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The Effect of CAMEL Model on Loan Portfolio Quality of the Haitian Banking Sector

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Abstract

This paper examines the impact of CAMEL approach on Non-Performing Loans (NPLs) of the banking sector in Haiti, using monthly data from October 2019 to April 2023. The statistical analysis is carried out using the Auto-Regressive Distributed Lagged (ARDL)-Error Correction Model (ECM) approach. The results confirm the "moral hazard" hypothesis that low-capitalization of banks implies deterioration of loan portfolio quality. Similarly, the findings support the "bad management II" hypothesis that past earnings are negatively associated with increases in problem loans. Banks' liquidly at times t and $t - 1$ has a positive and significant effect on NPLs, while at time $t - 4$ banks' liquidity is negatively and significantly correlated with NPLs. In contrast, management efficiency has no influence on NPLs. Regarding the control variable of the study, the exchange rate, at time t, it is positively and significantly related to NPLs, supporting the "exchange rate" hypothesis that an increase in exchange rate leads to problem loans. Though, the findings show a significant and negative effect of exchange rate on NPLs at time $t - 4$. In addition, the CUSUM and CUSUMSQ statistics are well within the 5% critical bounds, implying that short and long-term coefficients in the ARDL-ECM are stable. Lastly, our findings highlight the importance of taking into account CAMEL variables and macroeconomic variables like the exchange rate when assessing the loan portfolio quality of Haitian banks from a financial stability perspective.

Keywords

Non-Performing Loan (NPL), Capital Adequacy, Asset Quality, Management Efficiency, Earnings Quality, Liquidity Management, Auto-Regressive Distributed Lagged (ARDL)

1. Introduction

Non-Performing Loans (NPLs) are defined as loans in which borrowers are in default and have made no scheduled payment of principal or interest for a specified period, usually longer than 90 days. When a loan is more than 90 days past due, the likelihood of the borrower repaying it in full is considerably low. The bank must set aside more capital, in case the loan is not repaid. In addition, a continued increase in non-performing loans can lead to very high levels of write-offs, adversely affecting the profitability of banks, which could lead to considerable financial losses, thus eroding their capital. This lessens their ability to extend new loans, restraining the sources of financing for businesses, thus reducing the possibilities of investments at the level of the economy. This can also cause firms to create fewer new jobs and increase unemployment in the economy. A higher unemployment rate implies that unemployed workers have less disposable income, which can cause cut consumer spending and a decrease in aggregate demand. This in turn can result in a reduction in planned investment spending by firms, raising the risk of a deeper economic downturn. In order to keep financing the economy and being profitable and sustainable, banks need to put in place as required by regulators worldwide a robust and adequate risk management system that can help them enhance the quality of their loan portfolio by reducing at the most the non-performing loan ratio.

In Haiti, the national regulatory environment has evolved in terms of risk management. Circular 89-2 of the Bank of the Republic of Haiti (BRH, 2020) relating to minimum internal control standards stipulates that the risk management function is responsible for ensuring ongoing and through means dedicated to the identification, measurement, monitoring and management of the financial institution's risks, particularly credit risk. Though, the growing trend of NPL ratio of the banking sector has recently become a major concern for bankers and the regulator. As of April 2023, the NPL ratio of the whole banking system has increased to 11.8% (BRH, 2023). As shown in **Figure 1**, overall, from October 2019 to May 2022, the NPL ratio evolved jaggedly, ranging from 5% to 8%. But from June 2022 to April 2023, except the decrease observed in September 2023, the NPL ratio has shown an upward trend with values over 10.0%.

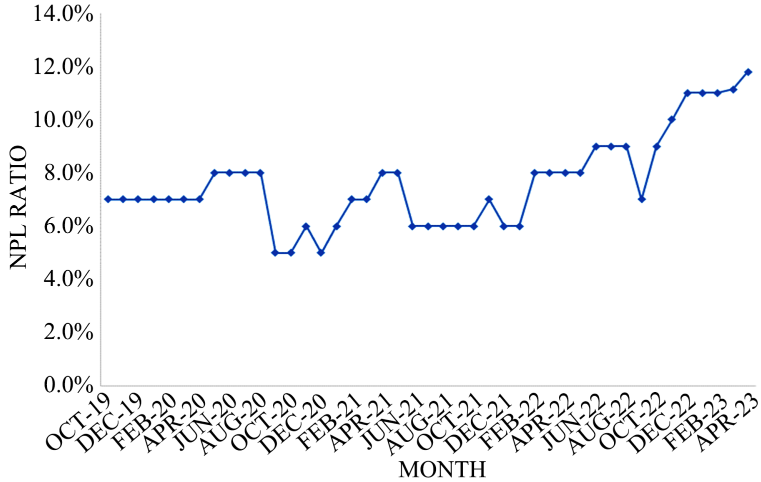

Figure 1. Trend of NPL ratio of the Haitian banking sector. Source: BRH, 2023.

With the purpose of addressing the deterioration of the loan portfolio quality of the Haitian banking sector, practitioners and the regulator must clearly understand the reasons why the NPL ratio is increasing and what affects the trend of the NPL ratio. This paper aims to shed light on this problem, using the CAMEL model. Its objective is to estimate the influence of the other variables of the CAMEL on the loan portfolio quality, measured by the NPL ratio. CAMEL stands for Capital adequacy, Asset quality, Management efficiency, Earnings quality, Liquidity. Capital adequacy emphasizes on maintaining capital requirement; Asset quality refers to loan's quality, Management efficiency focuses on reducing cost and efficiently utilizing resources; Earnings quality is related to increasing profitability,; Liquidity management is directly associated with the solvency of the bank. The components were assigned a rating on a scale of 1 to 5, with 1 being the highest rating and implying a strong compliance from the bank. CAMEL is a Moody's-recommended systematic methodology for assessing a bank's overall security, coherence, and soundness (Qureshi & Siddiqui, 2023).

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature related to our research topic and formulates hypotheses; Section 3 describes the data and the method used to conduct our statistical analysis; Section 4 presents and discusses the main findings of the research; and Section 5 concludes this study.

2. Literature Review and Hypotheses

Loan portfolio quality is one the issues receiving great attention regarding research carried out in the area of financial institutions. Many investigations conducted on the causes of bank failures have indicated that failing financial institutions show higher non-performing loans ratios, prior to failure and that asset quality is found to be statistically significant predictor of insolvency (Belaid & Bellouma, 2016). Many studies have investigated the factors affecting loan portfolio quality of banks, which are microeconomic or bank specific determinants, representing the variables in CAMEL model.

2.1. Capital Adequacy and Loan Portfolio Quality

The capital adequacy is one of the most wide-ranging indexes which reflects the risk of the bank, as well as the bank's resource-obligation management. The capital adequacy is largely used to measure the bank's value capital and various securities held as reserves against risky assets to protect against the likelihood of a bank failure (Ezike & MO, 2013). The moral hazard hypothesis associating the loan portfolio quality of banks with capitalization was tested in the literature on credit risk. Berger & DeYoung (1997) find that, for banks with low capital ratios, decreases in bank capitalization precede increases in problem loans measured through NPLs. Their result supports the evidence that under-capitalized banks may respond to moral hazard incentives by taking increased portfolio risks. In line with this hypothesis, banks with relatively low capital increase their loan portfolio leading to a rising number of problem loans which reflects the classical problem of excessive risk taking when another party is involved in the risk and cannot easily charge for or prevent such risk-taking.

Though, using data from the Greek banking sector, Louzis, Vouldis & Metaxas (2012) find no support of the moral hazard hypothesis, because bank's risk attitude, as proxied by the solvency ratio, does not have explanatory power for NPLs. Amazingly, investigating the factors influencing NPLs for all US commercial banks over the period of 1984-2013, Ghosh (2015) suggests that greater capitalization meaningfully increases NPLs. According to the author, the positive relationship between bank capitalization and NPLs is linked to the fact that managers of greatly capitalized banks may adopt a liberal lending policy under the concept of "too big to fail".

This paper formulates and will test the "moral hazard" hypothesis:

H1: Low-capitalization of banks implies deterioration of loan portfolio quality, conveyed by increase of NPLs ratio.

2.2. Management Efficiency and Loan Portfolio Quality

Management efficiency is one of the components of CAMEL model which examines the administration's productivity and effectiveness. The efficiency of the organizational management is measured through the organizational discipline, staff quality, controls management, and systems implemented by the management. Through management efficiency the quality of the administration to generate revenues and increase net profit is assessed (Aspal, Dhawan, & Nazneen, 2019).

Bank's cost efficiency is usually proxied for banks managers' skill in terms of monitoring borrowers, assessment of pledged collateral and credit scoring. In the empirical literature, this is called "bad management hypothesis" (Louzis, Vouldis & Metaxas, 2012). Many studies have investigated the relationship between loan portfolio quality and bank's cost efficiency. Berger & DeYoung (1997) examine the relationship between the problem loans and the cost efficiency, using data from a sample of US commercial banks during the period of 1985-1994, employing Granger-causality techniques to test their hypotheses. The study shows that decreases in measured cost efficiency result in an increase in future problem loans. Similarly, using data from the Czech banking sector over the period of 1994-2005, Podpiera & Weill (2008) find the existence of a negative relationship between measured cost efficiency and future problem loans. Ghosh (2015) analyzes the drivers of non-performing loans through evidence from US commercial banks, using data from 1984 to 2013. The result indicates that the greater cost inefficiency significantly increase NPLs.

The present paper tests the "bad management I" hypothesis stipulated as follows:

H2: There is a positive relation between cost inefficiency and future bad loans of banks.

2.3. Earnings Quality and Loan Portfolio Quality

Earnings quality demonstrates the persistence of net income. Earnings persistence generally refers to the stability of earnings, which is important for predicting earnings. It is the main determinant of a bank's profitability, which refers to a bank's ability to earn profits. Profitability is used as one of the key measures of a bank's performance.

The literature related to credit risk has examined the relationship between profitability and loan portfolio quality of banks and has claimed that bad performance may proxy lower quality of management skills concerning the lending activity, similar reasoning to the "bad management I" hypothesis, cost efficiency ratio being considered as a proxy for management quality. This indicates the existence of a negative association between past earnings and problem loans (Belaid & Bellouma, 2016). Using evidence from the Greek banking sector, Louzis, Vouldis & Metaxas (2012) show a negative relationship between performance (proxied by ROE) and problem loans measured by NPLs.

Therefore, this present study formulates and tests the "bad management II" hypothesis as follows:

H3: Past earnings are negatively connected with increases in problems loan.

2.4. Liquidity Management and Loan Portfolio Quality

Liquidity refers to a bank's ability to fulfill its cash associated obligations. It is critical for a bank to maintain a suitable level of liquidity. Banks have to be more cautious when it comes to invest, in order to earn more returns on their investments as well as to provide liquidity to the depositors. High liquidity proportion proves banks efficiency (Khatik & Nag, 2014). Thus, liquidity management is the process of lessening liquidity risk when it comes to a bank to meet cash requirements.

Previous studies have analyzed the association between liquidity risk and credit risk in banks. He & Xiong (2012) contend that the financial crisis of 2007-2008 has pointed out the significance of the relationship between debt market liquidity and credit risk. This relationship is due to the channel of the so-called rollover risk. In front of an illiquid market, levered companies cope with rollover losses deriving from issuing new debts at higher cost, so as to substitute maturing debts. In this instance, companies' shareholders bear the rollover loss, while debt holders are paid in full. Analyzing the non-performing loans for US commercial banks through the period of 1984-2013, Ghosh (2015) shows that liquidity risk measured by loans-to-assets ratio significantly increase NPLs. This is explained by banks' excessive credit risk taking behavior when they rise their credit supply. In other words, when banks expand their loans growth measured by loans-to-assets ratio, reflecting a rise in liquidity risk as loans are less liquid than other assets, they reduce their lending interest rates and diminish their minimum credit standard. In such case, banks grant loans to borrowers who are more likely to increase future problem loans.

Based on the aforementioned empirical evidences, the present study formulates and tests the following hypothesis:

H4: Future problem loans are negatively related to banking liquidity.

2.5. Exchange Rate and Loan Portfolio Quality

Besides the CAMEL variables, this paper uses the exchange rate as a control variable. An exchange rate is defined as a rate at which one currency will be exchanged for another currency and impacts trade and the movement of money between countries. Both the domestic currency value and the foreign currency value affect exchange rates.

In the literature related to credit risk, empirical studies have examined the relationship between exchange rate and non-performing loans of the banking sectors. Rahman & Hamid (2019) find that exchange rate has a significant positive relationship with NPL, suggesting that NPL would increase in the difference between lending rate and borrowing rate. Similarly, Hada et al. (2020) show that exchange rate is the main factor in increasing the NPL ratio of Romanian Banks. According to Nkusu (2011) and Castro (2013), with an increase in exchange rate, the profit performance of importing companies is adversely affected. This implies that with the depreciation of the national currency, imported goods become more expensive and the sales of importing companies diminish. As a consequence, companies face difficulty repaying their debts.

Though, studies like Zribi & Boujelbene (2011), Roy (2014) find an inverse association between nominal exchange rate and NPLs. This is indicated in these studies that the increases in the exchange rate lead foreign exchange revenues of exporting companies to increase. As a result, the capability of these companies to repay their loans in terms of national currency increases and NPLs decrease.

This paper formulates and tests the following hypothesis:

H5: Non-performing loan is positively associated with exchange rate.

Table 1 shows the definition of the variables and the hypotheses of this study.

Table 1. Description of variables and expected relationship.

Variable	Corresponding determinant	Measure	Hypothesis	Expected effect
Asset Quality	Non-performing loan ratio	$NPL = \frac{\text{Non-Performing Loans}}{\text{Gross Loans}}$	N/A	N/A
Capital Adequacy	Capital adequacy ratio	$RWA = \frac{\text{Owned Capital}}{\text{Risk-Weighted Assets}}$	H1: "Moral hazard" Hypothesis	(−)
Management Efficiency	Cost efficiency (Expenditure income ratio)	$EIR = \frac{\text{Total Operating Expenses}}{\text{Operting Income}}$	H2: "Bad Management I" Hypothesis	(+)
Earnings	Profitability (Return on Equity)	$ROE = \frac{\text{Net imcome}}{\text{Total Equity}}$	H3: "Bad Management II" Hypothesis	(−)
Liquidity	Liquidity ratio	$LR = \frac{\text{Current Assets}}{\text{Current Liabilities}}$	H4: "Debt rollover" Hypothesis	(−)
Exchange rate	Local currency (HTG) units per U.S. dollar	EXR = Local currency (HTG) units per U.S. dollar	H5: "Exchange rate hypothesis"	(+)

The proportion of non-performing loans plays a key role in the stability of the banking sector of a country. The factors that influence the NPLs include very significant information for both banks and regulators. However, studies in this area have received little attention in Haiti. In order to contribute to address this gap, this paper aims to investigate the drivers of NPLs of the Haitian banking sector.

3. Data and Methodology

3.1. Source of Data

The nature of this study requires the usage of secondary data. Data used are monthly time series and cover the period of October 2019 to April 2023, totalizing a sample of 42 observations. They are sourced from the Central Bank of Haiti database (https://www.brh.ht/?s=CAMEL). The analyses are carried out using R Software.

3.2. Research Method

This research uses the NPL ratio, which is a sub-parameter of asset quality of CAMEL model, as dependent variable. The other parameters and sub-parameters of CAMEL model are used as independent variables. In addition, the exchange rate is used as a control variable. To estimate the impacts of CAMEL model on the loan portfolio quality of banks in Haiti, this study employs the Auto-Regressive Distributed Lagged (ARDL) technique.

Auto-Regressive Distributed Lagged (ARDL) Model

The ARDL models are the standard Ordinary Least Squares regressions (OLS), which include lags of both dependent and independent variables as repressors (Erdoğdu & Çiçek, 2017). The basic form of an ARDL (*p*, *q*) regression model is given as follows:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \cdots + \beta_q Y_{t-q} + \alpha_0 X_t + \alpha_1 X_{t-1} + \cdots + \alpha_p X_{t-p} + \varepsilon_t$$

The same model can be written as follows in Equation (1):

$$Y_t = \beta_0 + \sum_{i=1}^{q} \beta_i Y_{t-i} + \sum_{i=0}^{p} \alpha_i X_{t-i} + \varepsilon_t \tag{1}$$

where ε_t is a disturbance term, the dependent variable is a function of its lagged values, the current and lagged values of other independent variables in the model; q lags are used for dependent variable while p lags for independent variables. The bounds testing procedure requires the estimation of Equation (2), which derives the relationship between Non-performing loan ratio (NPL) and Capital adequacy ratio (RWA), Expenditure income ratio (EIR), Return on Equity (ROE), Liquidity ratio (LR) and Exchange rate (EXR) as a conditional autoregressive distributed lag (ARDL):

$$\begin{aligned} \Delta \text{NPL}_t = {} & \alpha_0 + \sum_{i=1}^{q} \alpha_i \Delta \text{NPL}_{t-i} + \sum_{i=1}^{p_1} \alpha_{2i} \Delta \text{RWA}_{t-i} + \sum_{i=1}^{p_2} \alpha_{3i} \Delta \text{EIR}_{t-i} \\ & + \sum_{i=1}^{p_3} \alpha_{4i} \Delta \text{ROE}_{t-i} + \sum_{i=1}^{p_4} \alpha_{5i} \Delta \text{LR}_{t-i} + \sum_{i=1}^{p_5} \alpha_{6i} \Delta \text{LnEXR}_{t-i} \\ & + \beta_1 \text{NPL}_{t-1} + \beta_2 \text{RWA}_{t-1} + \beta_3 \text{EIR}_{t-1} + \beta_4 \text{ROE}_{t-1} + \beta_5 \text{LR}_{t-1} \\ & + \beta_6 \text{LnEXR}_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

where LnEXR is the natural log of exchange rate, Δ is the first difference operator, $p_1, p_2, p_3, p_4, p_5, q$ are the lag lengths. The null hypothesis in the long-run is:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0,$$

which indicates no cointegration. The calculated F-statistic is compared with critical values or *p*-values. If the F-test statistic is less than the lower bound, there is no cointegration. If the F-test statistic is greater than the upper bound, it means cointegration. Conversely, if the F-statistic is found between both critical values, no decision can be made.

If there is a long-run relationship among the variables, implying cointegration, then the long-run model is estimated using Error Correction Model (ECM). Conversely, for a short-run relationship, i.e. no cointegration, ARDL model is estimated. The long-run relationship model is specified in Equation (3):

$$\begin{aligned}\Delta \text{NPL}_t = {} & \alpha_0 + \sum_{i=1}^{q} \alpha_i \Delta \text{NPL}_{t-i} + \sum_{i=1}^{p_1} \alpha_{2i} \Delta \text{RWA}_{t-i} + \sum_{i=1}^{p_2} \alpha_{3i} \Delta \text{EIR}_{t-i} \\ & + \sum_{i=1}^{p_3} \alpha_{4i} \Delta \text{ROE}_{t-i} + \sum_{i=1}^{p_4} \alpha_{5i} \Delta \text{LR}_{t-i} + \sum_{i=1}^{p_5} \alpha_{6i} \Delta \text{LnEXR}_{t-i} \\ & + \lambda_7 \text{ECT}_{t-1} + \varepsilon_t \end{aligned} \tag{3}$$

where λ_7 is the coefficient of the error (or equilibrium) correction term (ECT). A negative and statistically significant error correction term confirms convergence of the dynamics to the long-run equilibrium. The significance of the error correction model gives further confirmation to the cointegration evidence, suggesting a long-run movement between the non-performing loan ratio and the independent variables.

In contrast, for the short-run relationship model, ARDL ($p_1, p_2, p_3, p_4, p_5, q$) is specified in Equation (4):

$$\begin{aligned}\Delta \text{NPL}_t = {} & \alpha_0 + \sum_{i=1}^{q} \alpha_i \Delta \text{NPL}_{t-i} + \sum_{i=1}^{p_1} \alpha_{2i} \Delta \text{RWA}_{t-i} + \sum_{i=1}^{p_2} \alpha_{3i} \Delta \text{EIR}_{t-i} \\ & + \sum_{i=1}^{p_3} \alpha_{4i} \Delta \text{ROE}_{t-i} + \sum_{i=1}^{p_4} \alpha_{5i} \Delta \text{LR}_{t-i} + \sum_{i=1}^{p_5} \alpha_{6i} \Delta \text{LnEXR}_{t-i} + \varepsilon_t \end{aligned} \tag{4}$$

4. Results and Discussion

4.1. Descriptive Statistics

Table 2 shows descriptive statistics for the dependent variable and the independent variables over the period under study (October 2019 to April 2023). As observed, NPL ratio has mean, median, maximum and minimum of 7.6%, 7.0%, 12.0% and 5.0% respectively, indicating deterioration of the loan portfolio of the banking system. In general, banks are required to keep their non-performing loan ratio under 5%. The standard deviation is 1.8%, suggesting that the variability in NPL ratios is not so wide for the time period examined. RWA has mean, median, maximum and minimum of 7.8%, 8.0%, 9.0% and 7.0% respectively, suggesting that the whole banking system has enough capital to cushion potential losses and protect depositors' money, because under Basel III, Tier 1 Capital divided by Risk-Weighted Assets needs to be at least 6%. Over the period under study, the standard deviation of the RWA was 0.7%, meaning that the capital

Table 2. Descriptive statistics of the data.

Variable	NPL	RWA	EIR	ROE	LR	EXR	LnEXR
Mean	7.6%	7.8%	183.0%	20.5%	53.0%	104.3	4.6
Median	7.0%	8.0%	58.0%	23.0%	53.0%	100.6	4.6
Std. Dev.	1.8%	0.7%	1073.4%	15.0%	2.1%	23.6	0.2
Minimum	5.0%	7.0%	−1515.0%	−61.0%	48.0%	63.0	4.1
Maximum	12.0%	9.0%	6797.0%	42.0%	58.0%	153.6	5.0
Observation	42	42	42	42	42	42	42

Source: Author's own calculation.

adequacy ratios were not so disparate. EIR has mean, median, maximum and minimum of 183.0%, 58.0%, 6797.9% and −1515.0% respectively, indicating that the Haitian banking sector has lack of efficiency, which probably reflects the bad health of some banks comprising the whole system. The higher the percentage, the less efficient the banks. Regarding the profitability, the average ROE is 20.5%, with a maximum of 42.0% and a minimum of −61.0%. Overall, the ROE of the Haitian banking sector is relatively favorable over the period under study. An ROE of 15% or higher is often considered as a good benchmark for financial health. LR has mean, median, maximum and minimum of 53.0%, 53.0%, 58.0% and 48.0% respectively. This indicates that with a minimum of 100% of LR required, the Haitian banking system might have difficulties managing expected net cash outflows in a 30-day stress scenario. Finally, EXR has evolved between 63.0 HTG/1USD and 153.6 HTG/1USD, with an average of 104.3 HTG/1USD and a standard deviation of 23.6 HTG/USD. These values suggest the depreciation of the local currency compared to the US dollar.

4.2. Test for Stationarity

Economic and financial time series data usually contains spurious results, because of non-stationary property of the data. Thus, unit root test is required prior to carrying out any analysis. To convert non-stationary data into stationary data, the first difference of the data is created. When the data is stationary at level zero, it is named I (0) and the first difference is known as I (1). There are several ways of testing the stationarity of a time series. Augmented Dickey-Fuller (ADF) Test and Phillips-Perron (PP) test are widely used. For this study, the Phillips-Perron (PP) test is employed. The null hypothesis is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process. Before conducting unit root test, the optimal lags have been selected, using AIC (Akaike Information Criterion).

Table 3 summarizes the results of the PP test for the dependent variable and the independent variables of the study. As observed, EIR and ROE are stationary at l (0), indicating that the null hypothesis can be rejected at 5% level of significance, with *p*-value respectively equals to 0.0100. Whereas NPL, RWA, LR and

Table 3. Phillips-Perron unit root test.

Variable	Integration order (I)	Test Stat	*p*-value
NPL	1	−40.5550	0.0100
RWA	1	−7.6271	0.0100
EIR	0	−6.3799	0.0100
ROE	0	−4.7692	0.0100
LR	1	−55.825	0.0100
LnEXR	1	−30.427	0.0100

Source: Author's own calculation from R Software.

LnEXR are stationary at I (1), with a *p*-value of 0.0100 for each variable, which is less than the 5% level of significance. Since all of the 6 variables are stationary, the ARDL model is then appropriate.

4.3. ARDL Model Estimation

The estimating ARDL model using the R package dLagM is ARDL (4, 4, 0, 4, 4, 1) model. Table 4 shows that there are significant effects of most of the lags of CAMEL method variables except EIR on the loan portfolio quality of the Haitian banking system. The first lag of RWA has a significant effect at 5% level. In addition, the sign of the coefficient is negative (−0.0284), indicating that a decrease in the first lag of RWA would probably imply an increase in NPL. This result supports the "moral hazard" hypothesis stipulating that low-capitalization of banks implies deterioration of loan portfolio quality, which is consistent with Berger & DeYoung (1997).

With a negative coefficient, the second and the third lags of ROE have significant effects on NPL at 10% level each, while the fourth lag is highly significant at 5% level with a negative coefficient. These results support the "bad management II" hypothesis, suggesting that past earnings are negatively connected with increases in problems loan. The findings are consistent with Belaid & Bellouma (2016) and Louzis, Vouldis & Metaxas (2012).

When it comes to the LR, it presents mixed effects on NPL. The effects of LR at time t and the ones of the first lag are statistically significant at 10% level with respective positive coefficients of 0.4547 and 0.4294. This suggests that an increase in LR could probably lead to an increase in NPL. This result does not support the "debt rollover" hypothesis. In contrast, the fourth lag of LR presenting a significant effect at 10% level with a negative coefficient confirms the "debt rollover" hypothesis stipulating that future problem loans are negatively related to banking liquidity.

Concerning the LnEXR, its effects are also mixed with a highly significant effect at time t at 5% level with a positive coefficient confirming the exchange rate hypothesis of the study. An increase in LnEXR would probably imply an increase in problems loan, which is consistent with Rahman & Hamid (2019). On the

Table 4. Results of ARDL (4, 4, 0, 4, 4, 1) model.

Variable	Coefficient	Std. Error	t-value	Pr (>|t|)
Constant	−0.0284	0.1868	−0.1520	0.8808
RWA.t	0.4073	0.4625	0.8810	0.3901
RWA.1	−1.4886	0.4668	−3.1890	0.0051**
RWA.4	−0.7377	0.5057	−1.4590	0.1618
ROE.t	−0.0196	0.0186	−1.0560	0.3048
ROE.1	−0.0457	0.0271	−1.6830	0.1096
ROE.2	−0.0673	0.0236	−2.8500	0.0106*
ROE.3	−0.0693	0.0257	−2.6940	0.0148*
ROE.4	−0.0302	0.0102	−2.9480	0.0086 **
EIR.t	−0.0002	0.0002	−0.9500	0.3548
LR.t	0.4547	0.1991	2.2840	0.0348 *
LR.1	0.4294	0.1864	2.3040	0.0334 *
LR.2	−0.2145	0.1243	−1.7260	0.1015
LR.3	−0.0354	0.1684	−0.2100	0.8360
LR.4	−0.2841	0.1329	−2.1370	0.0466*
LnEXR.t	0.1088	0.0359	3.0330	0.0072 **
LnEXR.1	−0.0511	0.0405	−1.2610	0.2235
LnEXR.2	0.0396	0.0488	0.8110	0.4282
LnEXR.3	0.0304	0.0452	0.6710	0.5106
LnEXR.4	−0.1197	0.0415	−2.8820	0.0099 **
NPL.1	0.8622	0.1391	6.2000	0.0000***
R-squared: 0.9470, Adjusted R-squared: 0.8882, *p*-value: 0.0000				

Note: *** significant at 0.01, ** significant at 0.05, * significant at 0.1. Source: Author's own calculation from R Software.

other hand, the fourth lag has a very significant influence at 5% level, but the coefficient is negative, suggesting that a decrease in LnEXR would probably lead to a decrease in NPL. NPL is highly influenced by its first lag at 1% level, with a positive coefficient. Definitely, the results indicate that 89% of the variability observed in NPL is explained by the ARDL (4, 4, 0, 4, 4, 1) model with a *p*-value of 0.0000 less than 5%.

4.4. ARDL Bound Test

In order to analyze the long-run relationship among the variables, we estimate the ARDL approach according to the cointegration. We then use the ARDL Bound test (Pesaran et al., 2001), which estimates the F-Statistic. As observed in **Table 5**, the F-Statistic is equal to 4.524. The latter is compared to the critical

Table 5. ARDL bound test results.

F-Statistic 4.524 Case 3 (model with unrestricted intercept and no trend)		
	Critical value	
Significance level	I (0)	I (1)
10%	2.458	3.647
5%	2.922	4.268
1%	4.030	5.598

Source: Author's own calculation from R Software.

values below and above the significance levels of 10%, 5% and 1%. Considering the 5% significance level, the results indicate that the F-statistic (4.524) is higher than both critical values of the lower bound (2.922) and the upper bound (4.268). These results attest a long-run relationship among the variables. This implies that the variables are cointegrated. Thus, the long-run model is estimated by means of Error Correction Model (ECM).

4.5. Error Correction Model Estimation

Table 6 shows the coefficient estimates and significance tests for the error correction model. The ECT indicates how much the disequilibrium is being corrected, i.e., the extent to which any disequilibrium in the previous period is being adjusted in current point. Thus, ECT directly estimates the speed at which a dependent variable returns to equilibrium after a change in other variables. While a negative coefficient indicates convergence, a positive coefficient indicates divergence. The error correction coefficient of this study is negative (−0.0562) as expected and highly significant with p-value (0.0000) less than 0.05, which is consistent with the ARDL bound test. This means that there is a significant long-run relationship or cointegration between the change in NPL and the exploratory variables.

4.6. Diagnostics Tests

4.6.1. Checking Model Stability

The stability of the model is an important issue to check before making a forecast. The cumulative sum (CUSUM) generated via recursive residuals is used to investigate the model stability. Recursive CUSUM of squares (CUSUMSQ) is used to identify instability in the variances of coefficients over time. The examination of plots in Figure 2 displays that CUSUM and CUSUMSQ statistics are well within the 5% critical bounds, implying that short and long-term coefficients in the ARDL-Error Correction model are stable.

4.6.2. Checking Normality, Autocorrelation and Homoscedasticity

In addition to the stability checking, it is critical to assess the model assumptions (normality, autocorrelation and homoscedasticity of residuals). For the normality

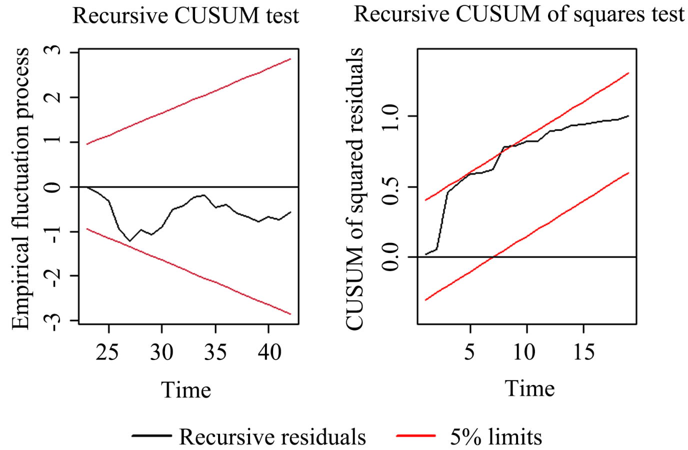

Figure 2. Recursive CUSUM, CUSUM of squares plots for the model stability. Source: Author's own calculation from R Software.

Table 6. Error correction model specification.

Variable	Coefficient	Std. Error	t-value	Pr (>|t|)
Constant	0.0044	0.0011	3.9360	0.0009***
ECT	−0.0562	0.0093	−6.0700	0.0000***
dRWA.t	0.0546	0.3267	0.1670	0.869
dRWA.1	1.0440	0.3485	0.1670	0.0074**
dRWA.2	1.5200	0.3412	4.4560	0.0074**
dRWA.3	1.2160	0.3439	3.5370	0.0022**
dROE.t	−0.0327	0.0143	−2.2870	0.0338*
dROE.1	0.2328	0.0377	6.1770	0.0000***
dROE.2	0.1250	0.0264	4.7410	0.0001***
dROE.3	0.0352	0.0082	4.2930	0.0004***
dEIR.t	−0.0001	0.0002	−0.6340	0.0004***
dLR.t	0.4212	0.1964	2.1450	0.0451*
dLR.1	0.7301	0.1288	5.6700	0.0000***
dLR.2	0.4965	0.1204	4.1240	0.0006***
dLR.3	0.2842	0.1122	2.5340	0.0203*
dLnEXR.t	0.1059	0.0297	3.5710	0.0020**
dLnEXR.1	0.0666	0.0267	2.4960	0.0219*
dLnEXR.2	0.1660	0.0333	4.7370	0.0001***
dLnEXR.3	0.1535	0.0324	4.7370	0.0001***
dNPL.1	−0.1399	0.1615	−0.8660	0.3972
R-squared: 0.8761, Adjusted R-squared: 0.7523, *p*-value: 0.0000				

Source: Author's own calculation from R Software.

checking, we use the Shapiro-Wilk test. The null hypothesis is that the residuals are normally distributed and the alternative hypothesis states that the residuals are not normally distributed. Since the *p*-value = 0.0626 is greater than 0.05, we accept the null hypothesis, which indicates that the residuals are normally distributed. For the assessment of homoscedasticity, the Breusch-Pagan test is used. The null hypothesis is that there is homoscedasticity and the alternative hypothesis is that there is no homoscedasticity. The *p*-value = 0.7565 is greater than 0.05, we then accept the null hypothesis confirming the presence of homoscedasticity. Regarding the autocorrelation in residuals, the Ljung-Box test is applied. The null hypothesis states that there is no autocorrelation and the alternative hypothesis is that there is autocorrelation. The *p*-value = 0.6275 is greater than 0.05, we then accept the null hypothesis, which means there is no autocorrelation in residuals. As the model assumptions are met, we can conclude that the model is a good fit for the data.

5. Conclusion

Since loan portfolio quality plays a key role in banks profitability, an increase in NPLs might be source of concerns for practitioners and regulators. However, in Haiti, from June 2022 to April 2023, except the decrease observed in September 2023, the NPL ratio of the banking system has displayed an upward trend with values over 10.0%. Thus, it is critical to investigate the factors that might influence the loan portfolio quality of the Haitian banking sector. This paper examines the impact of CAMEL method on loan portfolio quality, using monthly data from October 2019 to April 2023, giving a total of 42 observations. For the statistical analysis, the ARDL-ECM approach is adopted. NPLs ratio is used as dependent variable representing the component asset quality of CAMEL approach. The remainder CAMEL components are independent variables: capital adequacy, management efficiency, earnings quality, liquidity. In addition, the exchange rate is used as a control variable.

The results of the ARDL (4, 4, 0, 4, 4, 1) model show that the first lag of capital adequacy has a negative and significant effect on NPL ratio, which supports the "moral hazard" hypothesis that low-capitalization of banks implies deterioration of loan portfolio quality. Similarly, earnings quality measured by Return on Equity (ROE) is negatively and significantly associated with NPL ratio, confirming the "bad management II" hypothesis that past earnings are negatively connected with increases in problem loans. When it comes to banks liquidity, the effects of liquidity ratio at time t and the ones of the first lag are statistically significant and positive, suggesting that an increase in liquidity ratio could probably lead to an increase in NPL ratio. In contrast, the fourth lag of liquidly ratio is significantly and negatively related to NPL ratio, supporting the "debt rollover" hypothesis that future problem loans are negatively related to banks liquidity. While at time t the exchange rate has a significant and positive effect on NPL ratio, the fourth lag of the exchange rate shows a significant and negative impact on NPL ratio. Finally, the loan portfolio quality is significantly and positively affected by NPL ratio at time $t-1$.

Moreover, with a negative and statistically significant coefficient (−0.0562) of the error correction term, the study confirms that there is a significant long-run relationship or cointegration between the change in NPL ratio and the exploratory variables. Similarly, the CUSUM and CUSUMSQ statistics are well within the 5% critical bounds, implying that short and long-term coefficients in the ARDL-Error Correction Model are stable.

Finally, the deterioration of the loan portfolio quality of the Haitian banking system might be affected by other factors such as the gloomy economic situation, the political and social instability of the country. However, the findings of this study highlight the importance of taking into consideration CAMEL variables and macroeconomic variables like the exchange rate when assessing the loan portfolio quality of Haitian banks from a financial stability perspective.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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