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Examining Macroeconomic variables on Credit risk in the South African Banking System

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Abstract: Banks serve as foundational pillars in a nation's financial system, playing a critical role in providing liquidity within a market economy. Given their intrinsic significance and pivotal functions, banks inherently face a spectrum of risks. The primary **Objective** of this study was to employ quantitative research methods to scrutinize the correlation between credit risk and various macroeconomic variables. Building upon **Prior Research** validating the link between macroeconomic factors and credit risk, our **Approach** involved analyzing annual secondary macroeconomic and bank-specific data variables spanning from 2007 to 2022. The **Results** reveal a sustained relationship between credit risk and the examined macroeconomic variables over the long term. Notably, in the short term, only the GDP growth rate and exchange rate emerge as influencers of credit risk. The **Implications** of this study extend to banks, offering insights into comparative performance, and to academic researchers, providing a benchmark for their scholarly endeavors. **Value** by contributing to the existing body of knowledge on variables contributing to credit risk, this study underscores the significance of managing GDP and exchange rate as factors to mitigate credit risk.

Keywords: Non-performing loans; Credit risk; South African banks; GDP growth rate; exchange rate

JEL Classification: C30; G10; G21; G28; H63

1. Introduction

The banking sector holds a crucial position in both local and international economies, playing a significant role in their stability and growth. Banks serve as intermediaries, facilitating the flow of resources from those with excess cash to individuals and businesses seeking capital for investment purposes (Geletta, 2012). This credit allocation is vital for promoting investment and driving economic growth, as

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emphasized by Sheefeni (2015).

A stable financial system is essential for economic prosperity, mobilizing savings and transforming them into productive investments. It also plays a crucial role in risk management, reducing overall risk levels (Kjosevski & Petkovski, 2017). Globally, the banking sector is key to establishing and maintaining a stable financial system, reinforcing the connection between economic growth and banking sector stability (Bayar, 2019).

Profits in the banking industry stem from loans, making proper loan management crucial for a bank's survival. Lending is the cornerstone of the banking industry, constituting a significant portion of total assets and generating most of the operating income (Koch & MacDonald, 2006). Credit risk, defined by Al-Smadi and Ahmad (2009) as potential non-payment of promised cash flows from loans and securities, poses a significant threat to banks and is a major factor contributing to bank failures (Gup et al., 2009).

Nonperforming loans (NPLs) have a substantial impact on the performance of financial institutions, negatively affecting the quality of bank assets, profitability, and liquidity (de Lis, Pagés, et al., 2000; Mohanty, 2018). Identifying determinants of credit risk is crucial for sound bank management and financial stability, with microeconomic and macroeconomic factors being the main economic elements influencing credit risk (Pesaran et al., 2006).

In a developing country like South Africa, an individual's creditworthiness is influenced by various macroeconomic factors (Olena, 2010). Despite the South African banking system being liquid and well-capitalized, macroeconomic challenges like rising inflation and increasing unemployment could elevate credit risk exposure (IMF, 2022).

Poor credit management decisions have led to the collapse of several South African banks over the years. Major banks, such as Standard Bank, Nedbank, FirstRand, Absa, and Capitec, dominate the market share, emphasizing the need to understand and manage nonperforming loans to avoid vulnerabilities in the banking system (Geletta, 2012).

Macroeconomic variables, including GDP, inflation, and interest rates, are recognized as key factors influencing nonperforming loans. Unpredictable in nature, these variables pose a challenge for banks in managing credit risk. On the microeconomic level, factors like limited institutional capacity, unsuitable lending practices, and inadequate loan underwriting contribute to credit risk (Kithinji, 2010).

Various studies highlight the importance of analysing credit risk contributors, with research conducted by Khumalo et al. (2021) indicating the impact of macroeconomic factors on the profitability of South African banks. Despite existing studies, the question remains: how do macroeconomic factors influence credit risk

in the South African banking system? This study aims to analyse the factors contributing to nonperforming loans within South Africa, focusing on data from 2007 to 2022, including the impact of the global pandemic between 2019 and 2022 on loan defaults. To the best of the author's knowledge, no study has covered the same period and specific macroeconomic variables used in this research.

2. Literature Review

Financial institutions play a pivotal role in every country's economic and financial system, with their viability and expansion hinging on the increase of assets. To achieve this, they often utilize credit, in the form of loans, for financing their operations and services, exposing them to the concept of credit risk. Credit risk, as defined by Al-Smadi and Ahmad (2009), refers to the possibility that promised cash flows from loans and assets may not be fully repaid by borrowers. Consequently, effective credit risk management becomes crucial.

The development of non-performing loan risk is closely tied to the external economic environment's deterioration. The macroeconomic landscape is considered a key influencer of nonperforming loans, as highlighted by researchers like Nkusu (2011), Kharabsheh (2019), Tanaskovic, and Jandric (2015). Aver (2008) conducted an empirical study emphasizing the role of macroeconomic situations in explaining high nonperforming loan rates.

Khumalo et al. (2021) utilized gross domestic product, interest rate, exchange rate, and inflation to investigate their relationship with credit risk. Similarly, Gitonga (2014), Fatima (2017), and Gar (2013) employed the same variables, forming the basis for this study.

Theoretically, GDP growth signifies rising incomes, potentially enhancing borrowers' loan repayment abilities, thereby lowering credit risk. This relationship between GDP growth and credit risk aligns with earlier research by Kuzucu & Kuzucu (2019), Vogiazas and Nikolaidou (2011), Zribi and Boujelbene (2011), Aver (2008), and Fofack (2005). Beck et al. (2013) conducted a comprehensive study, finding a significant and strong relationship between GDP rate and nonperforming loans in 75 advanced and emerging economies from 2000 to 2010.

Contrastingly, Nkusu (2011) reported a negative relationship between GDP and credit risk in a sample of 26 advanced economies from 1998 to 2009. Warue (2013) and Castro (2013) supported this, suggesting that credit risk increases as GDP growth declines. In the Jordanian banking sector, Kharabsheh (2019) found no substantial link between GDP and nonperforming loans.

Inflation also impacts the banking industry, with high inflation affecting assets and equity negatively. Some studies, like Gunsel (2012) in North Cyprus and Wiryono

& Effendi (2018) in the Islamic banking system, found a positive correlation between inflation and credit risk. However, others, such as Zribi and Boujelbene (2011), Vogiazas and Nikolaidou (2011), Aver (2008), Bofondi & Ropele (2011), Castro (2013), Poudel (2013), and Khumalo (2021) observed a negative correlation in various banking systems.

The effective exchange rate also plays a role, as discovered by Castro (2013) and Nkusu (2011) in specific countries. Changes in exchange rates were found to influence the loan portfolio quality, either positively or negatively, depending on the economic context. However, Aver (2008) found no connection between changes in foreign exchange rates and the nonperforming loan ratio.

Lending interest rates are another crucial factor influencing credit risk. Warue (2013) investigated their impact on nonperforming loans in Kenyan commercial banks, supporting earlier findings by Beck et al. (2013) that higher lending interest rates correlate positively with increased nonperforming loans. Conversely, Park and Zhang (2012) discovered a negative link between credit risk and the interest rate in the United States before and during the recent financial crisis.

In summary, macroeconomic variables such as GDP, inflation, exchange rates, and lending interest rates significantly impact credit risk, with their effects varying across different economic contexts and banking systems.

3. Methodology

This research comprises a literature review and an empirical study aimed at clarifying the research design and methodology. The study employs quantitative research methods with a focus on secondary data. By gathering aggregate macroeconomic panel data pertaining to factors impacting credit risk, the study utilizes quantitative analysis to examine the correlation between credit risk and macroeconomic factors within the South African banking system.

3.1. Sample Selection & Data Description

This paper used a quantitative research approach with panel data analysis to analyse the influence of macroeconomic variables on credit risk within the South African banking system.

Annual data of macroeconomic variables from 2007-2022 was sourced from Quantec Easy Data. This study also accounts for nonperforming loans used as a proxy for credit risk, annual banks' NPLs data was collected from the South African Reserve Bank (SARB) and the five banks in South Africa namely, Absa Bank Ltd, FirstRand Bank Ltd, Nedbank Ltd Standard Bank of South Africa Ltd, and Capitec

Bank, were selected for this study the choice of these banks is due to their 90% of the market share of total banking sector assets. Therefore, this is a true representation of the South African banking sector.

3.1.1. Panel Data

Panel data, characterised by multiple cross-sections over time, merges cross-sectional and time-series features. Its utility lies in controlling unobservable variables across the dataset. Leveraging panel data analysis enhances the precision of individual outcome predictions. This method captures data dimensions inaccessible to cross-sectional and time-series approaches (Hsiao, 2014).

In this study, the examination of the correlation between credit risk and various macroeconomic variables employed the panel pooled mean group (PMG) model. This model is grounded in the Autoregressive Distributed Lag (ARDL) framework proposed by Pesaran et al. (1999). Notably, the ARDL technique, following Pesaran et al. (1999), has been applied in other studies, such as those by Garces-Ozanne (2006) and Shittu et al. (2012), to scrutinize long-term relationships within panel data. It is imperative to underscore that specific conditions and assumptions must be satisfied to apply the PMG ARDL approach in a study. The data should exhibit a normal distribution, be devoid of heteroscedasticity and autocorrelation, and the variables should not be cointegrating at level 2 or I (2), as prescribed by Pesaran (1999).

3.2. Model Specification

The function of the regression is to examine the relationship between the various independent variables and the dependent variable. The study formulates and estimates the following panel regression model:

3.2.1. Model

$Yt = \beta_0+\beta_1(GDPG)+\beta_2(INR)+\beta_3(EXR)+\beta_4(CPI)+\mu$

Dependent variable: Yt= non-performing loans (credit risk)

Independent variable:

GDPG=GDP growth rate

INR= Interest rate

EXR= Exchange rate

CPI= Inflation rate

μ= Error term

3.2.2. Variables

Table 3.1. Definition of Variables

Variables	Description	Predicted outcomes
Dependent variable		
Non-performing loans	Loans that are unpaid and overdue for a period	
Independent variables		
GDP growth rate	Measures the output of final goods and services within an economy from one year to the next	Negative
Interest rates	The rate at which banks lend money to borrowers.	Positive
Exchange rate	The value of one country's currency in terms of another country.	Negative
Inflation rate	Inflation is defined at the general price level	Positive

Source: Compiled by author

4. Empirical Results and Discussion

This section presents empirical results and discussion thereof. It starts by describing the descriptive statistics of the data used in this study. Then followed by correlation analysis, continue to proceed to analysis of long and short run relationship, however before that unit root test ids performed to check for then the regression is run to determine the long and short run on the viables.

4.1. Descriptive Statistics

Descriptive statistics analysis is valuable because it makes it possible to comprehend the properties of the data collected and utilized in this investigation. The following descriptive statistics are examined and analysed to offer an overview of the data used: mean, median, maximum, minimum, standard deviation, skewness, and kurtosis of all variables.

Table 4.2. Descriptive Statistics

	LNINTR	LNGDPG	LNCPI	LNEXR	NPL
Mean	2.284	0.627	1.707	2.383	2.577
Median	2.264	0.794	1.695	2.465	2.139
Max	2.716	1.679	2.794	2.795	12.133
Min	1.952	-1.193	1.952	1.952	0.000446

Std.Dev	0.181	0.754	0.297	0.297	2.451
Skewness	0.0771	-0.821	-0.206	-0.206	1.234
Kurtosis	3.780	3.306	1.450	1.451	4.634
N	70	70	70	70	70

Source: Compiled by author

The summary of descriptive data for macroeconomic factors and non-performing loans is shown in Table 4.1. The variable LNCPI, according to the descriptive statistics, represents a normally distributed data series since its kurtosis value is less than 3% and its skewness value is less than 1.88%, all of which indicate that the two variables have a normal distribution.

Additionally, the results of this study showed a considerable increase in the banks' non-performing loans (NPLs), which ranged from a minimum of 0.000446% to a maximum of 12.133% and an average value of 2.577%. Such a sharp increase is not ideal for the health of the bank's loan portfolio.

4.2. Correlation Analysis

An examination of correlation is essential when a study has more than two variables. One way to determine the linear relationship between variables is through correlation analysis.

Table 4.2. Correlation Results

	NPL	**LNEXR**	**LNGDPG**	**LNCPI**	**LNINR**
NPL	1.00				
EXC	-0.180	1.00			
GDP	0.713	-0.521	1.00		
CPI	-0.257	-0.180	0.135	1.00	
INT	0.212	-0.488	0.256	0.601	1.00

Source: Compiled by author

When the correlation confidence value between two variables is positive and approaches one, it signifies a robust positive linear relationship. The variables exhibit parallel expansion or movement due to the positive correlation. Conversely, a negative correlation coefficient nearing -1 indicates a negative linear connection, portraying an inverse relationship as the variables ascend in opposite directions. However, a correlation confidence value of zero, as opposed to -1 or +1, suggests no association between the variables (Brooks, 2014).

To assess variable multicollinearity, a combination of correlation analysis and linear association analysis is commonly employed, offering a comprehensive perspective on variable relationships. Multicollinearity is typically suspected when the correlation coefficient between variables exceeds 0.8, as advised by Gujarati (2009).

This threshold serves as a practical guideline for detecting multicollinearity in the dataset.

Table 4.2 displays the link between independent and dependent variables. The correlation matrix indicates a negative link (-0.180) between exchange rate and credit risk. Credit risk and GDP growth rate exhibit a positive correlation (0.713). Credit risk aligns favourably with interest rates and is inversely correlated with inflation (-0.257). The results indicate no cause for concern regarding multicollinearity among the variables, as all values are below 0.8. Consequently, the same regression equation may be employed to analyse or regress the variables.

4.3. Analysis of Long and Short Run Relationship

4.3.1. Unit Root Test

The unit root test for panel data serves a crucial role in assessing the stationarity of variables. It helps distinguish between stationary and non-stationary variables. Additionally, this test aids in establishing the order of integration for these variables. This determination involves discerning whether the variables are stationary at the first difference (integrated of order, I (1)), or they remain stationary at the level (integrated of order, I (0)). By effectively applying the unit root test, the risk of using non-stationary variables in regression analysis is mitigated. Such variables can lead to misleading regression results, as highlighted by Brooks (2014).

Table 4.3. Unit Root Test

Variables	Method		ADF	PP	
EXR	At level	Intercept	0.0000	0.0051	I (1)
		Intercept & Trend	0.4024	0.4073	
	1st Difference	Intercept	0.0124	0.0070	
		Intercept & Trend	0.0555	0.0374	
INR	At level	Intercept	0.0001	0.0476	I (1)
		Intercept & Trend	0.5099	0.5099	
	1st Difference	Intercept	0.0495	0.0511	
		Intercept & Trend	0.1888	0.2226	
GDPG	At level	Intercept	0.0098	0.0081	I (0)
		Intercept & Trend	0.0202	0.0001	

	1st Difference	Intercept	0.0002	0.0000	
		Intercept & Trend	0.0010	0.0000	
CPI	At level	Intercept	0.0000	0.0000	I (1)
		Intercept & Trend	0.0804	0.0504	
	1st Difference	Intercept	0.0267	0.0032	
		Intercept & Trend	0.1263	0.0127	
NPL	At level	Intercept	0.0169	0.0235	I (0)
		Intercept & Trend	0.0001	0.0000	
	1st Difference	Intercept	0.0000	0.0000	
		Intercept & Trend	0.0000	0.0000	

Source: Compiled by author

The panel root test results indicate that several variables can be categorised as either I (0) or I (1). Specifically, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) techniques yield p-values below 0.05 for GDPG and NPL when tested at the level. As a result, the null hypothesis is rejected, leading to the conclusion that both GDPG and NPL are stationary at the level.

On the other hand, the panel unit root test outcomes for EXR, INT, and CPI consistently show p-values exceeding the 0.05 significance threshold, whether evaluated with an individual intercept or an individual intercept and trend. These results indicate that none of these variables can be considered stationary, as they all possess a unit root at the level.

Given this, additional tests are necessary to assess stationarity at the first difference, considering the lack of stationarity at the level for these variables. In this context, the null hypothesis is rejected for EXR, INT, and CPI variables when their p-values fall below 0.05 during testing at the first difference. This implies that these variables are stationary at the first difference, indicating they are integrated of order I (1).

4.3.2. Long-run Relationship Analysis

In testing the long-run relationship between exchange rate, interest rate, inflation, and gross domestic product, using NPL as a measure of credit risk, the following model was formulated**:**

NPL=23.57-1.016INT-3.991CPI-1.078GDPG-4.698EXR

Table 4.4. Long-run results

Long-run		
Variables	**Coeff.**	**Prob.**
C	23.57	0.000*
LNINT	-1.016	0.000*
LNCPI	-3.99	0.000*
LNGDPG	-1.078	0.000*
LNEXR	-4.698	0.000*

Note: *, **, and *** indicates significance at 1%, 5%, and 10% respectively.

Source: Compiled by author

Through the examination of the results presented in Table 4.4, all the variables (LNLINT, LNCPI, LNGDPG, LNEXR) have a negative impact on credit risk, with coefficients of -1.016, -3.99, -1.078, and -4.698 respectively. Since there is a negative relationship, this indicates that if LINT and LNCPI were to change by one percent, this would decrease NPL by 1.016% and 3.99% respectively. With the two remaining variables LNGDP and LNEXR if these two variables were to change by one percent NPL would decrease by 1.078% and 4.698%.

In terms of significance level, all four variables are significant with p-values of 0.000, meaning that all four variables explain the credit risk levels at banks during the period of the study.

4.3.3. Short-run Relationship Analysis

Table 4.5. Short-Run Results

Short run		
Variables	**Coeff.**	**Prob.**
ECT	-0.734	0.017*
D(LNINT)	0.537	0.646
D(LNCPI)	2.589	0.216
D(LNGDPG)	1.600	0.015*
D(LNEXR)	2.885	0.044*

Note: *, **, and *** indicates significance at 1%, 5%, and 10% respectively.
Source: Compiled by author

Table 4.5 presents the error correction model for the NPL equation, where the most crucial terms are the sign and coefficient of the ECM term. As a general rule, the error term should be substantial and negative. In this case, the ECT equation's error term stands at -0.734, and its p-value of 0.017 signifies significance. The negative sign of the ECM term indicates that there is a process of credit risk and independent variables eventually reaching an equilibrium.

According to Bannerjee et al. (1998), a highly significant error correction factor suggests a stable long-term connection between variables. In the NPL model, the

error term of -0.734 implies that approximately 73.4% of the disequilibrium from the previous year has been rectified in the current year. Calculating 1 divided by 0.734832 yields 1.345, indicating that, as measured by NPL, the entire banking system takes 1.3 years to achieve credit risk equilibrium. Notably, only LNGDPG and LNEXR, with significant values of 0.015 and 0.044, respectively, emerge as crucial factors in the short term. This suggests that, as measured by NPL, LNGDPG and LNEXR can explain changes in credit risk in the short term.

5. Conclusion

The macroeconomic landscape plays a pivotal role in the nonperforming loan predicament. These variables not only shape borrowers' behaviour but also exert substantial pressure on the banking system, paving the way for underqualified borrowers and exposing banks to credit risk.

This study delved into the influence of macroeconomic variables on credit risk within the South African banking system. The findings underscored a robust statistical significance in the correlation between these factors, concluding that all variables wield a long-term negative impact on credit risk. However, interest rates and inflation were found to have negligible short-term effects, indicating a lack of meaningful immediate correlation with credit risk.

The empirical results highlight the imperative for effective supervision by bank managers and monetary authorities in the credit selection and allocation process. Additionally, the development of banking models that account for potential macroeconomic influences on borrowers' behaviour is crucial. Some studies recommend adopting the falling balance approach to loans, a strategy that could mitigate credit risk and significantly reduce the percentage of loan defaulters. In summary, financial regulators ought to devise a strategy aimed at bolstering credit risk management practices and curbing the rise of nonperforming loans in the South African economy.

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