions characterized by increases inflation and decreases in GDP growth rate were also associated with increases in the NPL ratio.

The maintenance of financial stability centers around safeguarding the conditions which ensure proper and efficient functioning of the financial system, in order to bolster real economic activity. Managing non-performing loans is key in ensuring the health of a bank's operations and the financial system at large. As such, regulators must continue efforts to foster an environment where banks are disincentivized to take on excessive risks. From a macroprudential standpoint, this involves closely monitoring excess capital, profitability and conducting routine stress testing. Additionally, it involves implementing policies which encourage banks to focus on their core business, all while regulators and authorities continue implementing growth strategies, debt reduction initiatives and inflation targeting efforts

Appendix

Table 1: Details of Independent Variables

	Variable	Abbreviation	Description	Expected Sign	Rationale
Macroeconomic	Real GDP Growth	GDP	Annual point to point real GDP growth rate	(-)	The NPL ratio has an inverse relationship with adverse macroeconomic conditions
	Unemployment Rate	UNEMP	Percentage of the unemployed labour force to the total labour force	(+)	The NPL ratio has an inverse relationship with adverse macroeconomic conditions
	Inflation Rate	INFL	Annual point to point inflation rate	(+)/(-)	High levels of inflation, combined with stagnant wages, can reduce borrowers' real incomes, making loan repayment difficult. Conversely, high inflation may also ease the burden of repayment by reducing the true value of loans. (1) loans (Makri, 2015; Babihuga, 2007; Jakubík and Schmieder, 2008; Nkusu, 2011; Castro, 2013).
	Debt to GDP Ratio	DEBT	Debt/GDP	(+)	The NPL ratio has an inverse relationship with adverse macroeconomic conditions
Bank-Specific	Capital Adequacy Ratio	CAR	Regulatory Capital/ Risk Weighted Assets	(+)/(-)	High capital adequacy ratios (CAR) may give banks incentive to engage in high risk activities, leading to high NPL rates, however banks with low capital adequacy ratios respond to moral hazard incentives by increasing the riskiness of their loan portfolio.
	Growth in non-Interest Income	NONINT	Growth rate of non interest income listed on profit and loss sheet	(+)	The growth in non-interest income was included as variables in the model to represent increases in activities outside banks' core business of lending. Boudriga, Taktak & Jellouli (2009) found that banks concentrating on credit activities experience low levels of NPL, therefore growth in non-interest income is expected to display a positive sign
	DTI Lending Interest Rate	LDR	Overall DTI weighted loan rate	(+)	Lower leading rates are assumed to lead to higher credit growth. This high credit growth is associated with reduced, rather than increased, levels of non-performing loans this being due to the suggestion that banks that concentrate on their credit activity are more likely to effectively evaluate the true credit quality of borrowers
	Liquid Assets to Total Assets	LIQ	Liquid Assets/ Total Assets	(+)/(-)	Excess liquidity that is managed poorly can lead to loan losses, however low levels of liquidity may suggest higher exposure to loans and increase the potential for loan losses (Zheng et al, 2020).
	Return on Equity	ROE	Net income / Shareholders Equity	(-)	The profitability variable ROE is expected to display a negative sign as it is generally linked to a bank's risk-taking behavior, this is because as profitability rises, fewer banks have incentives to engage in risk-taking behavior (Makri; 2014; Zheng 2020)

*Data sources include Bank of Jamaica's Finanicial Stability Department and Research and Economic Programming Division Databases.

Table A.2: Descriptive Statistics of Variables

	Description	Variables	Mean	Median	Maximum	Minimum	Std. Dev.
Macroeconomic	Non-Performing Loans Ratio	NPL	4.06	2.99	8.88	2.21	1.07
	Real GDP Growth	GDP	0.19	0.65	14.20	-18.39	4.09
	Unemployment Rate	UNEMP	11.40	11.62	16.27	6.23	2.34
	Inflation Rate	INFL	7.76	7.18	25.34	1.72	4.80
	Debt to GDP Ratio	DEBT	117.59	118.59	135.49	94.23	13.76
Bank-Specific	Capital Adequacy Ratio	CAR	15.76	15.24	20.70	14.04	1.57
	Growth in DTI Investments	INVEST	0.02	0.02	0.32	-0.06	0.05
	Growth in non-Interest Income	NONINT	0.06	0.04	1.49	-0.56	0.27
	DTI Lending Interest Rate	LDR	13.96	12.97	20.19	8.75	3.52
	Liquid Assets to Total Assets	LIQ	24.46	24.16	34.04	20.75	2.25
	Return on Equity	ROE	4.80	4.37	12.46	1.40	1.90

Figure A.1: Histogram of the NPL Ratio

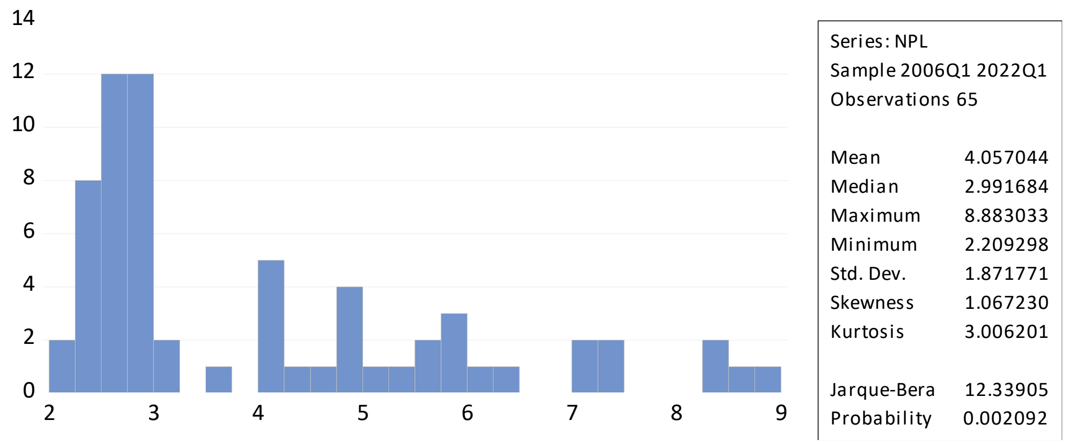


Figure A.2: CUMSUM of Squares for Macroeconomic Variables

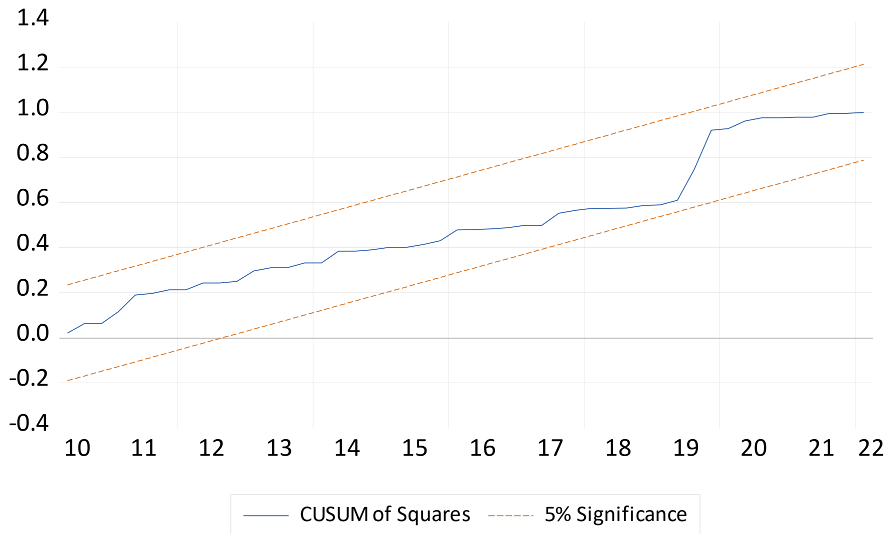
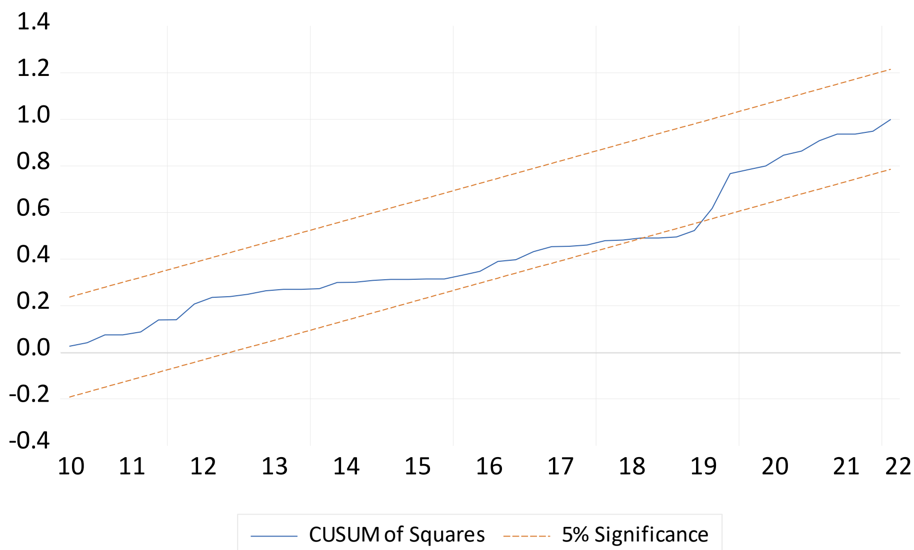


Figure A.3: CUMSUM of Squares for Bank-Specific Variables



References

Ari, M. A., Chen, S., & Ratnovski, M. L. (2019). The dynamics of non-performing loans during banking crises: a new database. *International Monetary Fund.*

Babihuga, R. (2007). Macroeconomic and financial soundness indicators: An empirical investigation. *IMF Working papers, 2007(115).*

Babouček, I., & Jančar, M. (2005). A VAR analysis of the effects of macroeconomic shocks to the quality of the aggregate loan portfolio of the Czech banking sector [Working Paper Series 1]. Praha: Česká národní banka.

Bank of Jamaica. (2020). *Quarterly Monetary Policy Report: June – September 2020*

Bank of Jamaica. (2010). *Annual Report- 2010*

Bank of Jamaica. (2013). *Annual Report- 2013*

Beck, R., Jakubik, P., & Piloiu, A. (2013). Non-performing loans: What matters in addition to the economic cycle?

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance, 21(6), 849-870.*

Boudriga, A., Taktak, N. B., & Jellouli, S. (2009, November). Bank specific, business and institutional environment determinants of nonperforming loans: Evidence from MENA countries. *In Economic Research Forum 16th Annual Conference Cairo.*

Castro, V. (2013). Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. *Economic Modelling, 31, 672-683.*

De Bock, R., & Demyanets, M. A. (2012). Bank asset quality in emerging markets: Determinants and spillovers (No. 12-71). *International Monetary Fund.*

De Lis, F. S., Pagés, J. M., & Saurina, J. (2001). Credit growth, problem loans and credit risk provisioning in Spain. *BIS papers, 1, 331-353*.

Espinoza, R. A., & Prasad, A. (2010). Nonperforming loans in the GCC banking system and their macroeconomic effects.

Ghouse, Ghulam, Saud Ahmed Khan, and Atiq Ur Rehman. "ARDL model as a remedy for spurious regression: problems, performance and prospectus." (2018): 1-29.

Greenidge, K., & Grosvenor, T. (2010) Forecasting Non-Performing Loans in Barbados. *Journal of Business, Finance & Economics in Emerging Economies, 5(1).*

Jakubík, P., & Schmieder, C. (2008). Stress Testing Credit Risk: Is the Czech Republic Different from Germany?. *CNB WP, (9).*

Jokivuolle, E., Pesola, J., & Virén, M. (2014). What drives loan losses in Europe?. *Bank of Finland Research Discussion Paper, (6).*

Jokivuolle, E., Viren, M., & Vahamaa, O. (2009). Transmission of macro shocks to loan losses in a deep crisis: the case of Finland. *Bank of Finland Research Discussion Paper, (26).*

Karadima, M., & Louri, H. (2020). Non-performing loans in the euro area: Does bank market power matter?. International Review of Financial Analysis, 72, 101593.

Keeton, W. R., & Morris, C. S. (1987). Why do banks' loan losses differ. Economic review, *72(5), 3-21*.

Khalaf, T., & Masih, M. (2018). Is the relationship between non-performing loans of banks and economic growth asymmetric? Malaysia's evidence based on linear and nonlinear ARDL approaches.

Koju, L., Abbas, G., & Wang, S. (2018). Do Macroeconomic Determinants of Non-Performing Loans Vary with the Income Levels of Countries?. *Journal of Systems Science and Information, 6(6), 512-531.*

Kripfganz, S., & Schneider, D. C. (2016, July). ardl: Stata module to estimate autoregressive distributed lag models. In Stata Conference, Chicago.

Makri, V. (2015). What triggers loan losses? An empirical investigation of Greek financial sector. *SPOUDAI Journal of Economics and Business, 65(3-4), 119-143.*

Makri, V., Tsagkanos, A., & Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus, 61(2), 193-206.*

Messai, A. S., & Jouini, F. (2013). Micro and macro determinants of non-performing loans. *International journal of economics and financial issues, 3(4), 852*.

Moudud-Ul-Huq, S., Akter, R., & Biswas, T. (2020). Impact of financial crisis on credit risk: Pre-and post-financial crises in an emerging economy. *FIIB Business Review, 9(2), 118-132.*

Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. *Journal of Statistical and Econometric methods, 5(4), 63-91.*

Nkusu, M. (2011). Nonperforming loans and macrofinancial vulnerabilities in advanced economies. *IMF Working Papers, 1-27.*

Pesaran, M. H. (1997). The role of economic theory in modelling the long run. *The economic journal, 107(440), 178-191.*

Pesaran, M. H., Schuermann, T., Treutler, B. J., & Weiner, S. M. (2006). Macroeconomic dynamics and credit risk: a global perspective. *Journal of Money, Credit and Banking, 1211-1261.*

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics, 16(3), 289-326.*

Touny, M. A., & Shehab, M. A. (2015). Macroeconomic determinants of non-performing loans: An empirical study of some Arab countries. *American Journal of Economics and Business Administration, 7(1), 11-22.*

Senior, A. (2015) Performing Macro-prudential Scenario Analyses of Jamaica Commercial Banking Sector within a Financial Programming and Policies Framework. *Available from internet:https://www.boj.org.jm/uploads/pdf/papers_pamphlets/papers_pamphlets_Performing_Macroprudential_Scenario_Analyses_of_Jamaica_Commercial_Banking_Sector_within_a_Financial_Programming_and_Policies_Framework.pdf*

Tracey, M. (2007). A VAR analysis of the effects of macroeconomic shocks on banking sector loan quality in Jamaica. *Available from internet: http://boj. org. jm/uploads/pdf/papers_pamphlets/papers_pamphlets_A_VAR_Analysis_of_ the_Effects_of_Macroeconomic_Shocks_on_Banking_Sector_Loan_Quality. pdf.*

Verma, R. (2007). Savings, investment and growth in India: An application of the ARDL bounds testing approach. *South Asia Economic Journal, 8(1), 87-98.*

Warue, B. N. (2013). The effects of bank specific and macroeconomic factors on nonperforming loans in commercial banks in Kenya: A comparative panel data analysis. *Advances in Management and Applied Economics, 3(2), 135.*

Zheng, C., Bhowmik, P. K., & Sarker, N. (2020). Industry-specific and macroeconomic determinants of non-performing loans: a comparative analysis of ARDL and VECM. *Sustainability, 12(1), 325*.