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DETERMINANTS OF NON-PERFORMING LOANS IN NAMIBIA'S BANKING SECTOR

A DISSERTATION SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR

THE DEGREE OF

DOCTOR OF PHILOSOPHY IN ECONOMICS

BY

VALDEMAR JOÃO UNDJI

3908831

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SUPERVISOR: PROF. JOHANNES P. S. SHEEFENI

(UNIVERSITY OF THE WESTERN CAPE)

Abstracts

This thesis comprises of six chapters and investigates issues related to non-performing loans (NPL), a proxy for credit risk, with a particular focus on the banking sector of Namibia. The issues covered include a) assessing the evolution of Namibia's financial system post-independence in 1990; b) determining the factors influencing the quality of Namibia's loan portfolio; c) examining the causality between NPL and the identified factors; d) a stress-testing analysis examining the credit risk vulnerability of Namibia's banking sector; and e) a forecast of the quality of Namibia's banking sector loan portfolio. These five issues are interwoven and are subdivided into three main sets of objectives which are extensively explored in Chapters II, IV and V.

Chapters II analysis the first objective that evaluates the evolution of the Namibian financial system post-independence in 1990. The structure and composition of the financial system is discussed along with its contributions to employment creation and economic growth. The ownership structure of the banking sector and its overall performance is also outlined. The finding reveals that the influence of non-bank financial intermediaries has grown significantly overtime, whilst the dominance of the financial sector has shrunk in the face of credit risk pressure. The financial sector's contribution to employment is minimum and it is likely to worsen as developments in the artificial intelligence world continue.

Chapter IV examines the second set of objectives ({b} and {c}) by developing and evaluating an empirical model that is particular to Namibia. With the assistance of the Autoregressive Distributive Lag (ARDL) and the Vector Autoregressive (VAR) pairwise Granger causality modelling approaches, a time-series dataset for the period 1996Q1-2021Q4 was employed to assess the aforementioned objectives. To garner the individual effects of various factors, the empirical estimations were done in stages. Firstly, a simultaneous model involving all the control variables was estimated followed by the reduced form model. The findings from the model consisting of the composite measures reveal that in both the short and long run, both the macroeconomic and interest rate indices affect NPL. Accumulations of NPL in the previous quarter as well as the governance (institutional) indicator are likewise reported to affect NPL in the short run. In terms of causality, the macroeconomic and the interest rate indicators have been *recorded to have a long run causal effect on NPL. However, over the short run, the results show that there is a strong causal effect running from the past quarter values of NPL to NPL itself as well as from the macroeconomic indicator to NPL.*

Chapter V investigates the third set of objectives ({d}-{e}) by developing a stress-testing framework for evaluating the fragility of Namibia's banking sector to credit risk as well as a forecast of the quality of its loan portfolio. The stress-testing results show that the indicators for early warnings are primarily from a positive shock in Non-performing loan (NPL) itself, followed by the monetary, institutional, bank-specific, and interest rate indicators, respectively. The results from the out of sample dynamic forecasting technique of the ARIMA model reveals that the forecast model is efficient and over the long-run Namibia's banking sector is susceptible to the risk factors underscored in this study. The riskiness of its loan portfolio is bound to persist beyond the stipulated benchmark region of 4.0%-points set by the Bank of Namibia throughout the forecast period, 2024Q1-2025Q4.

The policy interventions emanating from this study require that: a) the mechanisms for monitoring and evaluating individual banks in relation to credit risk are strengthened, b) existing policies are re-evaluated with the end goal of identifying irrelevant policies and get rid of them, c) a sound macroeconomic and financial environment is maintained, and d) individual banks are adequately capitalised. These policy implications, amongst others, ensure the bedrock upon which the stability of the banking sector relies upon.

Keywords*: ARIMA, Non-performing loans, Credit risk, Macroeconomic, Bank specific, Monetary, Interest rate, Financial, Institutional, Autoregressive Distributive Lag, Granger causality, Stress testing, Forecasting, Namibia*

Dedication

To my parents

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Declaration

I declare that the *determinants of non-performing loans in Namibia's banking sector* is my own work, that it has not been submitted before for any degree or assessment in any other university, and that all the sources I have used or quoted have been indicated and acknowledged by means of complete references.

--------------------------- 6 June 2024 -----------------

Signed **Data**

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List of Abbreviations

ARDL – Autoregressive Distributive Lag

ARIMA – Autoregressive Integrated Moving Average

BANK – Bank specific

BON – Bank of Namibia

CBN – Central Bank of Namibia

CESEE – Central and Eastern and South-Eastern Europe

Ceteris paribus – cp

CMA – Common Monetary Area

FINA – Financial

IMF – International Monetary Fund

INST – Institutional

INTER– Interest rate

MACRO – Macroeconomics

MONE – Monetary

NBFI – Non-Bank Financial Intermediaries

NAMFISA – Namibia Financial Institutions Supervisory Authority

NamRA – Namibia Revenue Agency

NPL – Non-Performing Loans

NSA – Namibia Statistical Agency

PCA – Principle Component Analysis

SSA – Sub-Saharan African

UMIC - Upper-Middle-Income Countries

WDI – World Development Indicator

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CHAPTER I: INTRODUCTION

1.1 Introduction

This chapter provides the overall introduction of the thesis. In particular, Section 1.2 outlines the background to the study at hand. Section 1.3 presents the thesis' statement of the problem. Section 1.4 describes the research objectives of the thesis. Section 1.5 underscores the corresponding research hypotheses. Section 1.6 highlights the contributions of the thesis to the body of literature. Section 1.7 touch base on the significance of the study. Finally, Section 1.8 provides the outline of the entire thesis.

1.2 Background to the Study

The crises brought about by the outbreak of the Coronavirus (COVID-19) pandemic in 2019 not only disrupted the world economies and caused unprecedented socio-economic impact, but also destabilised the quality of the loan portfolios for most banks around the world. Just like the global financial crises of 2008, such instabilities highlight the importance of credit risk management within the context of the banking sector and financial system (Naili & Lahrichi, 2022). Credit risk management, which entails identifying, assessing, controlling, and monitoring the risk associated with credit, requires a specific guideline aimed at managing credit portfolios (Sharifi et al., 2019). Failure to which it would reduce the ability of banks to determine the precise processes for allocating, assessing, supervising, and collecting loans. Perhaps one of the lessons to be learnt from the crisis of 2008, is the dangers posed by an uncontrolled growth in mortgage lending by unworthy borrowers which lead to rising Non-performing loans (NPL) (Messai & Jouini, 2013). Unsurprisingly, the COVID-19 pandemic, which negatively affected the performance of various financial systems around the world, has coincided with the rising levels of NPL in many economies, including Namibia's. Generally, NPL are defined as defaults in financial assets which have not yielded any interest or principal repayment for the lending institution over 90 days (Rifat, 2016; Tracey, 2007). In Namibia, the Bank of Namibia defines it as those loans whose borrowers have defaulted for a period of 90 days (Bank of Namibia & NAMFISA, 2022).

Even though not all financial instabilities experienced around the globe are caused by NPL, spiralling levels of NPL have the capability of causing severe financial crises like those experienced in 2008/09. For this reason, many researchers have rigorously investigated the root causes of NPL both at country as well as regional levels (Gashi, 2021; Ghorbani & Jakobsson, 2019; Kjosevski & Petkovski, 2021; Radivojevic & Jovovic, 2017; Staehr & Uusküla, 2021). However, the majority of the studies on the drivers of NPL mainly focused on two categories namely, the macroeconomic and bank specific indicators (Beaton et al., 2016; Gulati et al., 2019; Kepli et al., 2021; Kjosevski & Petkovski, 2017; Rehman, 2017; Us, 2018). Only the study by Nikolaidou and Vogiazas (2011) thoroughly examined a vast range of indicators culpable of influencing the levels of NPL within the Romanian banking system. Clearly, the determinants of NPL should not be exclusively limited to bank specific and/or macroeconomic factors. Due to the rareness of such holistic studies, coupled with a lack of innovation on the part of the majority of existing studies, this study uses Namibia, a small open developing economy, as a case study to contribute to the literature debates and profile its country-specific findings.

Whilst there are a number of studies on the root causes of NPL, both from the developed and developing world, very little attention is given by countries within the Sub-Saharan African (SSA) region, of which Namibia is a member (Mpofu & Nikolaidou, 2018). The unavailability of data is cited as one of the reasons why there are limited investigations on the subject at hand in a number of SSA countries (Kjosevski et al., 2019). For this reason, quarterly time-series data are often employed to circumvent the limitations presented by a short range of annual time-series. In the absence of suitable dataset, this remedy is second to none as it equips policy makers to be aware and fully understand the extent to which the risk factors could affect the asset quality of the banking sector.

Moreover, banks' failure in detecting the leading causes of credit risk, manifested through rising levels of NPL, limits their ability to address the phenomenon of rising credit risk levels (Gavin & Hausmann, 1998). Consequently, this may hinder the ability for the banking sector authorities to avert possible crises, thereby causing a catastrophic financial disaster for the overall economy. Given that an abrupt rise in credit risks has a domino effect on the financial system of any country, economies should adopt preventative macroprudential measures that ensures a sustainable lending environment (Tatarici et al., 2020). This should include measures that safeguard against any kind of risks associated with NPL.

Since the level of credit risk can affect and diminish the banks' profit margin, it is only natural that some banks are risk averse. Nevertheless, the averseness needs to be exercised with caution (prudently), in order to capitalise on the investment opportunities that present themselves. This can be achieved by firstly identifying and then understanding how the identified factors influence NPL (Adusei & Bannerman, 2022). For this motive, this study uses Namibia as a case study to holistically examine the leading indicators considered by a number of studies of causing high NPL in different parts of the world. The outcomes of study highlight the main drivers of NPL to bank managers, policymakers, and regulators. In addition, the findings aid the efforts by stakeholders to develop mechanisms for early warnings for risk. Such alerts are vital in formulating workable policies for combating rising levels of NPL while mitigating and hedging against future crises related to credit risk.

The banking sector plays an important intermediary role in the economic growth and development of any country (Ikram et al., 2016). They mobilise savings (by accepting deposits from mainly households who are the net savers and purchasers of securities) and improve the flow of capital into the market by extending their credit (lending) allocation to borrowers. The categories of borrowers are not limited to households and the government, but also financial players like investors and firms who also end up investing the money into gainful investment ventures. This being the case, loans are an integral part of most banks as they make up a huge bulk of their financial assets through which most of the revenues and profits are generated (Amuakwa-Mensah et al., 2017).

Statistics from the World Development Indicators (WDI) of the World Bank (WB), show that the average level of NPL amongst the six Upper-Middle-Income Countries (UMIC)[1] in the Sub-Saharan Africa (SSA) region for the period 2013-2021 was 5.80%. Amongst them, Namibia was ranked as having the lowest average levels of NPL during the said period. Despite this, the

[1] *Botswana, Equatorial Guinea, Gabon, Namibia, Mauritius, and South Africa. These are countries said to have a Gross National Income (GNI) per capita between US$ 4096-US$12695 as per the World Bank classification 2023FY.*

phenomenon NPL still requires to be under surveillance as the rates continues to trend beyond the benchmark of 4.0% set by the BoN.

The body of literature from both the developed or developing countries, presents a clear divergence on the types of data and variables used as a determinant of NPL, the methodologies employed and the findings obtained by different researchers around the world. For instance, the many studies that used time series data (Asiama & Amoah, 2019; Azar & Maaliki, 2018; Wood & Skinner, 2018) also employed different estimation techniques, such as the autoregressive distributive lag (ARDL), generalised least square (GLS), dynamic generalised method of moments (GMM), to mention but a few. Others utilised a panel dataset (Arham et al., 2020; Kordbacheh & Sadati, 2022; Rachid, 2019; Tatarici et al., 2020), whilst using different estimation methods.

Whereas there are inexhaustible studies that have tried to uncover the isolated effects of indicators on NPL, this study deemed it necessary to investigate the joint effects that various indicators bear on the level of NPL in Namibia's banking system. The reason for this quest is that, in reality the factors affecting NPL are multifaceted and of the existing studies in the body literature, only Vogiazas and Nikolaidou (2011)'s study attempted to explore an array of indicators that are likely to influence NPL using data from the Romanian banking system. Albeit, their results cannot be generalised nor applied to Namibia due to some unique characteristics that are particular to Namibia, which are discussed in the later sections of this study. Similarly, in Namibia, there has been a handful of studies (Kamati et al., 2022; Sheefeni, 2015a, 2015b) that only focused in examining the effects that the macroeconomic and bank-specific indicators have on NPL.

The current study differs from the aforementioned studies in that it employs a powerful technique, the Principal Component Analysis (PCA), that is used to consolidate a number of factors that are usually at play within the real economy. The technique is desirable as it produces unambiguous, realistic results and plausible conclusions. Despite the limited studies on the subject of NPL in Namibia, there are no studies that holistically examined the determinants of NPL. For this reason, a country-specific study providing a comprehensive perspective on the subject matter as it relates to the Namibian context is indispensable. Such country-specific studies are not only useful in identifying the root causes, but are also helpful to regulators and stakeholders in general.

Comprehensive studies of such nature are helpful in providing an understanding of the determinants of NPL phenomenon, while at the same time assisting legislators to enact targeted policy interventions that are effective in suppressing such a phenomenon from rising. Moreover, since evidence from one country may not necessarily be so useful in informing policy decision of another country, due to unique characteristics of each country, such studies are still very much relevant for individual countries.

In Namibia, like many other developing countries, loans (mainly mortgages) constitute the bulk of the banks' asset composition. Specifically, the exposure of Namibia's banking sector to credit risk due to mortgage lending for the year 2020 and 2021 stood at 52.3% and 53.4% of total lending respectively (Bank of Namibia, 2022; Bank of Namibia & NAMFISA, 2021). In as much as the role of lending that is facilitated by banks plays a pivotal role in the economic growth and development of any economy, it is disastrous when a bulk of such asset concentrations are tied up in mortgage lending that are non-performing. The fact that in Namibia a large part of the banking sector asset concentration is tied up in mortgage lending insinuates that the banking sector is highly exposed to dynamics of the housing market. Reason being, the housing price index is considered as one of variable interest for this study, just as in Canepa and Khaled (2018) and Kamati et al. (2022) studies.

Credit risks have long been considered as the leading causes of the global financial crises, especially when such risks emerge from the world's leading economies (Barra & Ruggiero, 2021; Rajha, 2017). The severity of the risk is largely dependent on the severity of borrowers' default, which is among the root causes of insolvency of most lending institutions (Mazreku *et al*., 2018; Musau, 2014). Whereas higher credit risks, used in this study to proxy NPL, are undesirable to banks, they are equally unwanted by any serious country striving to grow its economy. The rise of NPL is disdained due to its potential to spill over to other sectors of the economy; thereby, derailing the economic performance of the country. A dysfunctional economy diminishes the government's capability for revenue generation via the individual and corporate taxes, which makes it harder for the government to successfully execute its developmental agenda. This is especially true for countries like Namibia, whose fiscal budget is largely dependent on tax revenue collections[2].

As alluded to earlier on, the levels of NPL are proxies for credit risk and are used to examine the soundness (or fragility) of the banking sector and/or financial system. Other indicator of credit risk besides NPL include the loan loss provision (LLP), management quality, liquidity, capital adequacy and asset quality. Albeit, the NPL indicator is the most common measure of credit risk used in the literature body. The stability of the financial system is of vital importance for any successful economy as it instils investors' confidence (Amuakwa-Mensah *et al*., 2017). Nevertheless, the magnitude of the risk depends on whether the levels of NPL are low or high. Normally a rise in the levels of NPL signals the beginning of a financial crisis and/or a bad state of the banking system (Sheefeni, 2015b). There are usually a number of studies that have examined the resilience of banking systems by means of stress-testing techniques (Aboagye & Ahenkora, 2018; Patra & Padhi, 2022; Rakotonirainy et al., 2020).

In Namibia, Kamati et al. (2022) attempted to assess the vulnerability of Namibia's banking system by means of the stress-testing technique. Notwithstanding, their study is quite narrow in the sense that the stress-testing model only consisted of three independent variables[3], for which only two of the variable employed fell in the category of the macroeconomic indicator as per the classification of most studies(Amediku, 2006; Koju et al., 2018b; Vogiazas & Nikolaidou, 2011). Furthermore, the omission of other key macroeconomic factors[4], notwithstanding the other set of categories treated in this present study, understates the fragility of Namibia's banking system as portrayed in their study.

Should the scenario portrayed in the aforementioned study be inaccurate, Namibia's banking system may be caught off guard against some of the worst-case scenarios that could be brought about by stressful economic conditions. Relative to most past studies on the subject of credit risk, the present study is highly comprehensive and encompassing. This is because it incorporates an array of important factors, compacted into six categories of indicators, which have often been

[2] *The Namibia Revenue Agency (NamRA) managed to generate 42% of the total tax revenue target of the overall government expenditure budget of the anticipated N$60,1 billion for this current financial period (2022/23).*

[3] *Real GDP, Housing price growth, and Repo rate.*

[4] *Such as, Trade openness, Debt Stock, Output Gap, Unemployment, and Inflation.*

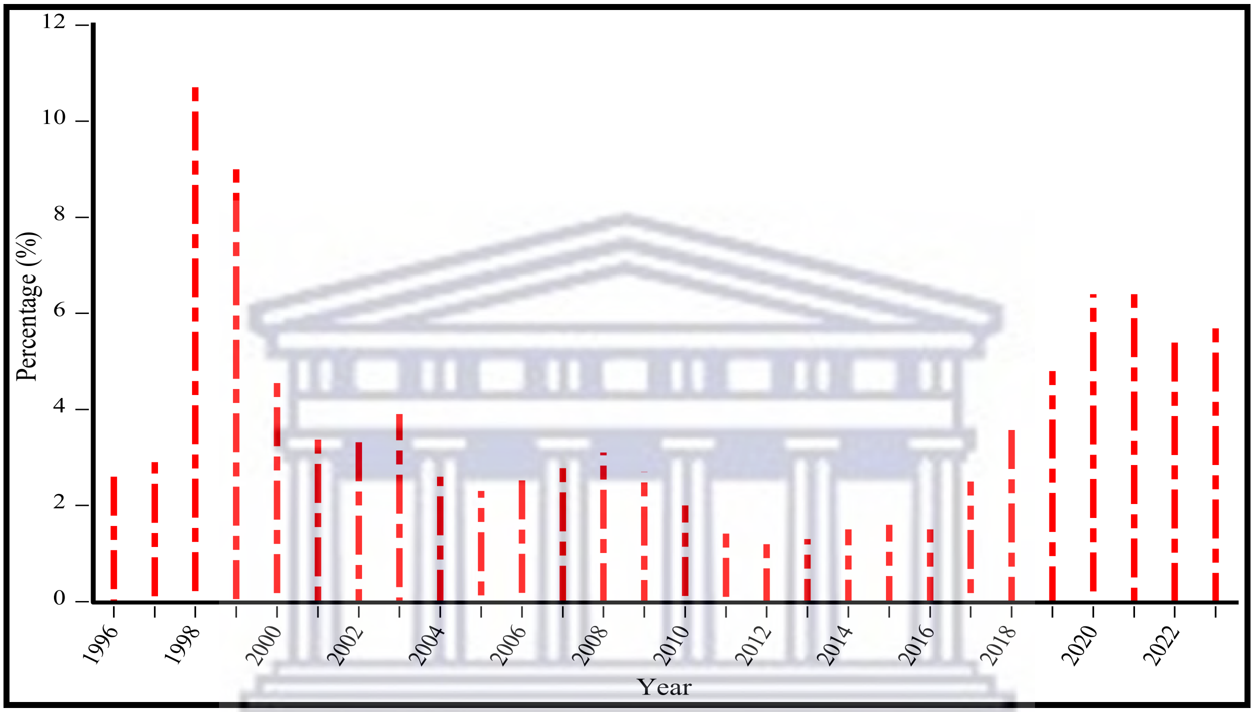
largely overlooked in the literature body, especially in Namibia. In addition, a relatively larger dataset, from the early years of Namibia's colonial independence is used in order to provide a much longer estimation memory.

Škarica (2014) argues that NPL causes uncertainty for commercial banks and impact the willingness and ability for banks to keep on with their role of lending, thereby affecting aggregate demand and investments. Not only that, the author also stresses that the level of unresolved NPL suppresses economic activities of currently overextended borrowers and traps resources in unproductive uses. Thus, a knowledge of the determinants of NPL helps bank management to hedge against potential pitfalls of bank losses. Moreover, the awareness of such factors is useful to policy makers as they devise mechanisms for stemming and minimising the level of NPL, thereby rescuing the financial system from collapsing. Whereas it is impossible to capture all the factors that may be responsible for causing a rise in the levels of NPL, any effort aimed at unveiling the key factors responsible for causing the level of NPL to rise is commendable.

Therefore, this present study is indispensable for Namibia's banking sector whose structure is oligopolistic in nature and is mostly dominated by foreign owned commercial banks which require a conducive financial system to operate in (Adongo & Stork, 2005). Not only is a sound financial system necessary for a successful operationalisation of the economy, but it also ensures the profitability of banks and investors (Amin et al., 2021). Namibia's economy has been experiencing a strong economic headwind since the year 2016. In fact, in 2018 it entered through a depression after consistently recording a series of negative GDP growth for 10 consecutive quarters. This prompted Moody's Investors service to downgrade the country into a junk status in August 2018. In February 21, 2019, another New York based Investment rating agency, Fitch Rating, downgraded Namibia's economic status from stable to negative.

The challenging economic conditions which resulted in the closure of a number of businesses has had its toll on the households of citizens who lost their jobs due to retrenchment. This in turn has continued to trigger increases in the levels of NPL since those who were formally employed failed to honour their debt obligations. Accordingly, the Bank of Namibia and NAMFISA (2023; 2022) reported a significant rise in the levels of NPL from 1.5% in 2016 to 6.4% in 2021 before dropping to 5.9% in 2023. The ratio of NPL in these periods were of big concern as it overshot beyond the benchmark of 4.0 % basis point as well as the supervisory intervention trigger point of 6.0%. Figure 1.1 shows the dynamics in the ratio of NPL from 1996 to 2023.

Figure 1.1: Non-performing loans (NPL) as a percentage of total loans



Source: Own computations using data from the NSA and BON

Figure 1.1 depicts the trend in the level of NPL in Namibia as total loan rises. It is worth noting that from 2016 to 2021 the NPL ratios have been deteriorating as depicted by its upward trajectory. However, Bank of Namibia (2022) reports that there has been some improvement in NPL ratios as it has declined from a 6.4% at the end of 2021 to 5.6 % by the end of 2022. Nonetheless, the banking system is still not yet out of the woods. Looking at the pattern of the past few years, it is inevitably concerning, especially when one considers the rise in credit risk patterns with long-term perspective of Namibia's financial stability.

Deterioration in the asset quality of Namibia's banking sector, especially depicted by the rising levels of NPL in recent years, is quite worrisome. This has been exacerbated by a slow economic progress registered since the year 2016. For instance, in 2015 the annual real GDP growth rate was registered to stand at 4.3%; whereas in 2020 Namibia recorded a record low of -8.0% GDP growth rate[5]. Needless to say, the economy is still not yet out of the woods. The high levels of NPL are indicative of the fact that the financial system still has problems associated with credit risk, which if not properly managed, could lead to catastrophic instabilities that are capable of spiking other social and political ills[6].

On the other hand, profitability indicators, the Return on Equity (ROE) and the Return on Assets (ROA), of Namibia's banking sector have also been declining. For example, from 2016 the ROE and the ROA were recorded to have decreased from 21.1% and 2.6% to 13.9% and 1.7% in 2021, respectively (Bank of Namibia, 2021). Such declines, coupled with rising NPL, are enough to undermine a country's economic progress and exacerbate the already dire economic condition that the country currently finds itself in. Therefore, by uncovering the factors/indicators responsible of influencings NPL and evaluating their impacts on NPL helps regulators and bank managers avoid the negative repercussions of NPL.

1.3 Problem Statement

The series of past financial crises causes one to appreciate the importance of credit risk management, which forms the basis for the stability of the financial system. Over the past couple of years, both the Bank of Namibia (BoN) and the Namibia Financial Institutions Supervisory Authority (NAMFISA) have consistently assured[7] the Namibian nation that the financial system remains resilient, despite of the global economic downturn. Their assertions, however, is not synchronised with the observed performance of the loan portfolios in the country. For instance, over the past couple of years, the levels of NPL have been rising at a relatively faster rate, pointing to a distressed banking sector. In 2021 for instance, the levels of NPL was reported to surpass the stipulated benchmark of 4.0% as well as the supervisory intervention trigger point of 6.0% established by the BoN. Thus, a concerted action is required to establish the forces behind this surge, thereby understanding its root causes and arrest this increasing trend.

[5] *The real GDP of -8.0 % is the lowest real GDP growth rate ever recorded in Namibia. The major cause of this decline was due to the spill over effect of the Corona virus (COVID-19) pandemic that plagued world economies*
[6] *The instabilities are likely to arise from various interest groups who are ambitious of a political ascent.*
[7] *Through their numerous joint annual "financial sector stability reports".*

According to Bank of Namibia (2021), the levels of NPL in 2016 stood at 1.5% with its corresponding GDP rate recorded at 1.1%. Five years later, in 2021, the level of NPL had risen to 6.44% and its GDP to 3.6%. In 2022, NPL slightly dropped to 5.6% while the rate of GDP rose to 5.3%. However, by the end of the year 2023 NPL had risen to 5.9% (closer to the BoN supervisory trigger point of 6.0%), meanwhile the rate of GDP eased to 4.2% in that same year (Bank of Namibia, 2023). Clearly, efforts to curtail the rise of NPL and possibly mitigate its unprecedented surge have bared little influence, especially when considering the limited empirical work on Namibia. The rapid rise in the portfolio of NPL is not only of a major concern to the financial system, but also for the economy. This in itself should cause researchers and policy makers not to relent in their pursuit of establishing the factors responsible for the rapid rise in NPL, thereby deter any further deterioration in it.

Evidently, the explosive rise in the overall level of NPL is a clear indication that overtime the phenomenon of NPL has been accumulating on the balance sheets side of most, if not all, banks in Namibia. Given the county's recovery efforts from the aftermath of the global economic downturn[8], exacerbated by the advent of the COVID-19 pandemic, a stable financial system is somewhat expected. Nevertheless, it is unclear how such efforts are transmitted through the various banking indicators. Thus, a country-specific study, that uniquely accounts for the specific characteristics that are peculiar to the Namibian[9] context is indispensable since it allows leads to devising of targeted policies that address and deter any further escalation of NPL.

Normally a persistent and an abnormal accumulation in the levels of NPL is considered to be undesirable for both the banking sector and the economy as a whole. Not only do high levels of NPL entail lower profitability for the banking sector, but they also portray an impending liquidity risk. Consequently, should the rising levels of NPL be left unabated, it may lead to banks' losses as well as bankruptcy (Adelopo et al., 2018, as cited in Rohman et al., 2022). Diminished banks' profits (or bankruptcy) negatively affect depositors, leading to a spill-over effect on the entire

[8] *Exacerbated by the global Corona virus (COVID-19) pandemic and the geopolitical tensions in Europe.*
[9] *Namibia is a small open economy endowed with a vast mineral based and whose economy and banking system is largely dependent and dominated by those found in South African. It has a very small population estimated at 2.6 million. Its currency is pegged on a 1 to 1 basis with the South African Rand under the common monetary Area (CMA) arrangement.*

economy. In addition, a reduced profitability also lessens government's revenues collected through taxation. This stifle and limits the extent to which government can deliver on its developmental agendas contained in various blueprints[10]. In essence, a persistent rise in the stock of NPL is the surest way of credit risk exposure and is indicative of a soon-to-be-troubled banking sector (Suarez & Serrano, 2018). Therefore, understanding the root causes of NPL is essential to better understand how to address it and hedge the banking sector from being depressed.

1.4 Research Objectives

The overarching goal of this dissertation is to analyse the dynamics of non-performing loans (NPL) in Namibia's banking sector during the period 1996 – 2021. More explicitly, this study contributes to debates on NPL in Namibia's banking sector by evaluating the following specific objectives: namely,

a) To analyse the evolution of Namibia's financial system.
b) To determine the relationship between NPL and its determinants.
c) To test for the causal relationship between NPL and its determinant.
d) To stress-test the credit risk vulnerability of Namibia's banking sector.
e) To forecast the quality of Namibia's banking sector loan portfolio.

1.5 Research Hypotheses

In line with the specific objectives of this thesis, the corresponding hypotheses applicable to objectives (a) to (e) are stipulated as follows:

#Hypothesis 1

H_N: The Namibian financial system has not evolved overtime.

H_A: The Namibian financial system has evolved overtime.

[10] *The country's Vision 2030 enacted in 2004 and the various targets in National Development Plans (NDPs).*

#Hypothesis 2

H_N: There is no significant relationship between NPL and its determinants.

H_A: There is a significant relationship between NPL and its determinants.

#Hypothesis 3

H_N: There is no causal relationship between NPL and its determinants.

H_A: There is a causal relationship between NPL and its determinants.

#Hypothesis 4

H_N: The quality of Namibia's banking sector loan portfolio is vulnerable to shocks.

H_A: The quality of Namibia's banking sector loan portfolio is resilient to shocks

#Hypothesis 5

H_N: The model used to forecast Namibia's banking sector loan portfolio is inefficient.

H_A: The model used to forecast Namibia's banking sector loan portfolio is efficient.

1.6 Contribution of the study

Although there are numerous studies on the phenomenon of NPL, the scope covered in most studies is quite narrow. In other words, a limited amount of studies that broadly examined the factors responsible for driving-up the levels of NPL in the various economies around the globe exist. For instance, in Namibia studies on this subject are not only limited and outdated, but are quite scarce. Against this background, the present study contributes to the body of literature, with specific focus on the Namibian banking sector, in the following ways:

Firstly, this study extends the scope of previous studies by broadly assessing indicators responsible for influencing NPL with a banking sector, with a special focus on Namibia. The study meticulously analyses six broad categories of indicators considered of influencing NPL in the body of literature. While previous empirical studies (Gulati et al., 2019; Kepli et al., 2021; Kjosevski & Petkovski, 2017; Sheefeni, 2015a, 2015b) did not examine more than two categories of indicators (bank specific and/or macroeconomic indicators), the point of departure for this study is that it comprehensively investigates the influence of six classes of indicators. Both the single models as well as a joint model (consisting of the macroeconomic, bank specific, monetary, interest rate, financial and institutional indicators) are investigated.

It is worth pointing out that, the aforementioned consolidated indicators are not completely ignored in the literature body as they have been examined on single basis but rarely on a joint basis. As such, this study attempts to adopt a model that holistically examines the factors influencing NPL in Namibia's banking sector. The technique of Principle Component Analysis (PCA)[11] is employed so as to minimise the wider spectrum of the multivariate dataset involved in this study into a relatively smaller dimension that would allow for the estimation of a joint model. In particular, the method is herein used to construct six indices which are representatives of the six categories of indicator used in assessing their effects on NPL in Namibia's banking sector.

Secondly, the study also examines the nature of causality amongst the group of indicators used in this study. Although this obvious practice is found to be somewhat rare in the literature, it is still very relevant due to the dynamic nature in which different factors might influence the levels of NPL of a particular banking sector.

Thirdly, from a country-specific perspective, the present study employs a much longer time frame, 1996 – 2021, as opposed to previous studies whose coverage were based on the existing dataset at the time of their investigation. Moreover, the results from previous studies, especially those older than 5 years, are futile for policy guidance as they fall short of accounting for recent global shocks that have long term effects on the banking sector. Basically, this means that past findings could prove to be irrelevant in informing policy as the unfolding dynamics experienced in the economy over the past few years might have drastically changed the way various factors influence NPL. For this reason, this study augments the existing debates on the subject at hand by utilising more recent data, thereby accounting for the dynamics of recent global shocks[12].

[11] *The PCA is an index constructed used to aggregate various variables under each of the six categories of indicators.*
[12] *such as, the entrance of COVID-19 and the geopolitical instability in Europe caused by the war betwixt Russia and Ukraine.*

Fourthly, as in many various studies, aggregated secondary time-series data are used to analyse the determinants of NPL whilst using a combination of modelling approaches not jointly used by any single study, including in Namibia. In this regard, the Autoregressive Distributive Lag (ARDL) bound test to cointegration, suitable especially when dealing with a smaller dataset - whose order of integration is either I (0) or I (1) or both – is used. The ARDL is extensively utilised not only to evaluate the effects that the series of indicators[13] have on the quality of the loan portfolio in Namibia, but to also examine the causal relationship between independent variables and NPL.

Undoubtedly, there is consensus in the body of literature regarding the important role played by factors such as bank specific, macroeconomic, monetary, interest rate, financial and institutional indicators in influencing non-performing loans. Notwithstanding, most of the studies are quite skewed as they tend to concentrate on one aspect or the other, leaving little insight in how the aforementioned risk factors are interwoven with each other (Canepa & Khaled, 2018). In light of all this, and given that very little is known regarding how various factors affect non-performing loans in Namibia's banking sector, this study contributes to the body of literature by addressing the aforementioned gaps.

1.7 Significance of the Study

A thorough understanding of the key indicators responsible for influencing the quality of the loan portfolio is fundamental to ensuring a stable banking/financial system. The fact that in recent years the quality of the loan portfolio (measured by levels of NPL) has deteriorated, requires comprehensive understanding of its the root causes. This is so that regulators and policy makers can effectively minimise and/or avert the undesirable consequences of deteriorations in the asset quality of the loan portfolio. Thus, this study helps to locate the Namibian stance on the global space where issues of the determinants of credit risk are profiled. The study also complements the existing findings on the subject and builds upon existing policy framework governing the management of credit risk. It also provides a comprehensive insight on the relatedness of indicators to NPL; meanwhile, gauging the resilience of the Namibian banking sector to credit risk shocks by means of stress-testing.

[13] *Macroeconomic, Bank-specific, Monetary, Interest rate, Financial and Institutional indicators.*

1.8 Chapters Outline

The structure of this thesis is subdivided into six (6) Chapters. In Chapter I, an introduction of the background to the study, statement of the problem, research objectives, hypotheses, and the study's significance is presented.

In Chapter II, assesses objective (a) by analysing the evolution of Namibia's financial system. The review contains a lucid summary of relevant information that helps readers to familiarise themselves with contents as well as the context for which the present study has been carried out.

In Chapter III, the literature review pertaining to this study is uncovered. The chapter provides an elaborate discussion of both the theoretical as well as empirical literatures relating to the interactions between the indicators (macroeconomic, bank specific, financial, interest rate and institutional indicators) and NPL.

In Chapter IV, the objectives (b) and (c), examining the determinants of NPL as well as the causality between NPL and the study's indicators are, respectively, investigated. Specifically, the chapter examines the long and short run relationship between the indicators and NPL, and whether a causal relationship between the indicators and NPL exists.

In Chapter V, the objectives (d) to (e) are, respectively, examined. Chiefly, the chapter commences by conducting the stress-tests for the resilience of the quality of the Namibian banking system's loan portfolio, thereafter it identifies the indicators for early warning of deteriorating loan qualities, before it ultimately forecasts the quality of its loan portfolio.

Last but not least, Chapter VI concludes by concisely synthesizing the major findings of the preceding chapters, including a discussion of policy implications directly drawn from the analysis carried out in the aforementioned chapters. The limitations and key contributions of this thesis to the vast body of knowledge is also presented, before concluding with some suggestions for future research work in this area.

CHAPTER II: AN OVERVIEW OF THE NAMIBIAN FINANCIAL SYSTEM

2.1 Introduction

This chapter presents an overview of the evolution of Namibia's financial system post-independence in 1990. Such an overview is crucial as it highlights key information required to comprehend the context through which the present study was undertaken. Section 2.2 presents a discussion of the structure of the Namibian financial system. Section 2.3 outlines the composition of the Namibian financial institution. Section 2.4 delves on the composition of Namibia's Non-Banking Financial Institutions. Section 2.5 presents a comparison of the contribution of the Namibian financial sector to GDP and Employment vis-a-vis the other related sectors within the top five tertiary industry. Section 2.6 revolves around the ownership structure of Namibia's banking sector, while Section 2.7 elaborates on the performance of the banking. Section 2.8 outline the regulatory and supervisory frameworks, before concluding in Section 2.9.

2.2 The structure of Namibia's financial system

Namibia is classified as an upper middle income[14] with an advanced financial system as per developing countries' standards. Its financial system comprises of a Central Bank (also known as the Bank of Namibia [BoN]), private banks, state-owned financial institutions, and non-bank financial institutions. Prior to Namibia's independence in 1990, Namibia (previously known as South West Africa) was simply a province of South Africa. As such, the functions of the central bank were predominantly performed by the South African Reserve Bank (SARB). The BoN, established by an Act[15] of the Namibian parliament, only managed to introduce its own currency - the Namibian Dollar (N$)- in 1993, despite it being in existence since 1990.

[14] *In 2009, the World Bank classified Namibia as a middle-income country. In 2014, the same institution classified it to be an upper middle-income country with GNI per capita of US$ 4 620 in 2016. The classification has often been disputed by many Namibians, including the current President (H.E Hage Geingob) who on multiple occasions has disputed and pled with the World Bank to declassify it from such a ranking. The reason being, Namibia suffers from huge inequality due to its colonial past that caused it to be one of the most unequal country in the world, with a GINI coefficient index of 59.1 % in 2015.*

[15] *Section 2, Act No.8 of 1990.*

During the early years of independence, Namibia's financial structure in terms of the total size of the financial system was strongly dominated by the banking sector (Bank of Namibia, 2002). However, decades later the influence of some Non-Bank Financial Intermediaries (NBFI) such as the pension funds and insurance companies, has become formidably dominant. In fact, from 1991 to 1995 the share of the banking sector, in relation to the total assets of the financial system gradually shrunk from 72.7% to 67.5% and further to 51.4% in 2001; this excludes the stock exchange. However, during that same time period, the share of non-banking financial institutions (total combination of pension funds, unit trusts and insurance companies) gradually rose from 23.3% to 32.5% and further to 48.6% in 2001. The percentage change in the amount of total assets for Namibia's banking sector for the period, 2020 - 2021 stood at 37.2% (Bank of Namibia, 2022). In contrast to the share of assets of NBFI, in 2021, 20% of its share of total assets was from the insurance companies (both long- and short-term combined) alone, whilst 57.5% was from the pension funds (NAMFISA, 2022b).

2.3 The composition of Namibia's financial institutions

The Namibian financial institution comprises of four specialised state-owned financial institutions, and nine privately-owned financial institutions. The state-owned institutions include: the Namibia Post Office (NamPost) Savings Bank - a division of NamPost Limited, the Agricultural Bank of Namibia Limited (AGRIBANK), the National Housing Enterprise Limited (NHE), and the Development Bank of Namibia Limited (DBN). On the other hand, the privately-owned institutions comprise of: Banco Privado Atlantico Europa Limited, Bank BIC Namibia Limited, Bank Windhoek Limited, First National Bank Namibia Limited, Nedbank Namibia Limited, Standard Bank Namibia Limited, Letshego Bank Namibia Limited, Trustco Bank Namibia Limited, and ABSA Ltd.

The NamPost Savings Bank provides basic savings and transactions services through the postal network and micro-loans to individuals across the country. The offices of the state-owned financial institutions are operational in all 14 regions of the country, thereby supporting the governmental objectives intended of widening the country's financial inclusion and development. With regards to farming activities, the AGRIBANK is the principal governing institution tasked with the mandate of extending financial assistance (through loans) to farmers and would-be farmers to assist them in purchasing livestock and/or any other related agricultural products, including housing finance for small-scale farmers (Bank of Namibia, 1991).

The Bank of Namibia (1991) describes the NHE as a statutory body in which the government is the sole shareholder mandated to provide/construct houses for the vast majority of citizens falling within the low and middle-income bracket. Through the NHE, citizens are afforded a dignified shelter, which is a constitutional the right. The DBN, formally formed in April of 2004, has an overarching goal of contributing to the socio-economic wellbeing and economic growth (Development Bank of Namibia, 2021). The institution is also responsible of sourcing funds intended to finance some of the country's developmental agendas as outlined in various developmental documents (Vision 2023, NDPs, HHPs, etc…). The institution is also allowed, if necessary, to fund individuals and businesses with bankable project proposals, amongst others. The total loans and advances during the 2020/21 financial year (FY) stood at N$7.92 billion. This amount is said to be lower when compared to the N$8.47 billion registered in the preceding FY. The decline is largely attributed to the shocks that occurred in the global economy at the time.

With regards to the privately-owned institutions, of the four largest (Bank Windhoek Limited, First National Bank Namibia Limited, Nedbank Namibia Limited, and Standard Bank Namibia Limited), three of them, headquartered in South African, were estimated to account for a combined total bank asset of 98% in 2018.

2.4 The composition of Namibia's Non-Banking Financial Institutions (NBFI)

There are quite a number of NBFI operating within the Namibian financial system. These include the pension funds, life insurers and the non-life insurers that are made up of insurance companies, microfinance institutions, medical aids, the Namibian Stock Exchange, trusts/money market funds and stockbrokers.

The NBFI plays a crucial intermediate role in the country's financial system by linking institutional investors to financial markets and banks. According to the International Monetary Fund (IMF)

(2018), the bulk of pension funds' assets are managed by investment managers, with a total of 37% of total assets invested within Namibia, while 41% is invested in South Africa and the rest trickles to other investment destinations around the world. Furthermore, the majority of life insurance companies directly manage their own investments, with only 5% of their investments placed under the guard of investment managers.

Insurance companies (life insurers and non-life insurers of both short term and long term) accounted for approximately 10% of the total assets of the Namibian financial system during the year 2001. However, according to NAMFISA(2022a)'s annual report, approximately 20% of total assets were recorded in 2021, which is a percentage lesser when compared to the records of the previous year. From 1994 to 2001, percentage share of unit trusts in terms of total financial assets rose from as little as 1%, since the formation of the first unit trust, to approximately 5.5%. By the end of the second quarter of 2022, unit trust schemes accounted for 27% of total assets per investor.

The number of asset managers and stoke brokers have continued to increase since the mid-90s, from zero to approximately 18 for asset managers and 7 stock brokers in 2001. In addition, the establishment of the Namibian Stock Exchange (NSX) in 1992 introduced regulations that required institutional investors to invest at least 35% of their assets domestically. The placement of the development capital portfolio of the Government Institutional Pension Fund (GIPF) with assets managements companies in 1994-95, were cited as some of the reasons for the rapid development of these institutions after independence.

Between the periods 1991 to 2001, the assets of pension funds averaged approximately 31.9% of the total assets of Namibia's financial system. From 2016 to 2021, approximately 55.9% of the total assets was derived from pension funds (NAMFISA, 2022a). With regards to the number of institutions, the pension funds institutions increased from as little as 200 institutions at independence to about 500 in 2001. As of 2022, there were 135 pension funds registered under the NAMFISA. Currently, the pension system consists of a universal, non-contributory pension, private, and occupational schemes which covers approximately 30% of the total labour force, including the GIPF. As of 2021, the assets of the pension fund sector stood at the tune of N$212,932,000, a figure higher than the previous year which stood at approximately 180,522,000.

Approximately 40% of pension fund assets are invested domestically while the remainder is split between South Africa/CMA and overseas investment destinations (International Monetary Fund, 2018).

The insurance market in Namibia is dominated and concentrated by subsidiaries from mainly South African financial groups. This sub-sector consists of 16 life insurers, 14 general insurers and one state owned reinsurer. Assets in the insurance sector include insured pension funds products providing an explicit capital guarantee. These pension fund assets are held on the balance sheets of the life insurance companies. Long term insurance companies make up the largest share of assets under management in terms of assets under administration per source of funds. According to NAMFISA (2022a)'s annual report, total assets of long and short-term insurance companies amounted to N$73,860,000 in 2021 as compared to N$68,168,000 in the previous year. With regards to the medical aid industry, though small, it has been growing. In 2016, the industry's total assets were N$1,443,000, but by the end of the year 2021, the figure had almost doubled to the tune of N$2,287,000.

In Namibia, the unit trust market includes the Money market unit trusts which invests in treasury bills, certificate of deposits, and direct deposits with banks. The first unit trust in Namibia was only established in August 1994 by Sanlam. Since then, the sub-sector has enormously grown to include eight registered unit trust management companies by the end of 2000. These included the Old Mutual Unit Trust Management company, the Sanlam Unit Trust Management company, the Commercial Bank of Namibia Unit Trust Management company, the Standard Bank Unit Trust Management company, and Investec Namibia. The benefits of unit trust membership come from the mutual pooling of resources for investment under professional management. It is important to note that activities in these funds fluctuate with liquidity in the banking sector. This is because banks compete through increased deposit rates as their liquidity needs increase.

In relation to the stock market, the Namibian Stock Exchange (NSX) is the only licensed stock exchange entity in the country as per the stock exchange control Act (No.1 of 1985). The listed securities on the stock exchange market comprise of mostly dual-listed South African companies and primary-listed Namibian companies. The NSX records low levels of liquidity due to the buyand-hold strategy that most investors in the country use as well as the partially insufficient instruments available. One of the reasons for investors holding on to trading instruments is due to the need of conforming to the local investment requirements. It is also important to note that there are four registered stockbrokers in Namibia that act as intermediaries between investors and the stock exchange. These institutions have risen since independence, although the services they offer are still very limited when compared to those offered by South Africa.

2.5 The contribution of Namibia's financial sector to GDP and employment creation

The importance of the financial sector, in terms of its contribution to GDP and employment, has continued to evolve through the years, after independence from colonialism. As seen from both Tables 2.1 and 2.2, the contributions have not always been consistently incremental, as in some years the sectors contributed little, while in others it contributed slightly more. Needless to say, in term of its contribution to GDP and employment creation, the financial sector has always been amongst the top 5 sectors (out of a total of 13 sectors) of the tertiary industry[16].

Table 2.1: Percentage contributions to GDP of the top 5 tertiary industries, 1996-2021

Tertiary industries	1996-2000	2001-2005	2006 – 2010	2011 – 2015	2016 – 2021	Avg.	[Rank]
Wholesale & retail trade, repairs	8.3	10.7	10.9	11.4	10.2	8.6	[1]
Real estate & business services	8.6	9.0	8.2	8.5	5.5	6.3	[2]
Arts, entertainment, & recreation	1.4	6.9	6.1	5.7	5.5	4.3	[3]
Financial & insurance services	3.1	3.9	4.8	5.9	7.2	4.2	[4]
Transport & Storage	3.6	2.7	2.7	2.8	3.0	2.5	[5]

Source: Own computations using data from the NSA and BoN

Tables 2.1 demonstrates that the average percentage contribution to GDP by the financial sector has consistently featured the top 5 most influential sectors, in terms of its percentage contribution to GDP in the tertiary industry. More specifically, the information reveals that the financial sector ranked third during the post-independence, 1996 – 2000 years. Nonetheless, between the periods 2001 – 2005, the Arts, entertainment, and recreation sector became increasingly developed, and

[16] *Other sectors being Hotels and restaurants; Information Communication; Professional, scientific and technical services; Administrative and support services; Public administration and defence; Education; Health; and Private household with employed persons.*

overtook the position of the financial sector causing it to decline into the fourth position. Between the periods, 2006 – 2021, it retained its initial position as can be observed from the reported descriptive statistics. Overall, the average percentage GDP contribution of the financial sector was calculated to be 4.2% during the periods 1996 – 2021, which caused it to rank as the fourth most contributing in the category of tertiary industries.

With respect to its employment contribution to total labour force (in Percentage), Table 2.2 presents a comparative analysis of the top 5 tertiary industries that contributed most to the total labour force, using the available statistics from the Namibia Statistics Agency (NSA) for the periods between 2012 to 2018.

Table 2.2: Employment (%) of labour force of the top 5 tertiary industries, 2012-2018

Tertiary industries	2012	2013	2014	2016	2018	Average	Rank
Wholesale & retail trade, repairs	11.9	N/A	11.6	12.1	10.7	9.3	1
Financial & insurance services	2.0	2.1	2.1	3.0	2.5	2.3	2
Transport & Storage	3.6	0.8	3.7	0.9	0.8	2.0	3
Real estate & business services	0.3	6.3	0.1	0.2	0.2	1.4	4
Arts, entertainment, & recreation	0.5	N/A	0.6	0.6	1.0	0.5	5

Source: Own computations using data from the NSA Labour Force Survey of 2012 - 2018. [17]

Based on Table 2.2, the average employment contribution to the total labour force by the financial sector, during the space of five years of available data point, was 2.3%. Such a contribution has caused it to rank as the second highest contributor, amongst the tertiary industries. This seems to back the recurring assertions made by several studies which argue that the financial sector plays an important social-economic role (Ikram et al., 2016; Naili & Lahrichi, 2022; Sheefeni, 2015a). The evolution of the Namibian financial system is unlikely to yield any significant future employment opportunities due to the evolutions taking place in the Artificial Intelligence (AI) world. The continual advancements in AI engenders financial institutions to explore alternative cheaper ways of conducting business, whilst simultaneously maximising their profits. The automation of most aspects of their businesses that used to be mechanical to robotics, signals a significant shift that will no doubt eclipse the future employment prospects for this sector.

[17] *Note that the 2012 Namibia Labour Force Survey (NLFS) is the earliest survey ever conducted in Namibia, whereas the 2018 NLFS is the latest survey at the time of this study.*

All in all, the financial sector's contribution to GDP growth rate has slightly increased over the year relative to other sectors within the tertiary industry. However, its contribution to employment creation, projected to decline due to advancements in AI, has since remained unchanged.

2.6 The ownership structure of Namibia's banking sector

Namibia's current banking system comprises of seven commercial banks, an E-bank, and a foreign bank branch. The banks include: Banco Privado Atlantico Europa Limited, Bank BIC Namibia Limited, Bank Windhoek Limited, First National Bank Namibia Limited, Nedbank Namibia Limited, Standard Bank Namibia Limited, Letshego Bank Namibia Limited, Trustco Bank Namibia Limited, and ABSA Ltd.

As a matter of fact, out of the four largest banks, three are subsidiaries of South African banks representing a combined total bank asset of 98% (International Monetary Fund, 2018). Banks operating with the Namibia's banking sector are subject to BoN's regulations and supervisions, despite the majority of them being externally owned. The Central Bank (the Bank of Namibia (BoN)) is the sole issuer of money supply, and the guarantor of financial and price stability that augments economic growth, amongst other mandates (Bank of Namibia, 2021).

2.7 The performance of Namibia's banking indicators

From the recession that was caused by the unfortunate COVID-19 pandemic in Namibia, the banking sector performance, though positive, has been deteriorating. On the other hand, levels of capital and liquidity continue to be well over the required amounts (in bank institutional terms). Additionally, the Namibian Financial Institution Supervisory Authority [NAMFISA](2021) reported an increase in liquid assets at the tune of N$19.0 billion to N$20.1 billion from 2019 to 2020, respectively. The increase is said to have been heavily influenced by Government's payments of deferred tax payments, Value Added Tax (TAX) refunds and the corporates repatriating funds. Furthermore, there has been a slightly improvement in the loan repayments by debtors operating within the banking sector. This is evident when one observes the sluggish declines recorded by the NPL ratios. The demands for credit from businesses and households has also been slowing down, as the growth in the private sector credit extension (PSCE) was recorded to have declined from 6.8% in 2019 to 2.4% in 2021 (Bank of Namibia, 2022).

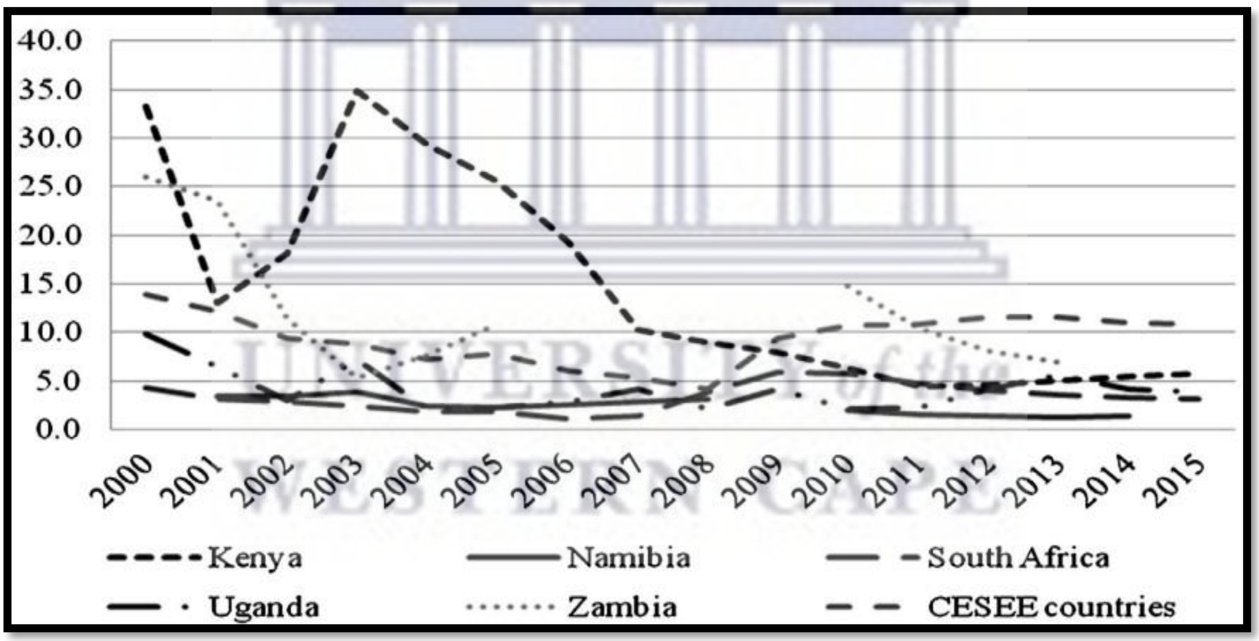
In terms of the banking sector's balance sheet, positive growth was still recorded during the recession. In fact, NAMFISA (2021) reported a 1.3% increase that amounted to N$144.0 billion at the end of 2020 from 2019. On the contrary, the net loans and advances reduced from N$101.2 billion to N$100.7 billion, during the review period. This is a further indication of a decline in the demand for credit. With regards to the liability side of the banking sector, more liabilities came from demand deposits. These deposits accounted for a rise of 51% of total funding from 47.1% and comprising of mainly wholesale deposits that are volatile and may pose a risk to the overall financial stability.

Furthermore, the NAMFISA (2021)'s report stated that the sector's total assets rose from N$142.2 billion in 2019 to N$144.0 billion in 2019, thus signifying a 1.3% growth rate that was lower than the previous year which was 7.6%. Likewise, the increasing rate of assets failed to exceed 2.2% average rate of inflation. Moreover, during the review period (2019 - 2020), total assets declined from 71.2% to 69.1% while net loans and advances continued to record the largest share of the asset's category. On the other hand, cash and balances with banks increased by 8.8% from N$13.6 billion in 2019 to N$14.8 billion in 2020.

With regards to capital and liabilities, the NAMFISA(2021) report indicated that non-banking institutions contributed the most in terms of funding the banking sector. The contributions consist of demand deposits, notice and fixed deposits as well as negotiable certificates of deposit. During the same review period mentioned earlier, 2020 recorded 1.6% non-bank funding unlike the 8.4% in the previous year. The non-banking deposits comprised the highest share of non-bank funds, which were largely made up of wholesale deposits. In terms of capital adequacy, the total risk-weighted capital (RWCR) slightly declined to 15.2% in 2020 from 15.3% in 2019, although it still remained above the statutory minimum of 11%. This implied that the banking sector is sufficiently capitalised due to its continuing to hold a capital position that is not below the domestic provident requirement of 11.0% for RWCR.

In 2021 the asset quality of the banking sector deteriorated as the level of non-performing loans (NPL) ratios rose to 6.4% (NAMFISA, 2021). This NPL ratio, which was considered to be very high as besides it being above the 4.0%-point limit set by the BoN, it was above the 6% trigger point, for times of crisis. The persistent rise in NPLs was attributed to factors such as the hostile economic conditions[18] and cash flow constraints that businesses and households were experiencing. The average rate of NPL for the period 1996 - 2021 was 3.5%. An earlier study by Nikolaidou and Vogiazas (2017), a comparative graphical presentation of the NPL for a few selected Sub-Saharan African (SSA) countries, in which Namibia was also included, together with countries of the Central East and South East European (CESEE) regions depicts some interesting facts that are worth noting (see Figure 2.1.).

Figure 2.1: Ratio of NPL for a select SSA and the CESEE countries, 2000 – 2015



Source: Nikolaidou and Vogiazas (2017) using World Development Indicators (World Bank) (WDI)

Even though the NPL information depicted in Figure 2.1 may not necessarily be speaking to the current phenomenon on NPL of the referred countries, as it contains only information dating the periods 2000 - 2015, the information is still relevant for comparison purposes. As can be seen, the

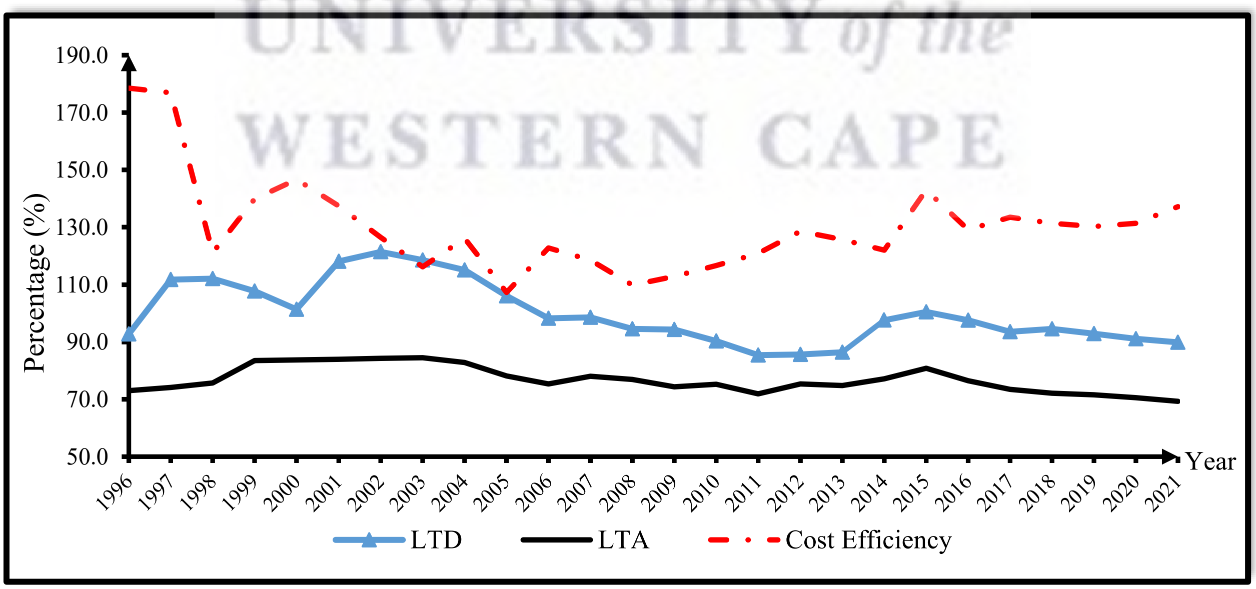
[18] *Exacerbated by the after-effects of the global Coronavirus pandemic which led a number of businesses to either scale down their operations or shut down completely.*

ratio of NPL levels for Kenya and Zambia were quite volatile, as characterised by high spikes, when compared to those of their counterparts in the SSA region. In reference to Namibia, it was reported to have had the lowest average rates of NPL estimated at 2.4%, followed by South Africa with a 3.3% and Uganda with an average of 4.2%.

With regards to the after-tax profits, the banking sector recorded a 33.4% reduction of N$1.8 billion in 2020 compared to the amount recorded in 2019 that was N$2.7 billion (NAMFISA, 2021). During this same period, the net interest income saw a huge percentage fall of 17.3% in line with the lower repo rate from Bank of Namibia along with decreasing interest by commercial banks. Conversely, the same report under that other operating income had risen by N$63 million whilst accumulating a total of 3.7 billion that saw a huge positive contribution to the rise in total income.

The loan to deposit ratio (LDR) of the Namibian banking sector has come under pressure over the years, thereby causing banks to explore alternative avenues of funding other than the conventional deposits. In terms of the cost efficiency ratio, it has over the years fluctuated downwards, with the ratio of loans to assets (LTA) not having any particular trend pattern as can be seen in Figure 2.2.

Figure 2.2: Liquidity and cost efficiency of Namibia's banking sector, 1996Q1 - 2021Q4



Source: Own computations using data from BoN

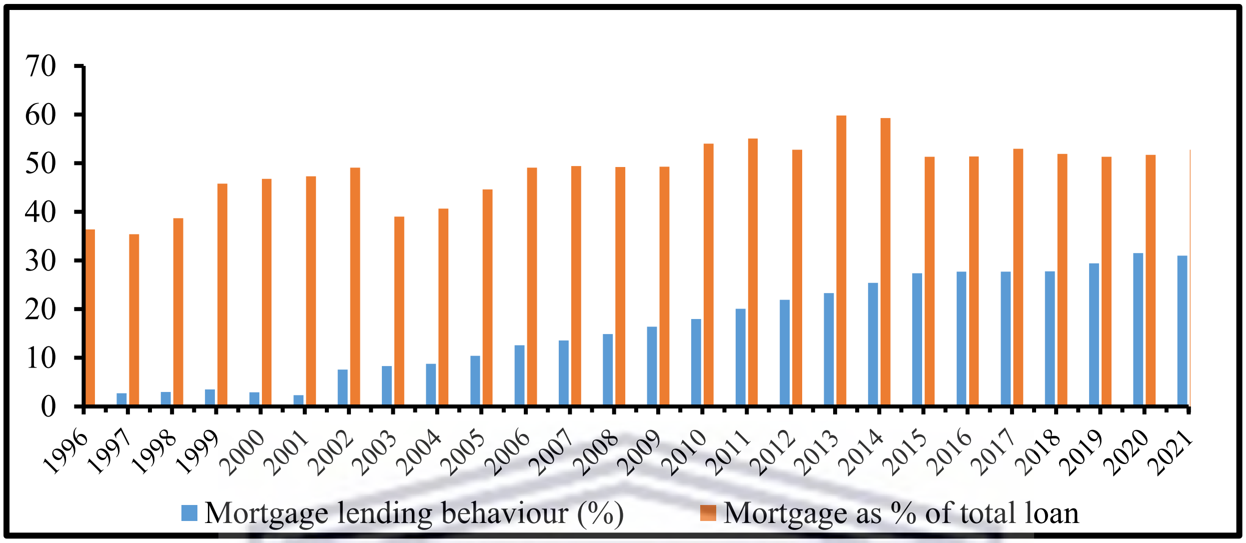
Based on Figure 2.2, the graphical presentation of the LDR for Namibia's banking sector averaged 97% from 1996 to 2021. The highest ratio (118.5%) was in 2003 whilst the lowest (85.4%) was recorded in 2011. The percentage of LTA shows that it has always been above 70%. The average rate for cost efficiency ratio stood at 130.4%. The peak of this ratio was recorded in 1996, whilst the lowest was registered in 2005.

With regards to mortgages, depicted in Figure 2.3, more than one-half of bank loans are directed to commercial and residential mortgages. Above all, individuals constantly dominate the total private sector credit. In 1995, individuals' total borrowing was recorded to approaching N$4.2 billion (Bank of Namibia, 2003). By the end of the year 2001, the amount had almost doubled to N$8.2 billion. During the same period, the credit extension to the business sector had doubled from as little as N$2 billion to N$4.5 billion. However, the share to total private sector credit to individuals accounted for approximately 65% whilst the remaining 35% was extended to the business sector.

According to NAMFISA (2021) the year 2020 recorded a higher mortgage loan percentage of 52.3% higher than its previous year (51.3% of total lending) on the banking sector balance sheet. This is not surprising because over the years, mortgage loans have dominated the category of loans and advances. Matter of fact, the share of mortgage as a percentage of total loans in the early 90s was merely 30%. The combination of the residential and commercial mortgage loans has continued to make up the largest component of the total loans and advances category, registering over 50% in both 2020 and 2021 (Bank of Namibia, 2021).

Regarding the year-on-year growths in the Namibia's banking sector assets, the growth rate was recorded to be below the average inflation rate of 3.6% registered in 2021. Nevertheless, the banking sector continues to make some positive strides as it has proven to be resilient amidst the challenging economic conditions facing the country. Figure 2.3 illustrates the dynamics in the percentage of mortgage lending behaviour and mortgage as a percentage of total loans between the periods under review.

Figure 2.3: Mortgage lending behaviour (%) and mortgage to total loans (%), 1996-2021

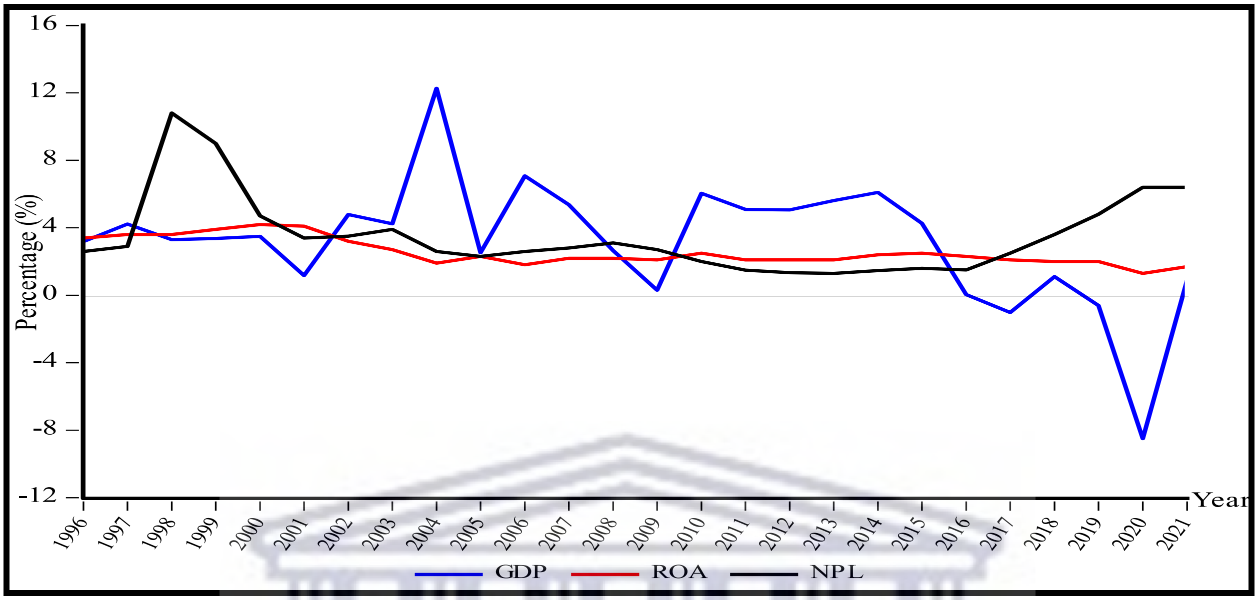


Source: Own computations using data from BoN

The data presented in Figure 2.3 indicates that the ratio of mortgage lending behaviour entered a double-digit zone beginning in 2005 up until the end of the study period. The share of mortgage as a percentage of total private loans averaged at 48.7% for the period under review. The highest mortgage as percentage of total loans (59.8%) was recorded in 2013, with 1997 being the year in which it recorded the lowest (35.4%).

The relatedness between the percentage growth rate of the economy, return on asset (ROA) and non-performing loans (NPL) for the period 1996 - 2021 is presented on Figure 2.4.

Figure 2.4: Percentage GDP growth rate, ROA and NPL, 1996Q1 - 2021Q4



Source: Own computations using data from BoN

Based on Figure 2.4, for the most part, the ratio of NPL has always hovered above the banking sector's ROA. This is not conducive for the banking sector in general as it ends up eating on their profit margins and may lead to bankruptcy if care is not taken. With regards to how the ratio of NPL relates to economic growth, except for the period 2016 -2021, it is not quite possible to tell without empirically investigating it, which is beyond the scope of this study. All in all, the rate of GDP growth appears to be very volatile, followed by the ratios of NPL and ROA, respectively.

2.8 Regulatory and supervisory frameworks

Namibia is a member of a currency board arrangement, the Common Monetary Area (CMA), other members being Lesotho, Eswatini and South Africa, which is the leader of the arrangement. To ensure import stability amongst member countries, the currencies are pegged on a one-to-one parity with that of the South African rand (the major trading partner to all the member countries in the CMA). This arrangement strips member states, who are subordinates of South Africa, of their ability to independently set a monetary framework of their choice.

Notwithstanding, through capital restrictions and prudential requirements, member states have some limited leeway in deviating from the repo rates adopted by the South African Reserve Bank (SARB). This manoeuvrability is what has enabled the Central Bank in Namibia (Bank of Namibia

(BoN)) to seldom maintain a differentiated repo rate from SARB, especially when it deemed it necessary to regulate its own domestic affairs relating to money supply and endogenously driven inflation (Sheefeni, 2013).

Moreover, CMA member states are required to maintain a minimum international reserve coverage, especially the South African rand, in order to ensure import price stability from its major trading partner – South Africa (Sheefeni, 2013 as cited by BoN, 2008). According to the International Monetary Fund (IMF) (2018), extensive regulatory regimes have been put in place for market risk, country risk and consolidated supervision, of anti-money laundering or combatting the financing of terrorism.

Furthermore, the effectiveness of the information-sharing provisions is another regulatory framework put in place with the SARB. The oversight regulation of the financial system is said to have considerably improved, owing to numerous legislations adopted in the financial sector (International Monetary Fund, 2018). The implementations of the upgraded bills on NAMFISA, BoN, Financial Institutions and Markets (FIM), Banking Institutions Act (BIA), Microlending, Deposit Insurance and Financial Services Adjudicator (FSA) have been established with international norms that are central in improving the regulation.

The quality of on-site supervision and the launch of risk-based supervision of banks, implemented since 2008, have over the years been of vital importance to the stability of the Namibia banking and financial system (International Monetary Fund, 2018). Equally important, the wide-range supervisory examination manual of the IMF plays a hand due to the challenging and severe on-site examination. Furthermore, the Prompt Corrective Action regime is an effective set of tools for addressing all forms of unsafe practices.

2.9 Summary

At independence in 1990, Namibia's financial system was strongly dominated by the banking sector. However, over the years, its dominance has continued to decline as the level of influence of the NBFI increased drastically. The influences of state regulatory bodies, like the BoN, NAMFISA and MoF, have been vital in guaranteeing the stability of the banking and financial system through their supervisory and policy legislation role. Notwithstanding, the stability of Namibia's banking and financial system is, for obvious reasons, hinged on that of the South African economy. Namely, a significant number of companies and financial institutions operating in Namibia have their parent companies headquartered in South Africa. Consequently, Namibia is prone to external influences emerging from South African firms. In addition, Namibia is also a member of a currency board arrangement, the Common Monetary Area (CMA), with its currency pegged on a one-to-one basis to that of the South African rand. For this reason, the Central Bank in Namibia plays a very limited monetarist role as it is incapable of independently operating a standalone monetary system without first aligning itself with the standards and guidelines of the CMA, whose lead country is also South Africa.

In terms of the influence of the financial sector's contribution to GDP and employment, the sector ranks fourth out of thirteen tertiary industries. Relative to other sectors within the tertiary industry, there has been a slight increase in its GDP growth rate contributions over the years. In terms of employment contribution, it ranks second, yet its contribution has not changed much. In fact, it is expected to dwindle with accelerated developments in AI, which has come to reshape the way the banking and financial system conducts its business operations. The advent of the COVID-19 pandemic also had a significant negative impact on the performance of the banking and the financial system as a whole. This is evident, especially when observing how the quality of the NPL ratios deteriorated over the last couple of years, surpassing the 4.0%-point benchmark set by the BoN.

Considering that the successful operation of the financial system is largely dependent on the stability of the banking sector, it is imperative to analyse the factors underlying the stability of such a sector. This will provide a detailed understanding of the underlying factors surrounding the dynamics in its credit risk measure (i.e., NPL). Although the factors underlying credit risk are multifaceted and at times hard to decipher, attempts to uncover the intricacies of this phenomenon are highly commendable, useful for policy formulation and valuable in safeguarding the stability of the overall economy.

For this reason, the proceeding chapters (four and five), consist of an in-depth analysis of the determining factors of credit risk (NPL) and measures the sensitivity of credit risk to such factors. The policy implications from these investigations could serve as the basis for which bank managers, policymakers and regulators get to tackle the factors influencing the behaviour of credit risk in Namibia. Thereby, ensuring a sound banking and financial environment that is conducive to economic growth and development.

CHAPTER III: LITERATURE REVIEW

3.1 Introduction

This chapter provides a review of both the theoretical and empirical literature. Section 3.2 explores the different theories related to the subject matter of NPL. Thereafter, Section 3.3 provides a selection of empirical literature emanating from both the developed and developing world.

3.2 Theoretical literature

Although there are various theories related to the aspect of credit risks, this study singles out six theories most relevant to the context and direction of this study. The following discussion covers: a) information asymmetry theory, b) moral hazard theory, c) adverse selection theory, d) Signalling theory, e) contract theory, and f) agency theory.

3.2.1 The information asymmetry theory

The information asymmetry theory, advanced by Akerlof (1970), refers to imbalances in distribution of information between lenders and borrowers, which has the potential to affect the assessment of creditworthiness and the likelihood of loan default. In relation to credit risk, banks are usually not privy to access private information that are relevant to determine borrowers' ability and intentions to repay their loans. The private information in possession of borrower may include, but not limited to, the practical details on the borrower's financial status as well as their ability and intention to repay the loan. On the other hand, borrowers are usually in the know of additional information regarding their real financial standing.

The problem of information asymmetry is quite prevalent in the banking sphere (Cincinell & Piatti, 2017). This is because it is often very difficult to distinguish bad borrowers from the good ones due to incomplete information at the disposal of the lending institution. As a result, lending institutions are bound to make wrong lending decisions. Kumar (2018) stresses that the inability for lending institutions to make the distinction could lead them to mistakenly lend to unfavourable borrowers who would be at high risks of defaulting whilst denying the good borrowers, who are credit worthy, from accessing the much needed funds. Unfortunately, most observable factors at the banks' disposal; such as credit scores, collateral, or income statements, are limited in their capabilities to fully evaluate a borrower's ability and willingness to repay the loan.

As a result of the aforementioned challenges, lending institutions end up charging higher interest rates, which are most of the times indiscriminate, which are reflective of the overall risk perception in the lending market. Such higher chargers may shun potential borrowers who could have been in a position to successfully honour the debt repayment obligation. Instead, it could pose dangers in attracting bad borrowers, who would fail to pay their debts due to unbearable interest burdens; thereby causing a rise in the level of non-performing loans (Dao et al., 2020). Also, lenders may opt to request some forms of collateral (such as properties or vehicles) backing, in order to compensate for increased risks associated with the unobservable characteristics associated with the loan.

3.2.2 The moral hazard theory

The term *Moral Hazard,* which has its roots in the insurance literature (Rowell & Connelly, 2012; Stiglitz, 1983), is often used by Economists to describe problems of asymmetric information which arise after a transaction has occurred. In financial markets, the term is used to characterise uncertain conditions faced by lenders with regards to borrowers' ability to disburse the loans that are due to the lending institutions (Pagano & Jappelli, 1993, as cited in Musa, 2017). Given that the theory hinges on the assumption that a low level of capitalisation by a bank could lead to higher NPL, Keeton and Morris (1987), who are the lead proponents of this theory, stressed that the tendency of lending institutions when faced with these issues is to respond by increasing the riskiness of their loan portfolio. This is, for instance, accomplished by them being able to charge higher interest rates on the credit they issue out to borrowers. Consequently, it ends up burdening borrowers since they now have to pay higher interest rates, which literally increases the loan repayment amount, making it harder for them to honour their contractual debt obligations, thereby increasing the levels of NPL.

Atoi (2019)'s study posits another assumption of the moral hazard theory when it stresses that the likelihood for borrowers involved in activities that guarantee the repayment of their debt cannot be determined ex-post by banks. Jensen and Meckling (1976), as cited in Novellyni and Ulpah (2017), identify two types of moral hazard problems that could cause bank managers to condescend to a riskier lending decision as opposed to one that would be optimal. First and foremost is the managerial rent-seeking problem which arises when a bank manager seeks after their own personal interests, i.e., by devoting the bank's lending in shady projects of individuals or companies, with the intension of gaining some forms of favour or benefit from the borrowers. Definitely, these illegal motives pose a devastating effect on the bank, especially when these transactions go wrong. The second form of moral hazard occurs when there is a conflict of interest between the shareholders of the bank and the creditors (clients) of the bank. This happens when, for instance, the bank's shareholders desire to invest in risky loans with the aim of obtaining higher return for their risky investments. Nonetheless, in the event that the banks incur some forms of risks, shareholders end up shifting the cost of these risks to their depositors. Wood and Skinner (2018) contend that banks with relatively low capital tend to actively respond to moral hazard incentives by raising the riskiness of their loans portfolio, which results in higher NPL in the long run.

3.2.3 The adverse selection theory

Adverse selection refers to a situation whereby one party (i.e., the borrower) has more market information than the other (i.e., the lender). As a result, lending institutions end up being caught up in scenarios whereby they are incapable of distinguish bad borrowers from the good ones. According to Kipyego and Wandera (2013), this poses some challenges to the lending institution in the sense that both good and bad borrowers may end up submitting high quality credit applications, while withholding relevant negative information that would have worked against their favour had the lending institution known about them. Information sharing is therefore considered to be a solution to the problems of adverse selection as it improves the credit information of financial institutions. Some benefits of information sharing (Pagano & Jappelli, 1993, as cited in Musa, 2017; and Kipyego & Wandera, 2013) are: (a) improvements in the pool of borrowers; (b) reduction in defaults rate (c) decrease in interest rates and (d) leads to growth of lending.

A number of studies have established that NPL tend to rise higher in the presence of both adverse selection and moral hazard, especially when the capital levels are inadequate.

3.2.4 The signalling theory

The signalling theory is based on the assumption that there exists information asymmetry between parties involved in a business transaction (Badawi & Hidayah, 2018). In the context of credit risk, borrowers deliberately share valuable unsolicited information which would give them an edge to be regarded as creditworthy by prospective lenders. The theory suggests that borrowers with favourable credit characteristics have an advantage to convey their unique attributes, thereby differentiating themselves from the masses of borrowers with higher credit risks. Borrowers intentionally disclose any additional information that would favour them to obtain amicable loan contracts with huge loan amounts and/or lower interest rates. Some of the common signals employed by borrowers to differentiate themselves from high risk borrowers and obtain more amiable loan agreements include:

a) Offering collateral in order to signal their strong commitment to repay the loan and minimise the lender's risks;

b) Availing repayment guarantees from third-party with excellent credit scores;

c) Providing a positive credit score which can be a positive signal to lenders of a borrower's ability and willingness to repay the loan and indicate that they can be relied upon should they be granted a loan.

d) Possessing a higher level of education and/or a stable employment history could signal to lenders that the borrower is financially stable and has positive future income prospects.

e) Maintaining a long-term relationship with a particular lending institution may also symbolise trustworthiness, reliability, a lower credit risk and ultimately creditworthiness.

On the other hand, lenders use borrowers' signals to meticulously evaluate the authenticity and reliability of the signals, given that some borrowers may attempt to take chances and counterfeit or misrepresent their creditworthiness. In addition, they may also consider factors other than the ones previously listed in their credit risk evaluation processes.

Jensen and Meckling (1976) (as cited in Novellyni & Ulpah, 2017) contend that, in turbulent times bank managers tend to unintentionally increase the rates of NPL by approving risky loans in hopes of capitalising on the returns that such risky investments promise. In turn, this may signal to the bank's shareholders that the bank is in financial trouble. As a result, shareholders who are keen to observe such indicators are often left with little choice, but to find alternative ways to recoup their initial investments and end their ownership position in the business. This entails that, shareholders should be in a position to weigh the options of whether to continue holding their shares in a risky bank or discontinue their ownership by selling their shares.

3.2.5 The contract theory

The contract theory offers a useful framework for understanding NPL and their resolution. The theory relates to the contractual agreements entered into by various actors (such as a borrower and a lender) with asymmetric information that are reflective of the risks associated with the loan agreement (Novellyni & Ulpah, 2017). Risks, such as systematic risk as well as idiosyncratic risk, which are peculiar to each borrower, are important factors that lenders consider when evaluating a client's creditworthiness. Since failure for borrowers to meet their contractual obligations causes a rise in NPL, the challenge faced by lenders is to figure out ways to minimise and ultimately mitigate these credit risks.

One way lenders can hedge themselves from the afore state risks is through debt restructuring. This entails modifying the terms of the contract in such a way that it is easier for the borrower to repay the debt. Nonetheless, the success of debt restructuring depends on a number of other factors, such as the borrower's willingness and ability to repay, the lender's bargaining power, and the institutional framework governing the debt restructuring. It is therefore in the lender's interest to carry out a thorough credit risk evaluation which may involve not only scrutinizing all available information on the borrower. Information which may give an insight into the past, and help to forecast the future financial status of the borrower must not be ignored.

Another way lenders can shield themselves from risks is through debt enforcement, which is heavily premised on the usage of legal means to recover the outstanding debt. The effectiveness of this depends on the ability for lenders to use the legal system with ease to enforce contracts or the ability for the lender to have full personal knowledge of the borrower (Akerlof, 1970). A major drawback of the debt enforcement is that it can be costly, time-consuming, and may result in losses for both parties in the agreement. This is especially true when it is coupled with the phenomenon of moral hazard, which affords incentives for borrowers to intentionally engage themselves in risky behaviours knowing too well that should anything go wrong, the lenders bear the costs.

Since the contract theory provides a comprehensive framework for understanding the challenges associated with NPL, it is incumbent on policymakers and practitioners to craft effective strategies that account for risks and incentives inherent in loan contracts, thereby minimising credit risk and the costs to stakeholders.

3.2.6 The agency theory

The agency theory is a phenomenon experienced by any organisation and it is not peculiar to the banks (Trung, 2021). At its centre is the aspect of principal-agent relationship, which is used to describe how one party (i.e., the principal) engages another (i.e., the agent) to perform specific tasks in their stead. In the context of NPL in banks, the shareholders being the principals entrust the management of their banks to managers whose chief responsibility is to make decisions that maximise profit and value for shareholders. Nevertheless, due to issues that have to do with conflicts of interest and information asymmetry, management may end-up engaging in riskier activities, such as imprudent lending, to advance their own interest. However, these actions may also increase the risk NPL, which could lead to reduced returns on investment and harm the interest shareholders. This creates a principal-agent dilemma in which the interests of shareholders and management are misaligned.

In light of the above, it is vital to understanding principal-agent theory as it very well relates to the dynamics of the principal-agent relationship between shareholders and bank management in the context of non-performing loans. It provides insights into how shareholders can be intentional in effectively designing contracts and incentives that promote responsible management behaviour which are in sync with their interests, thereby reducing the incidence of non-performing loans and leading into a win-win situation for all the parties. Some ways in which shareholders could influence the banks' management to act in the best interest is to award contracts that link management's remuneration to the bank's financial performance. They can monitor the management's lending behaviour by frequently reviewing the non-performing loan ratios, thereby encouraging prudent lending practices and provide incentives to promote sound decision-making.

3.3 Empirical literature

The occurrences of financial crises around the globe has led many researchers in both developed and developing economies to extensively investigate the driver of NPL, a key indicator of financial sector fragility. According to literature, the factors responsible for the rise in NPL are multifaceted. For this reason, this study attempts to exhaust all categories of indicators that are culpable of influencing NPL around the world. More specifically, this study focuses on six categories of indicators namely, the bank specific, macroeconomic, monetary, interest rate, financial and institutional indicators. This is necessary in order to offer a holistic insight into possible drivers for NPL in the context of Namibia. What follows next is an extensive review of existing empirical work that looked at any of the six categories indicators, which is the basis for which the independent variables used in this study is based upon.

3.3.1 Bank specific indicators

Globally, there is a vast literature on the relationships between bank specific indicators and non-performing loans. Moreover, a vast number of the existing literature is based on cross-sectional data, involving either a panel of countries of financial institutions, hence the use of panel data estimation techniques. On the other hand, there is also a sizeable number that used longitudinal data, in which case this study uses both.

Amongst such studies is the one by Radivojevic and Jovovic (2017), which analysed the determinants of NPL ratio using a panel data approach consisting of 25 emerging countries between the periods of 2000 to 2011. The study employs three methods of static panel data estimations (namely, the fixed effect estimation (FE), the random effect estimation (RE) and the pooled Ordinary Least Square (OLS) estimation) and three different method of dynamic panel estimation (namely, the Dynamic FE, 2-stage-least-squares (2SLS) regression and One-Step difference Generalized method of moments (GMM)). The finding revealed that the performance of banks has a significant influence on the level of NPL. In particular, the results revealed that the Return on Asset (ROA) negatively affected NPL, a suggestion that the banks' management might have been involved in riskier decisions. On the other hand, the capital to asset ratio (CAR) was found to significantly influence NPLs in a positive sense, which seems to supports the notion that banks tend to engage into riskier activities when the level of capital adequacy is favourable, thus creating risky loan portfolios which cause high NPL rates. Notwithstanding, the finding is not reflective of the behaviour of variables in these emerging economies as the estimations are not based on post-financial crisis data.

In another study by Gashi (2021) in which he uses both the FE and GMM on data from 18 banks in Poland, for the period 2005 – 2018, the findings revealed that return on equity (ROE) and growth of growth loans (GGL) have a significant impact on NPL. Although the author attempted to overcome the challenges posed by the FE model, which fails to account for individual heterogeneity in the model, by employing the GMM modelling approach, the GMM estimation has the tendency to increase the number of moment conditions at the order of T^2 which can create severe downward bias in finite sample (Hsiao, 2007). Kjosevski and Petkovski (2017) performed three alternative estimation techniques (FE model, difference GMM and system GMM) on a panel of 21 commercial banks in the Baltics States, for the period 2005 – 2016. The results showed that the equity to total assets ratio (ETA), ROA, ROE and GGL all have a negative and significant impact on NPL. This results are in agreement with Radivojevic and Jovovic (2017).

Another study is that of Azar and Maaliki (2018), in which they examined the determinants of the NPL ratio in Lebanese banks using the panel least squares method on annual dataset of 35 banks spanning between 2003 – 2013. Despite the fact that their study employed an array of both the bank specific and macroeconomic indicators, only three indicators (ROA, ROE, and growth in total assets) were found to significantly affect the ratio of NPL. A similar study by Wood and Skinner (2018) which was carried out in Barbados using time series dataset spanning the period 1991-2015, found that ROE, ROA, capital adequacy ratio (CAR) and loan to deposit ratio (LDR) all had a significant impact on NPL. In particular, ROE and ROA were found to be negatively related to NPL, whereas CAR and LDR were found to positively impact NPL.

Similarly, Ghorbani and Jakobsson (2019) evaluated the factors influencing NPL in Portugal, Italy, Greece and Spain using a balanced panel dataset spanning between 2006–2018. Unlike most studies on the subject, this study attempted to cater for unobserved heterogeneity and cross-sectional dependence in the data by implementing a model that has an interactive effect. Their results show that the bank profitability (ROE) and capitalisation are inversely related with NPL levels. Hajja (2022), analysed the factors influencing NPL in Malaysia over the period 1998 – 2015. The GMM technique was utilised and a stress-testing of NPL of the banking sector using VAR approach of monthly time series data was also used. The findings revealed that capital has an oscillatory effect on NPL. Meaning, an increase in capital will initially raise the levels of NPL up to a certain maximum threshold, after which an additional accumulation in capital will succeed in diminishing NPL. The study also found that higher levels in *GDP growth* and lending interest rates are positively related to the ratios of NPL. On the other hand, *inflation* was found to be inversely related the levels of NPLs.

Messai and Jouini (2013) applied a panel data approach on a sample of 85 large banks in three countries (Italy, Greece and Spain) for the period of 2004 - 2008. The study found the ROA to negatively affect NPL, whilst the variable loan loss reserves (LLR) and the real interest rate (RIR) had a positive influence on NPL. To account for the degree of biasedness, the authors employing three types of static panel estimations namely, the Fixed panel estimation (FE), the RE estimation and the pooled OLS estimation. Tanasković and Jandrić (2015) investigated the determinants of NPL using a selected Central and Eastern and South-Eastern Europe countries for the period 2006–2013. Likewise, a static panel data modelling approach was applied and the findings demonstrated that foreign currency loans ratio positively influences NPL. On the other hand, financial market development had negative effects NPL.

Another study by Koju et al. (2018b) in which they analysed both the macroeconomic and bank - specific determinants of NPL in the Nepalese banking system, the authors applied two panel data estimation techniques (the static and dynamic panel estimation) on a sample of 30 Nepalese commercial banks over the period 2003 - 2015. The results of the bank–specific indicators suggested that banks with higher *interest spread* are likely to register higher levels of NPL. This result is almost similar to that found by Kordbacheh and Sadati (2022) which concluded that the *net interest margin* is positively associated with rising levels of NPL. The variable *capital adequacy*, a measure of the level of solvency of banks, was found to negatively affect NPL. Other variables such as the *deposit ratio* and the *asset size* were significant, however the results obtained in this study turned to be inconclusive given that the authors used various models, each giving conflicting outcomes.

A much earlier study by Berger and DeYoung (1997) used a sample of US commercial banks to investigate the link between bank specific indicators and problem loans for the period 1985 - 1994. The Granger causality econometric approach was used to validate a series of hypotheses related to interaction between the loan quality, cost efficiency, and bank capital. The variables inefficiency and capital adequacy were used to respectively represent "poor management" and "moral hazard" hypotheses, other hypotheses being the "bad luck" and "skimping". Their study surmised that cost efficiency may be an important indicator of NPL and problem banks. Nonetheless, the authors acknowledged ambiguity in their results as they lacked clarity on whether or not researchers could cater for problem loans in efficiency estimation.

Guar, Mohapatra and Jena (2022) evaluated the relationship between the bank specific factors and credit quality of India's banking industry. The study relied upon a two-step GMM that used a sample of 37 banks, over the period 2015 - 2019. The study contributes by splitting bad loans into two classes, the gross NPL and the net NPL, the latter excludes the loan loss provisions and by assessing the impacts of the regulations of Basel III on NPL. The outcome of their study revealed that stringent capital requirements imposed by the reserve bank of India are instrumental in enhancing the credit quality of banks by reducing NPL. Furthermore, the results showed that the leverage ratio is positively related to NPL, entailing that a rise in it causes additional bad loans which adversely affects the asset quality of banks. Moreover, the liquidity risk measure provided by Basel III, liquidity coverage ratio, and the banks' age were found to insignificantly affect NPL. On the other hand, the capital adequacy ratio and the return on asset bore a negative relationship, implying that banks' profitability has a positive influence on credit quality.

With regards to assessments of effects of bank specific factors on NPL in G20 countries, Erdas and Ezanoglu (2022) made use of the dynamic panel data analysis using data for the period 1998-2017. The findings indicated that the lagged value of NPL, the ROE, the credit growth and credit costs all had positive influence on NPL, whilst capital adequacy was found to be negatively related to NPL. This study falls short in the sense that it mainly focused on bank specific determinants, when there are many other important drivers for NPL. Likewise, Ekanayake and Azeez (2015) analysed the determinants of NPL in nine (9) Sri Lankan commercial banks between the period 1999 - 2012. They employed a FE panel regression technique, highly critiqued due to its failure to account for individual heterogeneity in the model, and conclude that an inverse relationship between credit growth, bank size and NPL exists. In addition, the study also disclosed that NPL was bound to decline when Bank's efficiency increases.

Ćurak et al. (2013) investigated the determinants of NPL from South eastern European banking systems of 10 countries for the period, 2003-2010 using GMM estimator for dynamic panel models. The bank specific factors result showed that both the interest rate and solvency have been found to be positively associated with higher NPL, whilst bank size and performance (ROA) turned out to be negatively related.

With regards to the Namibian context, the studies investigating the determinants of NPL are scanty. It seems like there was only one study by Sheefeni (2015a) that attempted to investigate the possible bank specific drivers of NPL. The author used the Vector Autoregressive (VAR) modelling techniques on quarterly time series data for the period 2001- 2014. The findings reveal that ROA was found to negatively influence NPL while total assets and total asset ratio had a positive effect on NPL.

3.3.2 Macroeconomics indicators (stress-test related studies)

Generally speaking, there is a sizeable number of studies that focused on the effects that the macroeconomic indicators have on non-performing loans. The majority of the studies are based on cross-sectional data, involving a panel of countries, thereby justifying the use of panel data estimation techniques; whilst a number of them are based on the utilisation longitudinal data. The latter is used in this study.

Amongst the studies which analysed the determinants of NPL using a panel data approach is that of Radivojevic and Jovovic (2017), in which a panel of 25 emerging countries between the periods 2000 – 2011 was used. The study employs three methods of static panel data estimations and three different methods of dynamic panel estimation. The findings revealed that the following *macroeconomic indicators,* GDP, and unemployment rate negatively affect NPL. Simply put, when GDP, which represents economic activities in these countries drops, it has a devastating effect on the level of NPL in those countries. The finding that unemployment negatively affects NPL is against the finding obtained by Rehman (2017), using data of the Romania banking sector. Of course, the results by Radivojevic and Jovovic (2017) are not reflective of how the variables of these emerging economies would behave post-financial crises since their estimations were limited only on pre and during financial crises periods. Chances that the study might have been affected by degrees-of-freedom problems are high, given the shorter period of the cross-sectional dataset utilised.

Similarly, Gashi (2021) employed two panel data techniques, the FE and GMM, on data from 18 banks in Poland for the period 2005 – 2018. The results revealed that the most important macroeconomic factors influencing NPLs in Poland are GDP growth, domestic credit to the private sector (ceteris paribus), public debt and unemployment. More specifically, GDP and ceteris paribus were found to have a strong negative effect on the level of NPL, whereas public debt and UNEMP bore a positive effect on NPL. Some of these results are in line with those obtained by researchers (Arham et al., 2020; Vogiazas & Nikolaidou, 2011) with the exception of the debt component, in which case a negative relationship was established. Even though the author managed to overcome the drawbacks of using the FE model, which does not account for individual heterogeneity of the various banks, by applying the GMM technique, the GMM is limited in the sense that it is prone to increase the number of moment conditions at the order of T^2 which can create severe downward bias in finite samples (Hsiao, 2007). The finding that UNEMP influences NPL negatively, contradicts those obtained by Kjosevski et al., (2019) as well as Radivojevic and Jovovic (2017).

Kjosevski and Petkovski (2017) carried out three alternative panel data estimation techniques (FE model, difference GMM and system GMM) on a panel of 21 commercial banks in the Baltics countries (Estonia, Latvia and Lithuania), for the period 2005 – 2016. The results from the macroeconomics variables show that GDP growth, Inflation (INF) and export of goods and services (EXPG) have negative and significant effect on NPL. Unlike studies (Abid, Ouertani & Zouari-Ghorbel., 2014; Gashi, 2021; Radivojevic & Jovovic, 2017) that limited themselves to establishing the relationships between the drivers of NPL and NPL itself, Kjosevski and Petkovski (2017) went an extra mile to establish a causal between selected determinants and NPL. Messai and Jouini (2013) also applied a panel data approach on a sample of 85 banks in three countries (Italy, Greece and Spain) for the period of 2004 - 2008. Just like in Radivojevic and Jovovic (2017), Rachid (2019), Erdas and Ezanoglu (2022) and Gashi (2021) studies, their results also found GDP growth rate to have a significant negative effect on NPL, whilst the effects of unemployment were positive, which is similar to what Gashi (2021) observed.

Another interesting study by Canepa and Khaled (2018) assessed the effects that some macroeconomic fundamentals and the housing market have on credit risk. The study was based on a balanced panel dataset of 23 countries spanning from 2000 - 2012. The results showed that GDP and house prices are inversely related to credit risk, whilst the rate of unemployment, household affordability and household indebtedness were found to be positively related to credit risk. Nonetheless, this study was majorly limited on countries that suffered from major housing market contractions during the periods of financial crisis. Similarly, Wood and Skinner (2018) conducted a study on the determinants of NPL in Barbados using time series data for the period 1991-2015. The study utilised a multiple linear regression approach based on the OLS econometric technique, which is often employed under stricter assumptions. Their findings revealed that amongst the macroeconomic indicators employed, GDP growth was negative, unemployment was positive and interest rate was negative in influencing NPL. Inflation was found to be positively related to NPL, but insignificant.

Likewise, Tanasković and Jandrić (2015) investigated the macroeconomic determinants of the growth of NPL for a selected CESEE countries for the period 2006 - 2013. The study applied a static panel data model approach and the result showed *GDP growth* rate to be negatively related to the level of NPL. This finding is in line with the results obtained by other scholars (Abid et al., 2014; Gashi, 2021; Kjosevski & Petkovski, 2017; Radivojevic & Jovovic, 2017; Vogiazas & Nikolaidou, 2011). On the other hand, Hajja (2022) analysed the factors influencing NPL in Malaysia over the period 1998 – 2015. The GMM technique was utilised and a stress-testing of NPL of the banking sector using VAR approach of monthly time series data was used. The findings with respect to the macroeconomic indicators revealed that a rise in *GDP growth* is positively related to the ratios of NPL. Whereas, *inflation* was found to exert a negative impact on NPL levels. Kjosevski et al., (2019) also found a negative relationship between inflation and NPL.

Ghorbani and Jakobsson (2019) evaluated the determinants of NPL in Portugal, Italy, Greece and Spain using a quarterly balanced panel dataset covering the period 2006–2018. The study differs from a number of studies conducted on the same subject as it is incorporative of interactive effects meant to cater for unobserved heterogeneity and cross-sectional dependence. Their findings revealed that the *unemployment rate* has a positive impact on NPL levels. A similar conclusion was obtained in Kjosevsk et al., (2019)'s study that employed an ARDL modelling approach using time series data of period 2003Q4-2013Q4 from the Macedonian banking system. The banks' profitability, the loans growth, as well as the GDP growth, were all found to have a negative impact on NPL.

AlizadehJanvisloo and Muhammad (2013) investigated the relationship between bank loans quality and the macroeconomic variables using a dynamic panel data model on the Malaysian commercial banking system for the period 1997-2012. Their results revealed that GDP growth and domestic credit growth exert a negative effect on the NPL ratio, while inflation and FDI-net outflow had a positive effect. These findings that inflation is positively related to NPL is in accordance with those reached by Abid et al. (Abid et al., 2014) and Rehman (2017). The study also concluded that the impact of external shocks on the domestic banking system is more than internal shocks. The authors attempted to curtail the issues of endogeneity by employing the GMM estimation. They used the *consumer price index* as a proxy for inflation, but they fell short to justify why they could not use the rate of inflation in their estimation.

In another separate study by Koju et al. (2018b) in which they investigated both the macroeconomic and bank - specific determinants of NPL in the Nepalese banking system, the authors used both the static and the dynamic panel estimation approaches on a sample of 30 Nepalese commercial banks over the period 2003 - 2015. The macroeconomic findings revealed that the *ratio of export to import* was found to be positively related to NPL. On the other hand, *inflation* and *GDP growth rate* was found to exert a negative effect on NPL. The finding that inflation and GDP are negatively related to NPL may somewhat be strange but not peculiar to the Nepalese banking system as their results conform to those which were obtained by Radivojevic and Jovovic (2017), and Gashi (2021).

ALrfai *et al*. (2022) explored the determinants of credit risk in the Jordanian banks using a set of balanced macroeconomic data for the period 2008 – 2019. After estimating using the static panel data analysis, the finding outlined that *output gap*, *debt stock*, *remittance* all had a positive influence on credit risk. On the other hand, the authors found *foreign direct investment* and *personal income tax* to be negatively related to NPL. Although this study was sought to uncover the various factor influencing NPL, the study was limited in the sense that only two sets of indicators, the bank specific factors and the macroeconomic factors were examined. On the other hand, Anita et al. (2022) also examined the macroeconomic determinants of NPL for a panel of eight South Asian countries (Afghanistan, Bangladesh, Bhutan, India, Nepal, Maldives, Pakistan, and Sri Lanka) using annual data for the period 2008–2019. Upon employing the panel model of pooled OLS, fixed and random effects model, the study revealed that a significant positive relationship exists between NPL and government budget balance while for GDP, sovereign debt, inflation rate, and money supply were negatively associated. However, the study did not assess how fluid the issue of credit risk is in these countries even though the authors based their recommendations on such arguments.

In Namibia, there are literally only two studies (Kamati et al., 2022; Sheefeni, 2015b) that tried to examine the effects that a few macroeconomic variables have on NPL. Both studies employed the VAR modelling approach covering the periods 2004 – 2021 and 2001 – 2014, respectively. With respect to the macroeconomic indicators, Kamati et al. (2022)'s study concluded that a change in macroeconomic conditions has a strong impact on the banking sector. More specifically, the study found that real GDP growth negatively impacted NPL. This outcome is congruent with the short run results obtained by Sheefeni (2015b) who also found inflation to positively affect NPL in Namibia. Another study by Mpofu and Nikolaidou (2018), which used 22 cross-country panel dataset (Namibia included), covering the period 2000 – 2016, although the study is not specific to Namibia only, yet after employing various estimations techniques (pooled OLS, FE, 2 step difference and system GMM estimation techniques) their results affirmed that real GDP growth rate negatively affect NPL, whilst inflation rate, domestic credit to private sector, as a proxy of global volatility, trade openness and the dummy variable for global financial crisis, all had positive impact on NPL. The results from all these studies are somewhat comparable, despite the authors having used different estimation techniques.

3.3.3 Monetary indicators

Asiama and Amoah (2019) assessed the influence of monetary policy rate (using the central bank's repo rate as its proxy) on NPL in Ghana. The results from employing the ARDL econometric approach concluded that in the short run, monetary policy did not influence NPL. They argued that the reason this might have been the case was due to rising operating costs, brought about by the spread in the interest rate and the repo rate, which results in the rise of NPL. Nonetheless, in the long run, monetary policy was found to positively affect the growth in the level of NPL. Unconventional to the use of annual data, as is the case within most literature, this study used quarterly time series data spanning between the period 2000 – 2016. Moreover, the authors overlooked one of the requirements of using the ARDL techniques which requires that the dependent variable (NPL) be stationary after first difference and not in level.

Similarly, Anita et al. (2022) investigated the macroeconomic determinants of NPL for a panel of eight South Asian countries (Afghanistan, Bangladesh, Bhutan, India, Nepal, Maldives, Pakistan, and Sri Lanka) using annual data for the period 2008–2019. The study applied panel data techniques and found, amongst the multiple results, that the only monetary indicator (money supply) was negatively related to NPL. This led the authors to recommend that the supply of money ought to be moderate with the rate of inflation. The researchers did not assess issues pertaining to the resilience of these country's financial system, despite recommending that the issue be looked at by the stakeholders of the banking and financial authorities of these countries.

Vogiazas and Nikolaidou (2011) hypothesised that the macroeconomic-cyclical indicators, monetary aggregates, interest rates, financial markets, and bank specific indicators influence NPL in the Romanian banking system. The authors performed a basic OLS econometric technique using monthly time series which span from 2001 - 2010. In particular to monetary indicators, they found that both M1 and M2 negatively influenced NPL in Romania. For this study, it is not very clear whether the variables used in estimating their model satisfied the requirements of the classical linear regression model (CLRM). This is concerning given that the authors based their final decision of the variables' order of integration on the Augmented Dickey-Fuller (ADF) unit root test, which is often criticised for its weakness in failing to reject the null hypothesis of unit root. On the contrary, Hajja (2022) investigated the factors affecting NPL in Malaysia using monthly data for the period 1998 – 2015. The author employed the GMM technique and found that an expansionary monetary raises the level of NPL in banks. This was arguably the case due to higher lending rates.

Badar and Javid (2013) investigated the long- and short run associations between a series of variables and NPL in Pakistan for the period between 2002 – 2011. To assess whether the variables were cointegrated, the authors employed the Johansen and Juselius cointegration test and the results obtained showed that *broad money* supply (*M2*) was positively associated with NPL over the long run period. Their study mainly focussed on macroeconomic factors, and ignored the monetary factors likes the narrow money (M1) and/or the net foreign assets (NFA). On the contrary, Rifat (2016) used a different technique- the FE panel analysis- and found the ratio of M2 to GDP of being negatively related to NPL in Bangladesh. The differences in how the M2 was measured in each of the respective studies might explain the contrasting findings.

3.3.4 Interest rate indicators

In Namibia, Sheefeni (2015b) found interest rate (IR) to positively influence NPL in the short run. Similarly, Abid *et al.* (Abid et al., 2014) reported a positive relationship between *real lending rate* and NPL in Tunisia. Unlike Sheefeni (2015b)'s study that relied on quarterly time series data between the period of 2000 – 2014 and which was based on the VAR estimation techniques, Abid *et al.* (Abid et al., 2014)'s study used a dynamic panel data technique over the period 2003 – 2012.

Likewise, Arham *et al*. (2020) carried out a panel regression analysis to examine the root causes of NPL in 10 Asian countries and they also found *real interest rate* to be positively related to NPL. Canepa and Khaled (2018) also found *interest rate* to be positively related. In the same vein, Hajja (2022) found the *lending interest rate* of being positively associated to the ratios of NPL in Malaysia. These results are against the findings of Ekanayake and Azeez (2015), who also evaluated the determinants of NPL in the Sri Lankan banking sector between the period 1999-2012. After applying the fixed effect panel regression model, which is highly criticised for its inability to account for individual heterogeneity in the model, they found that the *prime lending rate* variable was positively associated with NPL.

On the other hand, Vogiazas and Nikolaidou (2011) found that amongst the *interest rate indicators* only the 3-month Euribor rate was found to bear a negative significant effect to NPL. This outcome was against the a priori expectation which postulates that declines in interest rate causes an increase in the appetite for households and corporations to borrow more, which leads to a rise in NPL. Likewise, Tanasković and Jandrić (2015) found that *exchange rate (EXR)* is positively related to NPL in CESEE countries.

3.3.5 Financial indicators

In the same study by Vogiazas and Nikolaidou (2011), they hypothesised that financial markets influence NPL in the Romanian banking system. After the authors employed basic ordinary least square (OLS) estimation using monthly time series for the periods 2001 – 2010, they concluded that none of the financial indicators employed turned out to be statistically significant. Rehman

(2017) investigated the factors responsible for influencing NPL in the banking system of the South Asian regions for the period 1999-2015. Due to the heterogenous nature of the dataset, the authors opted to apply the GMM estimation technique as well as the impulse response function for robustness of results. The study concluded that exchange rate depreciation leads to a rise in the levels of NPL.

Conversely, Viphindrartin *et al.* (2021) investigated the factors suspected of causing NPL of rural banks in Indonesia on a monthly basis for the period 2015 - 2018. After applying the Vector Error Correction Model (VECM) estimation approach, the researchers concluded that interest rates were positively related to NPL in both the short- and long run. On the other hand, the exchange rate variables were found to be negative and insignificant; nonetheless, the authors failed to justify why this was the case. Hajja (2022), amongst other findings, concluded that higher liquidity of the *stock market* are inversely associated with the NPL ratios. This entails that a rise in stock market, helps in reducing NPL levels.

3.3.6 Institutional indicators

With regards to the effect of institutional factors on NPL, not much is known in the literature, much less in the case of Namibia. For this reason, this study attempts to fill this gap by examining the effects of institutional indicators on NPL in Namibia.

Amongst the scanty studies is that by Rachid (2019), which attempted to uncover some of the determinants of NPL in 10 countries of the Middle East and North Africa (MENA) and 11 Central and Eastern European (CEE) countries for the period 1997 - 2016. Panel data estimation techniques were employed and the results suggested that institutional indicators such as the "rule of law" and "political stability" are positively related to NPL in MENA countries; whereas, in CEE countries they were found to negatively influence NPL. The author argued that one of the main reasons why a negative relationship between institutional factors and NPL exist for CEE countries is because these countries are plagued with political instabilities coupled with high corruption practices which translate into incompetent institutional capabilities, thereby causing an increase in the levels of NPL.

Arham et al. (2020), examined the determinant of NPL in 10 selected Asian economies; the authors employed a static panel data analysis using data for the period 2007 – 2017. The authors assessed how the interaction of governance indicators (control of corruption, government effectiveness, and regulatory quality) helps to reduce the impact of macroeconomics factors on NPL in these countries' banking systems. This study's approach of interacting the governance indicators with the macroeconomic variable is different from Rachid (2019)'s study that separately verified the influence of all the six governance indicators as published by the Worldwide Governance Indicators.

Likewise, Kordbacheh and Sadati (2022) studied the relationship between corruption and banking soundness using a panel dataset comprising of 98 countries from the period 2012 - 2015. The empirical findings emanating from this study suggested that countries plagued with higher levels of corruption are more prone to financial instability. The authors stressed that the adverse impact of corruption on banking soundness is more substantial in countries endowed with abundant natural resources. The study surmised that institutional quality, used to proxy the corruption variable, reduces NPL, thereby improving the soundness of the banking sector. Unlike other studies, the authors of this study declared to have addressed the problem of heterogeneity and autocorrelation by employing the generalised least squares (GLS) estimation method.

Equally, Ozil (2018) conducted an investigation on the determinants of banking stability in 48 African states using cross-sectional datasets for the period between 1996 - 2015. The paper employed the fixed effect panel data model and the findings in regards to institutional variables revealed that the coefficient of *political stability and absence of terrorism*, *rule of law index*, and the *regulatory quality* all were negatively associated to banking stability. Conversely, the coefficient of *control of corruption index* was found to be positively related with banking stability. Although the study attempted to encompass several indicator variables, the fact that dataset suffered from a significant amount of missing values, it made it impossible to estimate a GMM system of estimation, which is believed to produce robust estimations.

Tatarici et al. (2020) investigated the determinants of NPL in a panel of EEC countries covering the period 2005 - 2017. The authors applied a panel fixed effect model together with a dynamic GMM estimation technique using a series of indicators. The results specific to institutional indicators found that improvements in the *government effectiveness* helped to reduce the levels of NPL. Although, this conclusion appears to be consistent with the study's hypothesis on quality of regulation, the magnitude by which government effectiveness affect NPL is significantly smaller.

Similarly, Boudriga *et al.* (2010) analysed the determinants of NPL in 46 banks from twelve countries in the MENA countries for the period 2002 - 2006. Upon employing a random effect panel regression model, the specific results relating to institutional environment appeared to suggest that better enforcement of *rule of law*, sound *regulatory quality*, better *voice and accountability* had a positive impact in reducing the levels of NPL. In other words, they were negatively related to NPL. Despite the Hausman test selecting the fixed effect panel regression model as a the most appropriate estimation, the authors deliberately opted to ignore this choice in place of the random effect model that caters for both observed and unobserved cross-country heterogeneity.

3.4 Literature gap

Although there are numerous studies around the globe that investigated the relationships between various indicator variables and non-performing loans, the coverage in most of these studies, including in Namibia, is very narrow. For example, the only recent country specific studies found on the subject of how some variables influence the levels of non-performing loans in Namibia are mainly those carried out by Kamati et al. (2022) and Sheefeni (2015a, 2015b). In all these studies, the Vector Autoregressive (VAR) modelling technique was employed using time series data between 2004 - 2021 and 2000 – 2014, respectively. Not only does the current study use a much longer time period of dataset (1996 to 2021), it also attempts to include four additional classes of indicators that are often ignored in the body of literature, including the one from Namibia.

The holistic consideration of most indicators, uncover interesting dynamics occurring within the economy which have a much compelling insight of the outcomes on the current phenomenon of

NPL in Namibia. Therefore, this study extends the limited coverage by previous studies, such as those aforementioned.

Another thing is that the VAR model used in the literature for (Kamati et al., 2022; Sheefeni, 2015a, 2015b) has often been criticised to have an *a-theoretical* drawback due to its underlying assumption that all the variables entered in the system are endogenously determined. This might be misleading and lead to inaccurate conclusions that are inappropriate for policy recommendations. For this reason, the present study employs a more advanced modelling technique, the Autoregressive Distributive Lag (ARDL), considered to cater for some of these drawbacks.

Furthermore, the country-specific studies for most studies in the body of the literature, including those from Namibia (Kamati et al., 2022; Sheefeni, 2015a, 2015b), are quite limited as they mainly revolve around two sets of indicators (the bank specific and macroeconomic). The departure point of this thesis is that it attempts to go beyond the limited scope presented in most studies by incorporating six broader categories of indicators considered to be liable in influencing the levels of NPL in the banking sector. In other words, not only will this thesis incorporate four additional categories of indicators (monetary, interest rate, financial and institutional indicators) but it also uses more important variables which were never examined in the context of Namibia.

Even though there is a consensus in the body of literature regarding the role that various indicators play in influencing the levels of non-performing loans, in some countries the results turned out to be ambiguous. Actually, for most studies the assessment is rather one sided, as they tend to focus more on one area or the other (Canepa & Khaled, 2018). Given that very little is known regarding how most of the factors examined elsewhere would affect the levels of NPL in Namibia's banking sector, this study will therefore fill all the aforementioned gaps stipulated under this section. This ensures that Namibia's position is properly profiled in the midst of existing debates on the subject matter.

3.5 Summary

Based on the theoretical literature, there are various theories that can be associated with the banking sector credit risks exposure. This might be due to the fact that different economies possess unique characteristics and require their own specified hypotheses. With regards to most reviewed empirical studies, it was found that various indicator variables affect NPL in different ways[19]. In general, most studies found the indicators variables to significantly influence non-performing loans. Meanwhile, several of them found that the influence was negligible (i.e., insignificant). Due to a variation in the data time frame dealt by various researchers, a number of methodological approaches meant to account for the characteristics of the dataset have been applied in the literature[20].

Based on the studies reviewed, the majority of the studies were panel based. Also, the reviewed literatures overwhelmingly affirm that the factors affecting NPL are multidimensional and their effects differ from country to country. Even though the ways in which different studies investigate the effects of indicator variables on non-performing loans vary, it is unclear where to locate Namibia in the face of these conflicting views. For this reason, this leading study fills the literature gaps pertaining to a variety of factors that affect non-performing loans in Namibia's banking sector, but never yet been explored. In so doing, the country's position in the midst of all these global debates will be correctly represented.

[19] *The influence may end up being positive, negative or none.*

[20] *Although there are various Econometrical approaches that have been employed, it imperative that they are appropriately applied by satisfying the requirement criteria upon which they are hinged.*

CHAPTER IV: AN ANALYSIS OF NON-PERFORMING LOANS IN NAMIBIA

4.1 Introduction

The global economic meltdown that erupted after the advent of the global Coronavirus pandemic of 2019 (COVID-19) is likely to remembered as one of the worst challenging moments for most economies in the 21st century. The era of the COVID-19 pandemic threatened the survivability of mankind as millions around the world lost their lives, whilst world economies struggled as well. Prior to this, was the notorious global financial crisis of 2008 which spilled over from the United States of America (USA) property market due to a surge in lending, to unworthy borrowers (Canepa & Khaled, 2018). In their studies, Koju et al. (2020) argued that credit risk, a proxy of non-performing loans (NPL)[21], is an important indicator for gauging the stability of a country's banking sector. As alluded in chapter one, loans are considered to be non-performing when the borrowers of such loans fail to honour the scheduled payments of the principal or interest amount for a period spanning 90 days.

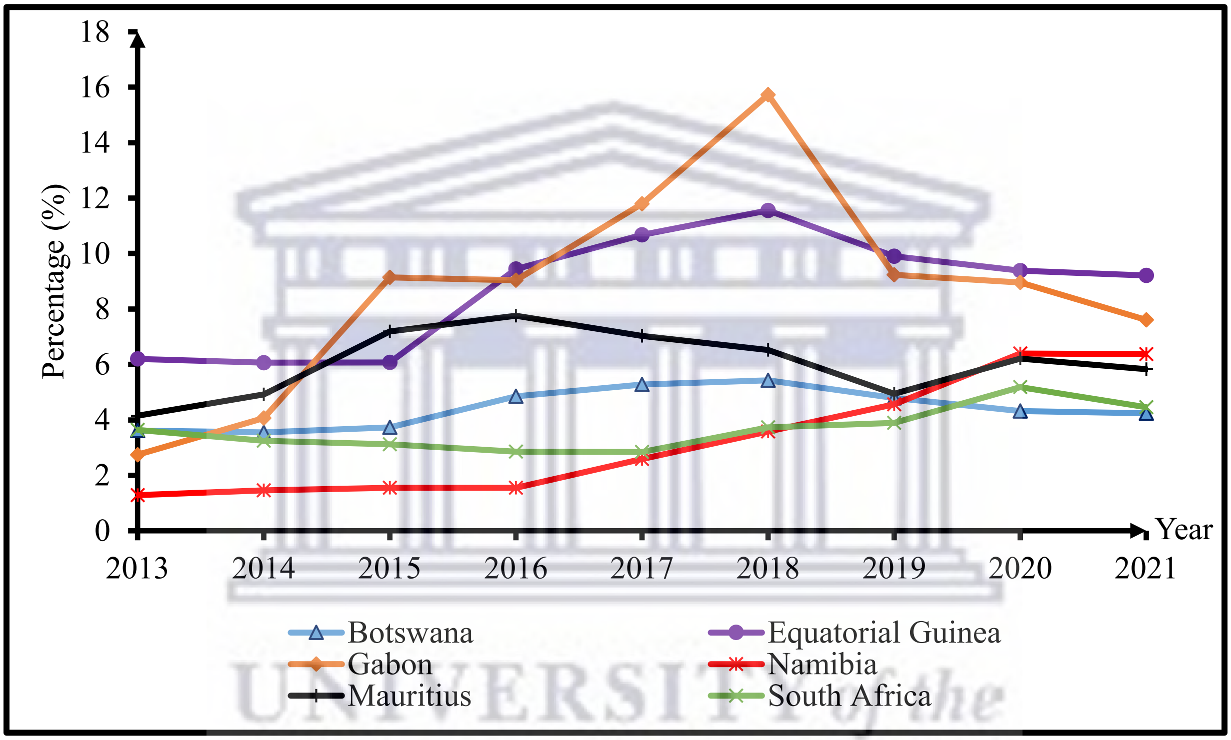
The banking industry faces numerous kinds of risks despite the role it plays in the financial and economic development of a country (Ikram et al., 2016; Naili & Lahrichi, 2022). Since loans are a major source of banks' income, credit risk tends to constitute the bulk of banking risks. Banking authorities must endeavour to understand the factors liable for destabilising the banking industry if they are to safeguard themselves against potential threats that are likely to undermine the stability of the banking system. A proper understanding will facilitate the bank managers as well as policy makers to legislate policies that can effectively address the intricacies underlying such determinants. Therefore, any effort to uncover the root causes of credit risk and establish the nature of causality amongst the variables of interest is invaluable in averting a possible crisis. It is not surprising, there is an ever-growing number of empirical studies on the factors influencing NPL all across the world (Ghosh, 2017; Us, 2017).

Based on statistics from the WDI, the average NPL for the six Upper-Middle-Income countries

[21] *In this study, NPL is measured as the ratio non-performing loans to total gross loans.*

(UMIC)[22] of Sub-Saharan Africa (SSA) for the periods 2013-2021 was estimated to stand at 5.80%. Of the six SSA countries, four were SADC member states with Namibia reporting the lowest annual average NPL ratio of 3.26%, followed by South Africa (3.66%), Botswana (4.42%) and Mauritius (6.06%). The remaining two non-SADC countries; Gabon and Equatorial Guinea, recorded an average NPL of 8.70% and 6.06%, respectively.

Figure 4.1: NPL for upper-middle-income countries of SSA, 2013 – 2021



Source: Own computations using data World Development Indicators (WDI)

From the average NPL ratio statistics aforementioned, it can be surmised that Namibia has enjoyed a relatively lower annual average rate of NPL in comparison to other UMIC in SSA region. Nevertheless, as illustrated in Figure 4.1, in the year 2020 Namibia's rate of NPL surpassed those of its peers within the SADC region (Botswana, Mauritius, and South Africa). Such developments are worrisome and detrimental to Namibia's financial development in the long run especially due to the fact that over the past few years there has been a rapid surge in the levels of NPL above the 4.0 benchmark and the supervisory intervention trigger point of 6.0% stipulated by the BoN. Such

[22]*The SSA UMIC for 2023* were: *Botswana, Equatorial Guinea, Gabon, Namibia, Mauritius, and South Africa. These are countries said to have a Gross National Income (GNI) per capita between US$ 4096-US$12695 as per the World Bank classification 2023FY.*

rapid rises are likely to lead to economic anomalies which may include capital outflows from Namibia to much more favourable investment destinations. Thus, the banking sector as a whole cannot afford to ignore nor relent in its pursuit of uncovering the leading causes of rising NPL. Such unrelenting efforts are necessary in devising workable strategies that can stem the rise of NPL. Failure to do so could have unintended repercussion not only for the banking sector, but the entire economy as a whole.

Just like in many countries, the bulk of Namibia's banking sector asset composition is composed of loans. Of this, a bigger chunk of credit risk exposure is made up of mortgage lending. For example, the annual average mortgage lending as a percentage of total lending for the periods 1996 – 2021 was 48.7%. However, between the periods 2010 – 2021 it averaged 53.7% with the year 2020 and 2021 registering 52.3% and 53.4%, respectively (Bank of Namibia, 2022; Bank of Namibia & NAMFISA, 2021). As much as the act of lending by banks plays a pivotal role in the economic growth and development of any country, a deterioration in the quality of such asset concentration is bad for the economy due to the risk exposure it creates for the banking and the financial sector (Barra & Ruggiero, 2021).

Historically, credit risks have been linked to some global financial crisis, especially when they happen to come from leading economies (Barra & Ruggiero, 2021; Rajha, 2017). Mazreku et al. (2018) contend that, the severity of credit risk is amongst the leading factors for insolvency of most lending institutions, thereby causing an unstable banking environment. Just as NPL, which are a proxy of credit risks, are unwanted to lenders, they are equally undesirable for any economy desiring to thrive. The undesirableness of NPL is mainly due to its negative spill-over effect on the overall performance of the economy. Moreover, rising credit risk could compromise the revenue collection base for a country like Namibia, whose fiscal budget is heavily reliant on government tax revenue[23], thereby making it harder for it to achieve its developmental agendas outlined in various strategic blueprints[24].

[23] *The Namibia Revenue Agency (NamRA) managed to generate 42% of the total tax revenue target of the overall Government expenditure budget of the anticipated N$60.1 billion for this current financial period (2022/23).*

[24] *Such as, the various National Development Plans (NDPs), Vision 2030, the Harambe Prosperity Plan 2 (HPP2) etc…*

Despite Namibia experiencing some years of impressive economic growth, with an annual average GDP growth rate of 4.5% for the period of 1996 - 2015, the succeeding years after 2015 have been characterised by immense economic headwinds. In fact, beginning from 2014 when the global economy plunged into a mild recession, brought about by shocks in the oil market, a number of other factors such as the rate of unemployment and debt stock were starting to get out of control. The issues of debt to GDP ratio became very topical in cycles due to the rate in which it was rising. The majority of citizens became very concerned with such developments as they feared that the then debt to GDP ratio of 23.6% was going to rise beyond the national fiscal threshold of 35.0%. Beyond this threshold, it would be unsustainable for tax payers to service such debt overhangs in the long run. By the end of 2015, the rate had risen to 38.4% coupled with rising unemployment rates, housing prices and NPL. As of 2022, the ratio of debt to GDP was registered to stand at 68.9%, which is considered way beyond the 60% benchmark for SADC member states.

The contractions of Namibia's economic growth over the past few years appear to have been increasing the rate of default in loan repayments supposed to be made by entities that have taken out such credits. As a result, the financial sector appears to have fallen short of the much-needed funds to revitalize the economy. This paper extends some of what has already been established in relation to NPL by various scholars. In particular, this study sought to analyse the determinants of NPL and establish the nature of causality amongst them. This quest is of utmost importance as it is the bedrock on which bank managers as well as the monetary authorities could base the policy position. The fact that the banking sector plays a crucial role in the economic development of any country obliges relevant players of the economy to ensure a well-functioning banking sector that is sound and resilient (Amuakwa-Mensah et al., 2017; Kepli et al., 2021). A sound financial system is indispensable for any country desiring to thrive economically. This is because, such a soundness boosts investors' confidence, which is a necessary requirement for investments by any serious investor to flow into any country, like Namibia which aims to become industrialised[25].

According to Erdas and Ezanoglu (2022) and Kjosevski and Petkovski (2021), the categories of

[25] *According to Vision 2030, a document that maps out the Namibia developmental agenda, the country aims to become industrialised by the year 2030.*

indicators[26] often culpable for influencing NPL are multifaceted. Nevertheless, most literatures on the determinants of NPL are mainly centred on two categories of indicators namely, the macroeconomic and the bank specific indicators (Erdas & Ezanoglu, 2022; Gulati et al., 2019; Kepli et al., 2021; Kjosevski & Petkovski, 2017). In general, the choice of the type of indicators a researcher decides to incorporate in a particular study is often influenced by several factors, which includes the availability of data, the study's objective, to mention but a few. This being the case, researchers are in most cases prone to leave out some indicators that are too vital to be ignored. Considering that the banking system does not operate in isolation, a gap exists in the literature for studies that will attempt to analyse the individual and collective influence of key factors that are suspected of affecting NPL. The present study bridges this vacuum by profiling both the evidence of the determining factors of NPL as well as the causal relationship between the indicators and NPL, using Namibia, a small open developing economy, as a case study.

The main aim of this chapter is to analyse the determinants of NPL in Namibia between the period 1990-2021. To do this, the chapter is organised as follows; firstly, Section 4.2 outlines the methodology, followed by Section 4.3 which presents the empirical results and finally, Section 4.4 summarises and draws conclusions.

4.2 Methodology

The methodology is divided into three main sections. Section 4.2.1 outlines the model specification. Section 4.2.2 discusses the data and description of variables used in this study. Section 4.2.3 describes the estimation procedure.

4.2.1 Model Specification

Building upon previous empirical work (Rachid, 2019; Radivojevic & Jovovic, 2017; Vogiazas & Nikolaidou, 2011, amongst others) in the field, this study explores new dimensions relating to the phenomenon of Non-Performing Loans (NPL), with special focus on Namibia. In order to answer

[26] *Such factors are usually classified into various categories of indicators, i.e., Macroeconomic, Bank-specific, Monetary, Interest rate, Financial, Institutional indicators, to mention but a few.*

the two objectives relating to this chapter, the empirical estimation is hereby conducted in stages. The initial stage evaluates all the control variables simultaneously. Thereafter, six reduced form models are estimated to gain insight into the individual indicators influencing NPL. Up next is the specification of the empirical models consisting of the composite indices (Section 4.2.1.1) and the six other categories of indicators (Section 4.2.1.2 to 4.2.1.7).

4.2.1.1 NPL model with the composite indices

In order to assess the first specific objective of this dissertation, which seeks to uncover the underlying indicators liable for influencing the level of NPL in the Namibian banking sector, the Autoregressive Distributive Lag (ARDL) bound testing modelling approach developed by Pesaran et al, (2001) is employed. The same modelling approach, substantiated by the Vector Autoregressive (VAR) pairwise Granger causality test model, is also used to test for the second objective of this study, which seeks to evaluate the causal relationship between the indicators and NPL. Thus, the generic ARDL model for evaluating the overall effect of the six broad-based indicators on NPL, has been specified as follows:

$$\Delta NPL_t = \gamma_0 + \sum_{i=1}^{p} \Psi_i \Delta NPL_{t-i} + \sum_{j=0}^{q} \varpi_j \Delta \boldsymbol{X}_{t-j} + \Phi_1 NPL_{t-1} + \Phi_n \boldsymbol{X}_{t-1} + \boldsymbol{\varepsilon_t} \qquad (4.0a)$$

Where NPL is the ratio of Non-performing Loans to total gross loans; Δ is the first difference operator; γ_0, Ψ_i, ϖ_j, Φ_1, and Φ_2 are parameter estimates; p represents the optimum number of lags of the dependent, q is the optimum number of independent variables and $n = 2, \dots, 7$, respectively; $\boldsymbol{X}_{t-i}$ is a K x 1 vector of the indicators (such as, the macroeconomic ($MACRO$), bank specific ($BANK$), monetary ($MONE$), interest rate ($INTER$), financial ($FINA$) and institutional ($INST$) indicators) which are later on used to individually evaluate the isolated effects that such indicators have on NPL; $\boldsymbol{\varepsilon_t}$ the white-noise error term with its usual properties[27] at time period t.

[27] $\mu_t \sim N[0\ ,\ \sigma^2]$ *that is, error term is randomly normally distributed with zero mean and constant variance.*

Based on Equation 4.0, the generic null hypothesis for no cointegration is defined as follows: $H_N: \Phi_1 = \Phi_n = 0$ (implying that there is no cointegration between $\boldsymbol{X}_{t-i}$ and NPL_t). Conversely, the alternative hypothesis for cointegration is $H_A: \Phi_1 \neq \Phi_n \neq 0$ (implying that a cointegration exists between $\boldsymbol{X}_{t-i}$ and NPL_t). The null hypothesis of no cointegration is rejected if the F-statistic lies outside the 5% critical bound, else if it falls within the bounds, the decision becomes inconclusive and this requires an alternative multiple restriction test[28] to reach a decisive conclusion. However, if its F-statistic lies below the lower critical bound it means there is no cointegrating relationship amongst the variables in the long run.

The short run ARDL (p, q) model is specified as:

$$\Delta NPL_t = \gamma_0 + \sum_{i=1}^{p} \Psi_i \Delta NPL_{t-i} + \sum_{j=0}^{q} \varpi_j \Delta \boldsymbol{X}_{t-j} + \Phi_1 NPL_{t-1} + \Phi_n \boldsymbol{X}_{t-1} + \emptyset ECM_{t-1} + \boldsymbol{\varepsilon_t} \qquad (4.0b)$$

Where Ψ_1 and Ψ_i capture the short run dynamics of the model's convergence to equilibrium and Φ measures the speed of adjustment to long run equilibrium in the event of shock in the system, and ECM is the error correction term derived from Equation 4.0a.

Since the existence of correlation does not necessarily imply causation, the pairwise Granger causality test developed by Granger (1988) is also employed in order to authenticate the causality results obtained through the ARDL's regressors' t-statistics test which seeks to examine the second specific objective of this thesis. More specifically, the objective of whether a causal relationship between the indicators and NPL exist is evaluated. In this study, the causality test is examined via the Error Correction Model (ECM) framework which contains information of the long run causality, which are useful in predicting the future outcome of one variable (i.e., variable Y) given the past information of another variable (i.e., variable X).

As previously mentioned, the causal relationship between NPL and the sets of indicators can be deduced by looking at the statistical significance of the coefficient of the Error Correction Term (ECT) presented in Equation 4.0b (the sign of the coefficient must be negative). On the other hand,

[28] *Such as the Wald test for multiple restrictions.*

the short run causalities are inferred by evaluating the significance of the regressors' *t*-statistics in the same mentioned equation. Besides this, the VAR pairwise Granger causality test results are generated to reveal the nature (unidirectional, bidirectional, or independent)[29] of causality amongst variables.

The generic pairwise Granger causality model involving NPL and the vector of indicators $(\boldsymbol{X})$ is specified as follows:

$$NPL_t = \varkappa_0 + \sum_{i=1}^{n} \varkappa_i NPL_{t-1} + \sum_{j=1}^{n} \varkappa_j \boldsymbol{X}_{t-i} + \boldsymbol{w}_{\boldsymbol{1t}} \quad (4.1a)$$

$$\boldsymbol{X}_t = \rho_1 + \sum_{i=1}^{n} \rho_i \boldsymbol{X}_{t-i} + \sum_{j=1}^{n} \rho_j NPL_{t-1} + \boldsymbol{w}_{\boldsymbol{2t}} \quad (4.1.\mathrm{b})$$

Where *n* is the optimal lag length determined through the VAR information criteria tests as per the Schwarz-Bayesian Information Criterion (SC); ρ_1 and $\varkappa_0$ are intercepts; the rest of the ρ_i, ρ_j, $\varkappa_i$ and $\varkappa_j$ are the short run dynamics coefficients of the model's adjustment to long run equilibrium; $\boldsymbol{w}_{it}$ are the stochastic error terms.

Thus, Equation 4.1a and 4.1b, the pairwise Granger causality approach tests the following null hypothesis:

$\boldsymbol{H}_N = \sum_{i=1}^{n} \varkappa_j = 0$ for $j = 1, \dots, n$, implying that, X_{t-1} does not Granger cause NPL_t.

Similarly, another hypothesis is expressed as:

$\boldsymbol{H}_N = \sum_{i=1}^{n} \rho_j = 0$ for $j = 1, \dots, n$, according to which NPL_{t-i} does not Granger cause X_t.

[29] *Note: a) A unidirectional causality happens when the causality is running from one series to the other exists, but not the other way around, b) A bidirectional causality happens when the causality is two-way, and c) independence is when there is no causal relationship between the series.*

The null hypothesis of no causality is rejected in favour of the alternative *iff* the p-value is less than the 5% significance level. However, if the p-value is equal to or greater than the 5% significance level it means that there is insufficient evidence to reject the null hypothesis of no causality. Proceeding is an in-depth model speciation of the interaction between each class of indicator and NPL.

4.2.1.2 NPL model with the macroeconomic indicators

The model specifications relating to the interaction between the macroeconomic ($MACRO$) variables and NPL is specified in its reduced form as:

$$\Delta NPL_t = \beta_0 + \beta_1 t + \sum_{i=1}^{p} \psi_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \psi_j \Delta \Gamma_{t-j}^{A} + \Phi_1 NPL_{t-1} + \Phi_i \Gamma_{t-1}^{A} + \mu_t \tag{4.2}$$

Equation 4.2 represents an ARDL- Unrestricted Error Correction Model (UECM) specification used to measure the long run effects of MACRO factors on *NPL*. Where the vector $\Gamma^A = f(OPEN_t, DEBT_t, GAP_t, HP_t, UN_t, INF_t)$ consists of variables resembling the macroeconomic indicator, with $OPEN$ = Trade openness, *DEBT* = debt stock, *GAP* = Output gap, *UN* = Unemployment, *HP* = House price index and *INF* = inflation. Δ denotes the first difference operator; μ_t is the white - noise error term at time *t* with its usual properties[30]; β_0 is the constant term, β_1 is the estimated coefficient associated with a linear trend, ψ_1 and ψ_i represents the ARDL short run terms, Φ_1 and Φ_i[31] are long run terms, $t - i$ and $t - j$ represents past values of the dependent and independent variables, respectively. The rest of the denotations are as previously defined.

Based on Equation 4.2, the null hypothesis of no cointegration is formulated as $H_N: \Phi_1 = \Phi_2 = \Phi_3 = \Phi_4 = \Phi_5 = \Phi_6 = \Phi_7 = 0$ and the alternative hypothesis of cointegration is $H_A: \Phi_1 \neq \Phi_2 \neq \Phi_3 \neq \Phi_4 \neq \Phi_5 \neq \Phi_6 \neq \Phi_7 \neq 0$. The null hypothesis of no cointegration is rejected if the F-

[30] $\mu_t \sim N[0\ ,\ \sigma^2]$ *that is, error term is randomly normally distributed with zero mean and constant variance.*
[31] *Where* $i = 2, \dots, 6$.

statistic lies outside the 5% critical bound, else if it falls within the bounds, the decision becomes inconclusive and this requires an alternative multiple restriction test[32] to reach a decisive conclusion. However, if its F-statistic lies below the lower critical bound it means there is no cointegrating relationship amongst the variables in the long run.

In the event that cointegration is confirmed in Equation 4.2, the conditional ARDL long run model for *MACRO* factors and *NPL* is estimated as:

$$\Delta NPL_t = \beta_0 + \beta_1 t + \sum_{i=1}^{p} \psi_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \psi_j \Delta \Gamma_{t-j}^{A} + \mu_t \qquad (4.3)$$

Where all the variables are as previously defined. The reparametrised ARDL model of order (p, q) is selected using the Schwarz Information Criterion (SIC) which tends to choose a more parsimonious model when handling a relatively smaller sample dataset, which is the case with the data used in this study. The ARDL (p, q) was specified as:

$$\Delta NPL_t = \beta_0 + \beta_1 t + \sum_{i=1}^{p} \psi_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \psi_j \Delta \Gamma_{t-j}^{A} + \emptyset ECM_{t-1} + \mu_t \qquad (4.4a)$$

Where ψ_1 and ψ_i capture the short run dynamics of the model's convergence to equilibrium and $\emptyset$ measures the speed of adjustment to long run equilibrium in the event of shock in the *MACRO* factors, and ECM is the error correction term derived from Equation 4.2.

In relation to the long run causal relationship between NPL and the macroeconomic factors, it is inferred through the statistical significance of the coefficient of the Error Correction Term (ECT) presented in Equation 4.4*a* (the sign of the ECT coefficient must also be negative for long run causality to be inferred). On the other hand, the short run causalities are inferred by evaluating the significance of the regressors' *t*-statistics in the same stated equation. In addition, the VAR pairwise Granger causality test is employed to determine the nature (unidirectional, bidirectional,

[32] *Such as the Wald test for multiple restrictions.*

or independent) of causality amongst variables.

The reduced form equation for the pairwise Granger causality model involving NPL and the macroeconomic factors (Γ^A) is specified as follows:

$$NPL_t = \alpha + \sum_{i=1}^{k} \psi_1 NPL_{t-i} + \sum_{j=1}^{k} \theta_j \Gamma_{t-j}^{A} + \mu_{1t} \qquad (4.4b)$$

$$\Gamma_t^A = \beta + \sum_{i=1}^{k} \theta_j \Gamma_{t-j}^{A} + \sum_{j=1}^{k} \psi_1 NPL_{t-i} + \mu_{2t} \qquad (4.4c)$$

Where k is the optimal lag length determined via the VAR lag selection information criteria test as per the Schwarz-Bayesian Information Criterion (SC); α and β are intercepts; ψ and θ are the short run dynamics coefficients of the model's adjustment to long run equilibrium; μ_{it} are the stochastic error term.

Thus, using Equation 4.4*b* and 4.4*c*, the Granger causality approach tests the following null hypothesis:

$\boldsymbol{H}_N = \sum_{i=1}^{k} \theta_j = 0$ for $j = 1, \dots, n$, implying that, Γ_{t-j}^{A} does not Granger cause NPL_t.

Similarly, another hypothesis is expressed as:

$\boldsymbol{H}_N = \sum_{i=1}^{k} \psi_1 = 0$, according to which NPL_{t-j} does not Granger cause Γ_t^A.

The null hypothesis of no causality is rejected in favour of the alternative *iff* the p-value is less than the 5% significance level. However, if the p-value is equal to or greater than the 5% significance level it means that there is insufficient evidence to reject the null hypothesis of no causality.

4.2.1.3 NPL model with the bank specific indicators

The model specification relating to the interaction between the bank specific ($BANK$) variables and NPL is specified in its reduced form as:

$$\Delta NPL_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} \emptyset_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \emptyset_j \Delta \Gamma_{t-j}^{B} + \lambda_1 NPL_{t-1} + \lambda_j \Gamma_{t-1}^{B} + v_t \qquad (4.5)$$

Equation 4.5 represents an ARDL-UECM specification used to measure the long run effects of $BANK$ factors on *NPL*. The vector $\Gamma^B = f(ROA_t, ROE_t, CAR_t, LB_t, NIM_t, LDR_t, LG_t)$ consists of variables denoting the bank specific indicator, with ROA = Return on assets, ROE = Return on Equity, CAR = Capital adequacy ratio, LB = Lending behaviour, NIM = Net interest margin, LDR = Loan to deposit ratio, and LG = Loan growth. Moreover, Δ denotes the first difference operator; v_t is the white-noise error term at time t with its usual properties[33]; α_0 is the constant term, $\alpha_1$is the estimated coefficient associated with a linear trend, $\emptyset_1$ and $\emptyset_j$ represents the ARDL short run terms, λ_1 and λ_j[34] are long run terms, $t - i$ and $t - j$ represent past values of the dependent and independent variables, respectively. The rest of the denotations are as previously defined.

Based on Equation 4.5, the null hypothesis of no cointegration is formulated as $H_N: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = \lambda_8 = \lambda_9 = 0$ and the alternative hypothesis of cointegration is $H_A: \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq \lambda_6 = \lambda_7 \neq \lambda_8 \neq \lambda_9 \neq 0$. The null hypothesis of no cointegration is rejected if the F-statistic lies outside the 5% critical bound, else if it falls within the bounds, the decision becomes inconclusive and this requires an alternative multiple restriction test[35] to reach a decisive conclusion. However, if its F-statistic lies below the lower critical bound it means there is no cointegrating relationship amongst the variables in the long run.

In the event that cointegration is confirmed in Equation 4.5, the conditional ARDL long run model for $BANK$ factor and NPL is estimated as follows:

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[33] $\mu_t \sim N[0\ ,\ \sigma^2]$ *that is, error term is randomly normally distributed with zero mean and constant variance.*
[34] *Where* $i = 2, \ldots, 8$.
[35] *Such as the Wald test for multiple restrictions.*

$$\Delta NPL_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} \emptyset_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \emptyset_j \Delta\Gamma_{t-j}^{B} + \mu_t \tag{4.6}$$

Where all the variables are as previously defined. The reparametrised ARDL model of order (p, q) was selected using the Schwarz Information Criterion (SIC) which tends to choose a more parsimonious model when handling a relatively smaller sample dataset, which is the case with the data used in this study. The ARDL (p, q) was specified as:

$$\Delta NPL_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} \emptyset_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \emptyset_i \Delta\Gamma_{t-j}^{B} + \tau ECM_{t-1} + v_t \tag{4.7a}$$

Where $\emptyset_1$ and $\emptyset_j$ capture the short run dynamics of the model's convergence to equilibrium and τ measures the speed of adjustment to long run equilibrium in the event of shock in the *BANK* factors, and ECM is the error correction term derived from Equation 4.5.

With regards to the long run causality between NPL and the bank specific factors, it is deduced through the statistical significance of the coefficient of the Error Correction Term (ECT) presented in Equation 4.7*a* (the sign of the ECT coefficient must also be negative for long run causality to be inferred). On the other hand, the short run causalities are inferred by evaluating the significance of the regressors' *t*-statistics in the same stated equation. In addition, the VAR pairwise Granger causality test is employed to determine the nature (unidirectional, bidirectional, or independent) of causality amongst variables.

The reduced form equation for the pairwise Granger causality model involving NPL and the bank specific factors (Γ^B) is specified as follows:

$$NPL_t = \emptyset_0 + \sum_{i=1}^{n} \emptyset_1 NPL_{t-i} + \sum_{j=1}^{n} \emptyset_j \Gamma_{t-j}^{B} + v_{1t} \tag{4.7b}$$

$$\Gamma_t^B = \beta_0 + \sum_{i=1}^{n} \beta_j \Gamma_{t-j}^B + \sum_{j=1}^{n} \beta_1 NPL_{t-i} + v_{2t} \qquad (4.7c)$$

Where n is the optimal lag length determined via the VAR information criteria test as per the Schwarz-Bayesian Information Criterion (SC); $\emptyset_0$ and β_0 are intercepts; $\emptyset_1$, β_1 $\emptyset_j$, and β_j are the short run dynamics coefficients of the model's adjustment to long run equilibrium; v_{it} are the white-noise error terms.

Thus, using Equation 4.7*b* and 4.7*c*, the Granger causality approach tests the following null hypothesis:

$\boldsymbol{H}_N = \sum_{i=1}^{n} \emptyset_j = 0$ for $j = 1, \ldots, n$, implying that, NPL_{t-j} does not Granger cause Γ_t^B.

Similarly, another hypothesis is expressed as:

$\boldsymbol{H}_N = \sum_{i=1}^{n} \beta_1 = 0$, according to which NPL_t does not Granger causes NPL_t.

The null hypothesis of no causality is rejected in favour of the alternative *iff* the p-value is less than the 5% significance level. However, if the p-value is equal to or greater than the 5% significance level it means that there is insufficient evidence to reject the null hypothesis of no causality.

4.2.1.4 NPL model with the monetary indicators

Thirdly, are the specifications relating to the monetary ($MONE$) variables and NPL is specified in its reduced form as:

$$\Delta NPL_t = \Lambda_0 + \Lambda_1 t + \sum_{i=1}^{p} \Omega_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \Omega_j \Delta \Gamma_{t-j}^C + \delta_1 NPL_{t-1} + \delta_j \Gamma_{t-1}^C + \xi_t \qquad (4.8)$$

Where the vector $\Gamma^C = f(M1_t, M2_t, NFA_t)$ consists of variables representing the monetary indicator, with M1 = Narrow money, M2 = Broad money, and NFA = Net foreign assets. Δ denotes the first difference operator; e_t is the disturbance term at time t with its usual properties[36]; Λ_0 is the constant term, Λ_1 is the estimated coefficient associated with a linear trend, Ω_1 and Ω_j represents the ARDL short run terms, δ_1 and δ_j[37] are long run terms, $t-i$ and $t-j$ represent past values of the dependent and independent variables, respectively. The rest of the denotations are as previously defined.

Based on Equation 4.8, the null hypothesis of no cointegration is formulated as $H_N: \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$ and the alternative hypothesis of cointegration is $H_A: \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq 0$. The null hypothesis of no cointegration is rejected if the F-statistic lies outside the 5% critical bound, else if it falls within the bounds, the decision becomes inconclusive and this requires an alternative multiple restriction test[38] to reach a decisive conclusion. However, if its F-statistic lies below the lower critical bound it means there is no cointegrating relationship amongst the variables in the long run.

In the event that cointegration is confirmed in Equation 4.8, the conditional ARDL long run model for $INTER$ factor and *NPL* is estimated as follows:

$$\Delta NPL_t = \Lambda_0 + \Lambda_1 t + \sum_{i=1}^{p} \Omega_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \Omega_j \Delta \Gamma_{t-j}^{C} + \xi_t \quad (4.9)$$

Where all the variables are as previously defined. The reparametrised ARDL model of order (p, q) was selected using the Schwarz Information Criterion (SIC) which tends to choose a more parsimonious model when handling a relatively smaller sample dataset, which is the case with the data used in this study. The ARDL (p, q) was specified as:

$$\Delta NPL_t = \Lambda_0 + \Lambda_1 t + \sum_{i=1}^{p} \Omega_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \Omega_j \Delta \Gamma_{t-j}^{C} + \Theta ECM_{t-1} + \xi_t \quad (4.10a)$$

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[36] $\mu_t \sim N[0\,,\ \sigma^2]$ *that is, error term is randomly normally distributed with zero mean and constant variance.*
[37] *Where* $i = 2, \dots, 4$.
[38] *Such as the Wald test for multiple restrictions.*

Where Ω_1 and Ω_j capture the short run dynamics of the model's convergence to equilibrium and Θ measures the speed of adjustment to long run equilibrium in the event of shock in the $MONE$ factors, and ECM is the error correction term derived from Equation 4.8.

In relation to the long run causal relationship between NPL and the monetary indicators, it is implied through the statistical significance of the coefficient of the Error Correction Term (ECT) presented in Equation 4.10*a* (the sign of the ECT coefficient must also be negative for long run causality to be inferred). On the contrary, the short run causalities are implied by evaluating the significance of the regressors' *t*-statistics in the same stated equation. Moreover, the VAR pairwise Granger causality test is employed to determine the nature (unidirectional, bidirectional, or independent) of causality amongst the variables.

The reduced form equations for the pairwise Granger causality model involving NPL and the monetary factors (Γ^c) is specified as follows:

$$NPL_t = \emptyset_0 + \sum_{i=1}^{p} \emptyset_1 NPL_{t-i} + \sum_{j=1}^{p} \emptyset_j \Gamma_{t-j}^{B} + \xi_{1t} \qquad (4.10b)$$

$$\Gamma_t^B = \beta_0 + \sum_{i=1}^{p} \beta_j \Gamma_{t-j}^{B} + \sum_{j=1}^{p} \beta_1 NPL_{t-i} + \xi_{2t} \qquad (4.10c)$$

Where p is the optimal lag length determined via the VAR information criteria test as per the Schwarz-Bayesian Information Criterion (SC); $\emptyset_0$ and β_0 are intercepts;$\emptyset_1$, $\emptyset_j$, β_1, and β_j are the short run dynamics coefficients of the model's adjustment to long run equilibrium; ξ_{it} are the stochastic error terms.

Thus, using Equation 4.10*b* and 4.10*c*, the Granger causality approach tests the following null hypothesis:

$\boldsymbol{H}_N = \sum_{i=1}^{p} \emptyset_j = 0$ for $j = 1, \dots, n$, implying that, Γ_{t-j}^{B} does not Granger causes NPL_{t-j}.

Similarly, another hypothesis is expressed as:

$\boldsymbol{H}_N = \sum_{i=1}^{p} \beta_1 = 0$ for $j = 1, \ldots, n$, according to which NPL_{t-1} does not Granger causes $\boldsymbol{X}_t$.

The null hypothesis of no causality is rejected in favour of the alternative *iff* the p-value is less than the 5% significance level. However, if the p-value is equal to or greater than the 5% significance level it means that there is insufficient evidence to reject the null hypothesis of no causality.

4.2.1.5 NPL model with the interest rate indicators

The model specification relating to the interaction between the interest rate ($INTER$) variables and NPL is specified in its reduced form as:

$$\Delta NPL_t = \sigma_0 + \sigma_1 t + \sum_{i=1}^{p} \vartheta_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \vartheta_j \Delta \Gamma_{t-j}^{D} + \gamma_1 NPL_{t-1} + \gamma_j \Gamma_{t-1}^{D} + e_t \tag{4.11}$$

Where the vector $\Gamma^D = f(REPO_t, LEND_t, DEPO_t, IS_t, TBILL_t)$ consists of variables denoting the interest rate indicator, with REPO = Repo rate, LEND = Lending rate, DEPO = Deposit rate, IS = Interest spread, and TBR = Treasury bills rates. Δ denotes the first difference operator; e_t is the disturbance term at time t with its usual properties[39]; σ_0 is the constant term, $\sigma_1$is the estimated coefficient associated with a linear trend, ϑ_1 and ϑ_j represents the ARDL short run terms, γ_1 and γ_j[40] are long run terms, $t - i$ and $t - j$ represents past values of the dependent and independent variables, respectively. The rest of the denotations are as previously defined.

Based on Equation 4.8, the null hypothesis of no cointegration is formulated as $H_N: \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \gamma_6 = 0$ and the alternative hypothesis of cointegration is $H_A: \gamma_1 \neq \gamma_2 \neq \gamma_3 \neq \gamma_4 \neq \gamma_5 \neq \gamma_6 \neq 0$. The null hypothesis of no cointegration is rejected if the F-statistic lies outside the 5% critical bound, else if it falls within the bounds, the decision becomes inconclusive and this

[39] $\mu_t \sim N[0, \sigma^2]$ *that is, error term is randomly normally distributed with zero mean and constant variance.*

[40] *Where* $i = 2, \ldots, 6$.

requires an alternative multiple restriction test[41] to reach a decisive conclusion. However, if its F-statistic lies below the lower critical bound it means there is no cointegrating relationship amongst the variables in the long run.

In the event that cointegration is confirmed in Equation 4.8, the conditional ARDL long run model for $INTER$ factor and *NPL* is estimated as follows:

$$\Delta NPL_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} \vartheta_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \vartheta_j \Delta\Gamma_{t-j}^{D} + e_t \tag{4.12}$$

Where all the variables are as previously defined. The reparametrised ARDL model of order (p, q) was selected using the Schwarz Information Criterion (SIC) which tends to choose a more parsimonious model when handling a relatively smaller sample dataset, which is the case with the data used in this study. The ARDL (p, q) was specified as:

$$\Delta NPL_t = \alpha_0 + \alpha_1 t + \sum_{i=1}^{p} \vartheta_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \vartheta_j \Delta\Gamma_{t-j}^{D} + \tau ECM_{t-1} + e_t \tag{4.13a}$$

Where ϑ_1 and ϑ_j capture the short run dynamics of the model's convergence to equilibrium and τ measures the speed of adjustment to long run equilibrium in the event of shock in the *INTER* factors, and ECM is the error correction term derived from Equation 4.11.

As for the long run causal relationship between NPL and the interest rate factors, it is assumed through the statistical significance of the coefficient of the Error Correction Term (ECT) presented in Equation 4.13*a* (the sign of the ECT coefficient must also be negative for long run causality to be inferred). In contrast, the short run causalities are inferred by examining the significance of the regressors' *t*-statistics in the same stated equation. Additionally, the VAR pairwise Granger causality test is applied to determine the nature (unidirectional, bidirectional, or independent) of causality amongst variables.

[41] *Such as the Wald test for multiple restrictions.*

The reduced form equation for the pairwise Granger causality model involving NPL and the interest rate factors (Γ^D) is specified as follows:

$$NPL_t = \alpha_{01} + \sum_{i=1}^{m} \vartheta_1 NPL_{t-i} + \sum_{j=1}^{m} \vartheta_j \Gamma_{t-j}^{D} + e_{1t} \tag{4.13b}$$

$$\Gamma_t^D = \alpha_{01} + \sum_{i=1}^{m} \vartheta_j \Gamma_{t-j}^{D} + \sum_{j=1}^{m} \vartheta_1 NPL_{t-i} + e_{2t} \tag{4.13c}$$

Where m is the optimal lag length determined via the VAR information criteria test as per the Schwarz-Bayesian Information Criterion (SC); α_{01} and α_{02} are intercepts; ϑ_1, and ϑ_j are the short run dynamics coefficients of the model's adjustment to long run equilibrium; e_{it} are the stochastic error terms.

Thus, using Equation 4.13*b* and 4.13*c*, the Granger causality approach tests the following null hypothesis:

$\boldsymbol{H}_N = \sum_{i=1}^{m} \vartheta_j = 0$ for $j = 1, \dots, n$, implying that, Γ_{t-j}^{D} does not Granger cause NPL_t.

Similarly, another hypothesis is expressed as:

$\boldsymbol{H}_N = \sum_{i=1}^{m} \vartheta_1 = 0$ for $j = 1, \dots, n$, according to which NPL_{t-i} does not Granger cause Γ_t^D.

The null hypothesis of no causality is rejected in favour of the alternative *iff* the p-value is less than the 5% significance level. However, if the p-value is equal to or greater than the 5% significance level it means that there is insufficient evidence to reject the null hypothesis of no causality.

4.2.1.6 NPL model with the financial indicators

The model specifications relating to the interaction between the financial ($FINA$) variables and NPL is specified in its reduced form as:

$$\Delta NPL_t = \pi_0 + \pi_1 t + \sum_{i=1}^{p} \omega_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \omega_j \Delta \Gamma_{t-j}^{E} + \sigma_1 NPL_{t-1} + \sigma_j \Gamma_{t-1}^{E} + \zeta_t \qquad (4.14)$$

Where the vector $\Gamma^E = f(RER_t, PSCE_t, OIL_t, COVID19_t, SHARES_t)$ consists of variables typifying the financial indicator, with RER = Real exchange rate, PSCE = Private sector credit extension, OIL = Oil prices, and SHARES = Stock prices. Δ denotes the first difference operator; ζ_t is the disturbance term at time t with its usual properties[42]; π_0 is the constant term, $\pi_1$is the estimated coefficient associated with a linear trend, ω_1 and ω_j represents the ARDL short run terms, σ_1 and σ_j[43] are long run terms, $t-i$ and $t-j$ represent past values of the dependent and independent variables, respectively. The rest of the denotations are as previously defined.

Based on Equation 4.14, the null hypothesis of no cointegration is formulated as $H_N: \sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = \sigma_5 = \sigma_6 = 0$ and the alternative hypothesis of cointegration is $H_A: \sigma_1 \neq \sigma_2 \neq \sigma_3 \neq \sigma_4 \neq \sigma_5 \neq \sigma_6 \neq 0$. The null hypothesis of no cointegration is rejected if the F-statistic lies outside the 5% critical bound, else if it falls within the bounds, the decision becomes inconclusive and this requiring an alternative multiple restriction test[44] to reach a decisive conclusion. However, if its F-statistic lies below the lower critical bound it means there is no cointegrating relationship amongst the variables in the long run.

In the event that cointegration is confirmed in Equation 4.14, the conditional ARDL long run model for $FINA$ factor and NPL is estimated as follows:

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[42] $\mu_t \sim N[0\ ,\ \sigma^2]$ *that is, error term is randomly normally distributed with zero mean and constant variance.*
[43] *Where* $i = 2, \ldots, 6$.
[44] *Such as the Wald test for multiple restrictions.*

$$\Delta NPL_t = \pi_0 + \pi_1 t + \sum_{i=1}^{p} \omega_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \omega_j \Delta\Gamma_{t-j}^{E} + \zeta_t \tag{4.15}$$

Where all the variables are as previously defined. The reparametrised ARDL model of order (p, q) was selected using the Schwarz Information Criterion (SIC) which tends to choose a more parsimonious model when handling a relatively smaller sample dataset, which is the case with the data used in this study. The ARDL (p, q) was specified as:

$$\Delta NPL_t = \pi_0 + \pi_1 t + \sum_{i=1}^{p} \omega_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \omega_j \Delta\Gamma_{t-j}^{E} + \Psi ECM_{t-1} + \zeta_t \tag{4.16a}$$

Where ω_1 and ω_j capture the short run dynamics of the model's convergence to equilibrium and Ψ measures the speed of adjustment to long run equilibrium in the event of shock in the $FINA$ factors, and ECM is the error correction term derived from Equation 4.14.

In reference to the long run causality between NPL and the financial factors, it is deduced through the statistical significance of the coefficient of the Error Correction Term (ECT) presented in Equation 4.16*a* (the sign of the ECT coefficient must also be negative for long run causality to be inferred). On the other hand, the short run causalities are inferred by evaluating the significance of the regressors' *t*-statistics in the same stated equation. In addition, the VAR pairwise Granger causality test is employed to determine the nature (unidirectional, bidirectional, or independent) of causality amongst variables.

The reduced form equation for the pairwise Granger causality model involving NPL and the financial factors (Γ^E) is specified as follows:

$$NPL_t = \pi_{01} + \sum_{i=1}^{q} \omega_1 NPL_{t-i} + \sum_{j=1}^{q} \omega_j \Gamma_{t-j}^{E} + \zeta_{1t} \tag{4.16b}$$

$$\Gamma_t^A = \pi_{02} + \sum_{i=1}^{q} \omega_j \Gamma_{t-j}^E + \sum_{j=1}^{q} \omega_1 NPL_{t-i} + \zeta_{2t} \qquad (4.16c)$$

Where q is the optimal lag length determined via the VAR information criteria test as per the Schwarz-Bayesian Information Criterion (SC); π_{01} and π_{02} are intercepts; ω_1 and ω_j are the short run dynamics coefficients of the model's adjustment to long run equilibrium; ζ_{it} are the stochastic disturbance terms.

Thus, using Equation 4.16*b* and 4.16*c*, the Granger causality approach tests the following null hypothesis:

$\boldsymbol{H}_N = \sum_{i=1}^{n} \omega_j = 0$ for $j = 1, \dots, n$, implying that, Γ_{t-j}^E does not Granger causes NPL_t.

Similarly, another hypothesis is expressed as:

$\boldsymbol{H}_N = \sum_{i=1}^{n} \omega_1 = 0$ for $j = 1, \dots, n$, according to which NPL_{t-j} does not Granger causes Γ_t^E

The null hypothesis of no causality is rejected in favour of the alternative *iff* the p-value is less than the 5% significance level. However, if the p-value is equal to or greater than the 5% significance level it means that there is insufficient evidence to reject the null hypothesis of no causality.

4.2.1.7 NPL model with the institutional indicators

The model specification relating to the interaction between the institutional ($INST$) variables and NPL is specified in its reduced form as:

$$\Delta NPL_t = \partial_0 + \partial_1 t + \sum_{i=1}^{p} \pitchfork_1 \Delta NPL_{t-i} + \sum_{j=0}^{q} \pitchfork_j \Delta\Gamma_{t-j}^F + \Pi_1 NPL_{t-1} + \Pi_j \Gamma_{t-1}^F + \varepsilon_t \qquad (4.17)$$

Where the vector $\Gamma^F = f(VA_t, PS_t, CC_t, RQ_t, GE_t, RL_t, ACC_t)$ consists of variables resembling the institutional indicator, with VA = Voice and accountability, PS = Political stability and absence of violence/terrorism, CC = Control of corruption, RQ = Regulatory quality, GE = Government effectiveness, RL = Rule of law, and ACC = Anti-corruption commission. Δ denotes the first difference operator; ε_t is the disturbance term at time t with its usual properties[45]; ∂_0 is the constant term, $\partial_1$is the estimated coefficient associated with a linear trend, $⫛_1$ and $⫛_j$ represents the ARDL short run terms, Π_1 and Π_j[46] are long run terms, $t-i$ and $t-j$ represent past values of the dependent and independent variables, respectively. The rest of the denotations are as previously defined.

Based on Equation 4.17, the null hypothesis of no cointegration is formulated as $H_N\colon \Pi_1 = \Pi_2 = \Pi_3 = \Pi_4 = \Pi_5 = \Pi_6 = \Pi_7 = \Pi_8 = 0$ and the alternative hypothesis of cointegration is $H_A\colon \Pi_1 \neq \Pi_2 \neq \Pi_3 \neq \Pi_4 \neq \Pi_5 \neq \Pi_6 \neq \Pi_7 \neq \Pi_8 \neq 0$. The null hypothesis of no cointegration is rejected if the F-statistic lies outside the 5% critical bound, else if it falls within the bounds, the decision becomes inconclusive and this requires an alternative multiple restriction test[47] to reach a decisive conclusion. However, if its F-statistic lies below the lower critical bound it means there is no cointegrating relationship amongst the variables in the long run.

In the event that cointegration is confirmed in Equation 4.17, the conditional ARDL long run model for $INST$ factor and *NPL* is estimated as follows:

$$\Delta NPL_t = \partial_0 + \partial_1 t + \sum_{i=1}^{p} ⫛_1 \, \Delta NPL_{t-i} + \sum_{j=0}^{q} ⫛_j \, \Delta\Gamma_{t-j}^{F} + \varepsilon_t \tag{4.18}$$

Where all the variables are as previously defined. The reparametrised ARDL model of order (p, q) was selected using the Schwarz Information Criterion (SIC) which tends to choose a more parsimonious model when handling a relatively smaller sample dataset, which is the case with the data used in this study. The ARDL (p, q) was specified as:

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[45] $\mu_t \sim N[0\ ,\ \sigma^2]$ *that is, error term is randomly normally distributed with zero mean and constant variance.*
[46] *Where* $i = 2, \dots, 8$.
[47] *Such as the Wald test for multiple restrictions.*

$$\Delta NPL_t = \partial_0 + \partial_1 t + \sum_{i=1}^{p} \pitchfork_1 \, \Delta NPL_{t-i} + \sum_{j=0}^{q} \pitchfork_j \, \Delta \Gamma_{t-j}^{F} + \rho ECM_{t-1} + \, \varepsilon_t \qquad (4.19a)$$

Where $\pitchfork_1$ and $\pitchfork_j$ capture the short run dynamics of the model's convergence to equilibrium and Ψ measures the speed of adjustment to long run equilibrium in the event of shock in the $INST$ factors, and ECM is the error correction term derived from Equation 4.17.

As for the long run causal relationship between NPL and the institutional factors, it is ascertained through the statistical significance of the coefficient of the Error Correction Term (ECT) presented in Equation 4.19*a* (the sign of the ECT coefficient must also be negative for long run causality to be inferred). Contrary wise, the short run causalities are inferred by evaluating the significance of the regressors' *t*-statistics in the same stated equation. Furthermore, the VAR pairwise Granger causality test is also applied to determine the direction (unidirectional, bidirectional, or independent) of causality amongst variables.

The reduced form equation for the pairwise Granger causality model involving NPL and the institutional factors (Γ^F) is specified as follows:

$$NPL_t = \partial_{01} + \sum_{i=1}^{r} \pitchfork_1 \, NPL_{t-i} + \sum_{j=1}^{r} \pitchfork_j \, \Gamma_{t-j}^{F} + \varepsilon_{1t} \qquad (4.19b)$$

$$\Gamma_t^{A} = \partial_{02} + \sum_{i=1}^{r} \theta_j \Gamma_{t-j}^{F} + \sum_{j=1}^{r} \psi_1 NPL_{t-i} + \varepsilon_{2t} \qquad (4.19c)$$

Where r is the optimal lag length determined via the VAR information criteria test as per the Schwarz-Bayesian Information Criterion (SC); ∂_{01} and ∂_{02} are intercepts; $\pitchfork_1$ and $\pitchfork_j$ are the short run dynamics coefficients of the model's adjustment to long run equilibrium; ε_{it} are the stochastic error term.

Thus, using Equation 4.19*b* and 4.419*c*, the Granger causality approach tests the following null hypothesis:

$$\boldsymbol{H}_N = \sum_{i=1}^{n} ⫛_j = 0 \text{ for } j = 1, \dots, n \text{, implying that, } \Gamma_{t-j}^{F} \text{ does not Granger causes } NPL_t.$$

Similarly, another hypothesis is expressed as:

$$\boldsymbol{H}_N = \sum_{i=1}^{n} ⫛_1 = 0 \text{ , according to which } NPL_{t-i} \text{ does not Grange causes } \Gamma_t^F.$$

The null hypothesis of no causality is rejected in favour of the alternative *iff* the *p*-value is less than the 5% significance level. However, if the *p*-value is equal to or greater than the 5% significance level it means that there is insufficient evidence to reject the null hypothesis of no causality.

4.2.2 Data and description of variables

Next is a discussion of all the variables featured in the aforementioned models, where they were sourced from, how the variables were measured and the rationale for including such variables.

4.2.2.1 Data

This study relies on secondary quarterly time-series data ranging from the period 1996 – 2021. The data were sourced from various website databases of both national and international organisations. The national web pages included those from the BoN, the Namibia Statistics Agency (NSA), First National Bank (FNB) and the Namibia Stock Exchange (NSX). The international websites included those of the British Petroleum (BP), Worldwide Governance Indicators (WGI), and the World Bank (WB). Despite some data being sourced externally, the majority were sourced locally, mainly from the Central Bank of Namibia.

Several variables had their dataset availed in a higher frequency format (i.e., monthly data) and others were only available in a lower frequency format (i.e., annual data).[48] In both cases, the data had to be transformed into quarterly data frequency in order to satisfy the Statistical requirement of having at least a minimum of 30 sample observations needed to conduct any sensible econometric analysis using time series data. The interpolation method used for this conversion is available in the Econometrics Views (*EViews*) software (version 13). Although *EViews* has a variety of conversion methods[49], for this study the quadratic (match average) method and average observations were chosen due to their suitability in handling a limited data point, especially when the source data is fairly smooth.

The rationale for selecting the variables used in this study was informed by the stance of economic theories evolving from some leading literature work on the subject at hand as well as the availability of data. The minimum data point requirement needed to be observed in order to account for issues pertaining to problem of degrees of freedom losses. As a matter of consideration, only those variables considered in various literature were of utmost importance in capturing their effect on NPL. In light of this, the following section consist of detailed discussion of the *a priori* expectations of the variables employed in this thesis as well as the reasoning behind such expectations.

4.2.2.2 Description of the dependent variable

Just like in most studies in the body of literature, NPL (measured as the ratio between non-performing loans to total gross loans (%)) has been used as the dependent variable to proxy the credit risk of Namibia's banking sector. Considering that a significant number of studies (Gaur et al., 2022; Koju et al., 2018; Radivojevic & Jovovic, 2017, amongst others) have found that accumulations of past *NPL* tend to influence *NPL* in the present period, and the fact that some of the econometrics techniques employed in this study are dynamic in nature, the lagged variable of *NPL* (NPL_{t-1}) is also included as one of the regressors in this study. This ensures that the persistency of credit risk (*NPL*) is evaluated, thereby avoiding problems of misspecification

[48] *The high frequency variables included the house price index, narrow and broad money supply, PSCE, repo rate, deposit rate, and the lending rate; whereas, the low frequency variables included GDP, debt, oil price, unemployment and all the governance indicators.*
[49] *Constant, Quadratic, Cubic, Point, Denton, Chow-Lin, Litterman, and No up conversions.*

brought about by omitted variable bias. Given that there is an overwhelming number of studies that found past NPL positively relate to NPL in the present time period, a positive relationship between NPL_{t-1} and NPL is expected.

4.2.2.3 Description of the independent variables

4.2.2.3.1 The composite indices

As in Yildirm (2021), the Principal Component Analysis (PCA) approach, formulated by Hotelling (1933), is utilised to construct the six broad-based indices (MACRO, BANK, INTER, MONE, FINA, and INST) that are likely to influence NPL. The approach helps identify and retain key variables, meanwhile excluding the irrelevant ones, suspected of influencing credit risk. The Kaiser (1960)'s criterion is used as a guideline for selecting the number of components (factors) to retain. Only factors with eigenvalues greater than unity should be retained. The retention of the factor is premised on the fact that factors with eigenvalues less than unity have no much variance of explanatory power, causing its usefulness to be disregarded. Thus, usefulness of the PCA methodology is hinged in identifying the patterns of association across a set of variables. Appendix A offers a detailed discussion on the methodology of the PCA technique, whilst Appendices B to G contain the estimations of the eigenvalues, principal components (loadings), the charts of Orthogonal loadings as well as the time graphs of each of the six broad-based indices.[50]

The main criteria for including the aforementioned indicators, besides their availability and importance in influencing the performance, lies in the mixed literature findings on the subject matter. In other words, the literature on stress-testing of banking sectors offer conflicting results regarding the variables that influence the stability of the banking sector. For this reason, only those key variables that have been considered by various studies (Rachid, 2019; Radivojevic & Jovovic, 2017; Vogiazas & Nikolaidou, 2011) are considered.

Given that the VAR is a dynamic model, the accumulations of past values NPL are equally

[50] *The results of the Rotation-Factor Matrices and the weighting of the Rotated Principal Component matrices have been omitted as they go beyond the scope of this study as they are computed using a separate method, the factor analysis.*

examined as they are expected, especially if care is not taken, to retard a country's economic progress. In fact, there is a large number of studies that have obtained a direct relationship between the present values of NPL and its own past values (Erdas & Ezanoglu, 2022; Gaur et al., 2022; Hajja, 2022; Koju et al., 2018b). Vogiazas and Nikolaidou (2011) maintained that since economic theory suggests that a good economic environment promotes good quality of the loan portfolio[51], it is highly likely for economic development to be linked to the stability of the banking sector. Thus, a negative relationship between the MACRO index and NPL is expected.

The BANK index is a vital indicator for assessing the combined effects that the bank specific factors exert on the resilience of the banking sector. The index has been employed to relay any credit risk problems that might have been caused by the inefficiencies of the banking sector (Vogiazas & Nikolaidou, 2011). In general, a high rise in such an index suggests a healthier and stable banking system. This means that an increase in such an index diminishes the levels of NPL of the banking sector. Thus, an inverse relationship between the BANK index and NPL is expected.

The MONE index is yet another index which is largely influenced by the narrow money (M1), broad money (M2) and net foreign assets (NFA), used to capture the economic activities (i.e., GDP growth) of a country. The expectations of the MONE index may turn out to be ambiguous for obvious reasons. For instance, while a higher monetary index (i.e., an expansionary monetary policy brought about by lower interest rate) may, in some instances, be associated with reduced likelihood of NPL, it might not always be the case as shown in Rifat (2016). This is so, especially if there are excessive and/or uncontrolled lending occurring in the banking sector causing the levels of NPL to rise. Thus, a positive or negative effect is expected to be found between the MONE index and NPL.

With regards to the INTER index, which is an index consisting of a basket of the prevailing interest rate environment, a rise in this index symbolises two possible outcomes related to NPL. Namely, as the rates of the prevailing interest rate increase, old bank debtors will find it harder to service their loans, thereby leading to rising NPL. This is because it limits borrowers' ability to service their debts (Ranjan & Dhal, 2003). On the other hand, an increase in the prevailing interest rate

[51] *In this study NPL is also used to proxy of the asset quality of the loan portfolio.*

may cause newer borrowers to reconsider taking up loans and perhaps even forgo the whole idea of incurring debt completely due to the deterring cost of servicing the loan. Thus, a positive or negative relationship is expected between the INTER index and NPL.

As for the FINA index, which represents the financial condition of both the banking sector and the financial system, it is also a crucial indicator for assessing the soundness and stability of Namibia's banking sector. Since financial systems are influenced by a range of factors, the underlying variables namely, the real exchange rate (RER), the private sector credit extension (PSCE), the oil prices (OIL), the share prices (SHARE), and a dummy variable (COVID-19) were considered in constructing the FINA index. Notwithstanding, based on the principal components (PC1 and PC2) loading presented on Table F1.2 of Appendix F, the variables PSCE, SHARE, OIL and COVID-19 are considered to majorly contribute to the weighting of the FINA index. In the context of the specified contributing variables, a rise in the FINA index is expected to reduce the levels of NPL. Hence, a negative relationship is expected between the FINA index and NPL as a higher FINA index is normally associated with lower credit risks.

Lastly, the institutional (INST) index has been employed due to the fact that institutional quality have been found to influence the stability of a country's banking system (Ozili, 2018). The INST index used in this study evaluates the extent to which the regulatory and governance environment influences the level of credit risk in the Namibian banking system. Normally, a rise in the INST index is indicative of the effectiveness and efficiency of a country's institutions. In the context of the governance indicators used to construct the INST index, a rise in this index typifies a stable political environment characterised by good governance and peace, which are essential for a country's future economic prospect. On the other hand, a weak institutional environment may signify: a) inadequate risk management practices, b) insufficient internal controls and checks, c) lack of accountability, d) corruption and mismanagement, and e) lack of investor confidence in the banking sector, to mention but a few. Since a decline in the INST index resembles a form of inefficiency, a rise in this index is expected to be negatively associated with NPL.

Table 4.1 summarises the variables featured in the stress-testing model for Namibia's banking system as well as the *a priori* expectation for each of the six indices.

Table 4.1: Composite indices

Variable	Description of indicator used in the index	A priori	Source
MACRO index	Trade openness (OPEN), Debt stock (DEBT), Output gap (GAP), Unemployment (UN), House price index (HP) and Inflation (INF)	(-)	Derived using PCA
BANK index	Return on assets (ROA), Return on Equity (ROE), Capital adequacy ratio (CAR), Lending behaviour (LB), Net interest margin (NIM), Loan to deposit ratio (LDR) and Loan growth (LG)	(-)	Derived using PCA
MONE index	Narrow money (M1), Broad money (M2) and Net Foreign Assets (NFA)	(±)	Derived using PCA
INTER index	INTER index involve: Repo rate (REPO), Deposit rate (DEPO), Interest spread (IS) and Treasury bills rates (TBR)	(+)	Derived using PCA
FINA indexr	Real exchange rate (RER), the private sector credit extension (PSCE), the oil prices (OIL), the share prices (SHARE), and a dummy variable (COVID-19)	(-)	Derived using PCA
INST index	Voice and accountability (VA), Political stability and absence of violence /terrorism (PS), Control of corruption (CC), Regulatory quality (RQ), Government effectiveness (GE), Rule of law (RL), and Anti-corruption commission (ACC)	(-)	Derived using PCA

Source: Own compilation

Note: the summary statistics, unit root tests as well as the optimum lag selection criteria of the above time-series variables are presented in Appendix H.

It is worth noting that out of the total of thirty-two variables presented on Table 4.1, thirty-two of them have been collapsed into one of the six categories of indicators using the PCA technique (see, Appendices A to G).[52] The variables obtained from the BoN included: DEBT, NPL, ROA, ROE, CAR, NIM, LG, M1, M2, NFA, REPO, DEPO, and TBR. INF was sourced from NSA. HP was obtained from FNB. SHARE was obtained from the NSX. OIL was sourced from the BP while

[52] *The PCA is a reduction technique used by researchers to re-express multivariate data with fewer dimensions. The technique is also useful in identifying patterns of association across variables.*

UN was from the WB. The variables GAP and OPEN were derived using data from NSA. LDR and IS were derived using data from BoN. However, LB was computed using data from both BoN and NSA. The INST indicators were obtained from the WDI.

4.2.2.3.2 The macroeconomic ($MACRO$) indicators

The variables used to estimate the isolated influence of the *MACRO* factors on *NPL* are: Trade openness, debt stock, Output gap, Unemployment, House price index and Inflation. The subsequent discourse covers a description of each of the *MACRO* variables and the rationale for selecting such variables.

a) *Trade openness* (*OPEN*): *OPEN* is defined as the sum of imports and exports to real Gross Domestic Product (GDP). In this case, trade openness measures the degree[53] of Namibia's openness to international trade. In general, a country with a trade openness ratio of close to 1.0 or above 1 is considered to be vulnerable to external shocks from the global economy. Based on the obtained trade openness ratios for Namibia, it is safe to say that the country has a high degree of openness, and since it is a small open economy, which is heavily dependent on international trade, it entails that for the most part, the degree of openness is likely to be positively related to NPL just as shown in Mpofu and Nikolaidou (2018).

b) *Debt stock* (*DEBT*): *DEBT* is a percentage ratio consisting of the sum of internal and external government debt to real GDP. The debt stock variable is included in the set of the macroeconomic indicators because of its importance to proxy the role of the government's fiscal policy on NPL. For many years Namibia has pursued an expansionary fiscal policy tool fuelled by an overreliance on borrowing which has seen its debt stock levels rise to unprecedented national and regional benchmarks[54] of the SADC trading block, of which Namibia is a member. As of October 25, 2022, Namibia's debt to GDP ratio was reported to stand at 69.6%; this is expected to rise even further due to the prolonged aftereffects of COVID-19 and the ongoing global economic shocks caused

[53] *Other alternative ways used to measure an economy's degree of openness is by expressing it in terms of the ratios of export/GDP or Import/GDP.*

[54] *The acceptable national benchmark is 35%, whereas for the SADC region is 60%. Beyond these levels the level of debt stock may be considered unsustainable.*

by the Russia - Ukraine conflict. Since debt accumulation especially during such challenging global economic environments, causes the indebted country to incur higher debt-serving costs[55], the coefficient of *DEBT* is expected to be positively related with NPL.

c) *Output Gap* (*GAP*): *GAP* is generally defined as the difference between actual output and potential output. In this study, GAP is the percentage ratio of the difference between real GDP and potential GDP over the potential GDP. There are various methods[56] used to estimate the output gap of an economy, however, for this study the Hedrick-Prescott Filter (HPF) approach is used to predict potential output in Namibia. The output gap is used as a proxy for the business cycle. The HPF approach is selected amongst other available approaches due to its flexibility in tracing fluctuation patterns in the output over time. In this regard, real GDP resembles the log of actual output while potential output is the HPF trend actual output. An economy is said to be operating below its full potential level when the rate of the output gap is negative. On the other hand, when the value of the output gap is positive, the economy is said to be operating at its full potential. Alrfai, Salleh and Waemustafa (2022) pointed out that output gap is positively related to NPL as a rise of it hinders the ability of borrowers to meet their loan payments. Therefore, a positive relationship is also expected.

d) *Unemployment* (*UN*): *UN* is a percentage rate measured by dividing the total number of unemployed workforces by the total labour force. The rate of unemployment serves as an indication of economic activity.[57] Since unemployment tends to strip individuals' financial capabilities, thereby hindering borrowers' ability to service their debts, it is thus expected that as the rate of unemployment rises, the level of NPL will equally rise (Radivojevic & Jovovic, 2017). Given the significant rise[58] in the levels of unemployed Namibians, worsened by the advent of the 2019 novel Coronavirus pandemic, the coefficient of unemployment is expected to turn out to be positively related to NPL.

[55] *Debt servicing costs continue to rise above the desired benchmark of 10% of the government's revenue collection.*
[56] *Such as, the multivariate HPF trends, linear time trends, HPF trends, unobservable component model and the production function model.*
[57] *A higher rate of unemployment implies that the country's economy is operating below its potential level; as a result, households' disposable incomes are diminished – making it harder for them to meet their debt obligations.*
[58] *For instance, statistics data from NSA indicated that in 2018, the unemployment rate stood at 33.4%, whilst youth unemployment rate was recorded to be at 46.1%. With the entrance of the COVID-19 pandemic, this figure could be even much higher, i.e., above 50%.*

e) *House prices index* (*HP*): *HP* refers to the swings in housing prices and it is used to proxy the role of the property market in influencing the levels of *NPL* in Namibia. The First National Bank (FNB) of Namibia is the custodian and compiler of the house price index in Namibia. The demand for housing coupled with a shortage of housing, is perhaps one of the biggest challenges faced by the government since independence. For years Namibia has experienced an inordinate demand in the property market, coupled with high prices, driven primarily by high property demands by many Angolan citizens whose economy was at the time doing exceptionally well. Due to the exceptional performance of the oil market, some Angolans took advantage to heavily invest in Namibia's property market.

Namibia's housing backlog[59] is quite high, especially when considering its small population density[60] spread across a vast amount of land. One of the chief reasons is because the housing market in Namibia is unregulated[61]. Notably, the role of the property market cannot be overlooked as over 50% of banks' assets are concentrated in mortgages. The unabated excess demand for housing, especially in urban areas, is expected to keep house prices high; consequently, affordability becomes a challenge for those borrowers who would have qualified to get a loan up to a particular threshold. As a result, the degree of credit risk in banks' loan portfolios is bound to diminish, thereby improving the collateral value that borrowers sign up for (Canepa & Khaled, 2018, p. 10). Therefore, a negative relationship between housing prices and NPL is expected in Namibia.

f) *Inflation* (*INF*): *INF*, which is generally defined as a persistent rise in the general prices of all goods and services, measures the growth in the consumer price index and it is a matter of concern for most developing economies. That is why one of the main goal of Namibia's monetary authority is to achieve price stability. Economic theory postulates that a rise in inflation causes the real value of a borrower's debt to depreciate, thereby enabling the borrower to easily service their debt

[59] *Presently, Namibia's housing backlog is estimated to be over 300 000 housing units.*
[60] *Namibia has a population of roughly 2.5 million, with a total surface area of 824,292* km^2. *It is considered to be the country with the lowest population density in Africa, 3 people per square kilometre.*
[61] *The absence of regulation is what has been responsible for causing the leading players in the property market to collude in fixing high property prices, thereby causing a rapid rise in the housing prices.*

(Radivojevic & Jovovic, 2017). On the other hand, an increasing rise in inflation diminishes purchasing power, causing it to be harder for borrowers to honour their debt servicing obligations (Gaur et al., 2022, p. 243). Based on this, a mixed outcome is the possibility of defaulting increases as inflation rises/falls. Therefore, a positive/negative relationship between inflation and NPL is expected.

Table 4.2 summarises the discussions on the macroeconomic variables alongside their expected signs and the sources from whence these data were obtained.

Table 4.2: Macroeconomic indicators

Indicators	Sign	Definition	Source
Trade openness (OPEN)	(+)	Calculated as the logarithm of the sum of imports and exports to real Gross Domestic Product (GDP).	Computed using NSA dataset
Debt Stock (DEBT)	(+)	Calculated as the ratio of total Government debt to GDP.	BON
Output Gap (GAP)	(+)	GAP is the difference between actual and potential output. It is measured as $\left(\frac{\text{Real GDP} - \text{Potential GDP}}{\text{Potential GDP}}\right) x\ 100$.	Computed using NSA dataset
Unemployment (UN)	(+)	Represents the number of unemployed work force as a % of total labour force.	WDI
House price index (HP)	(-)	Represents house price index, used as a proxy for demand for housing in Namibia.	FNB
Inflation (INF)	(±)	Is the rate of inflation, measured by the changes in the growth of ceteris paribus.	NSA

Source: Own compilation

Note: BON= Bank of Namibia; NSA = Namibia Statistics Agency; WDI = World Development Indicators (World Bank); FNB = First National Bank

4.2.2.3.3 The bank specific (*BANK*) indicators

The variables used to estimate the isolated influence of *BANK* variables on *NPL* are: Return on assets, Return on Equity, Capital adequacy ratio, Lending behaviour, Net interest margin, Loan to deposit ratio, and Loan growth. The following discussion revolves around each of the *BANK* variables utilised in this thesis as well as the rationale for including such variables in this study.

a) *Return on Assets* (*ROA*): *ROA* represents the banks' ratio between the net income after tax to total assets. It measures the banks' ability to generate revenue to total assets[62], thus it is used as a proxy for banks' profitability or financial performance. In other words, the ability of banks to weather the risks of *NPL* levels is improved as the banks have proved to be more profitable. Therefore, a negative relationship between ROA and NPL is expected (Kjosevski & Petkovski, 2017; Radivojevic & Jovovic, 2017).

b) *Return on Equity* (*ROE*): *ROE* is calculated as the ratio of the banks' net income to shareholders' equity. It serves as an alternative measure of banks' profitability, which is an indicator of the banking sector's financial performance. A rise in *ROE* implies that the banking sector's performance has improved. This means that a negative relationship is expected between *ROE* and *NPL*, just as obtained by some researchers in the literature (Radivojevic & Jovovic, 2017; Sheefeni, 2015a, etc...).

c) *Capital Adequacy Ratio* (*CAR*): Based on Basel III[63] accord of 2019, which has a much stricter capital requirement for banks operating in an international sphere, banks are required to have an adequate capital base consisting of the sum of Tier 1 capital[64] and Tier 2 capital[65] divided by the risk-weighted assets[66] of the bank (Gaur et al., 2022, p. 242). *CAR* is therefore an indicator that measures the capital strength of banks. Moreover, Berger and DeYoung (1997) contend that it is a crucial indicator of moral hazard; Whilst Koju *et al*., (2018a, p. 2) argue that it is a straightforward proxy for regulatory capital which determines the extent to which banks can deal with unexpected losses. This is to say that, CAR helps to determine whether the banks have enough capital base to cover their assets. Against this background, a rise in *CAR* is expected to minimise the banks' credit risk. Therefore, a negative relationship between *CAR* and *NPL* is expected.

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[62] *The ratios of income/sales or income/equity are used as proxy of profitability.*

[63] *Under Basel III, banks are expected to have a CAR not less than 8%. Since Tier 1 Capital is considered more important, banks are equally expected to have in their possession a minimum amount of it. Still under Basel III, the ratio of Tier 1 Capital to Risk-Weighted Assets is at minimum required to be 6%.*

[64] *Tier 1 Capital includes: shareholder's equity and retained earnings.*

[65] *Tier 2 capital Includes: revalued reserves, undisclosed reserves, and hybrid securities.*

[66] *Risk-Weighted Assets consists of the sum of banks' assets (such as cash, debentures, and bonds), weighted against their specific risks.*

d) *Lending Behaviour* (*LB*): *LB* is calculated as the ratio between mortgage and real GDP. As in Canepa and Khaled (2018), the ratio of mortgages to GDP is herein used to account for the impact of banks' mortgage lending behaviour on NPL. This is a crucial indicator, not only because it makes up a huge bulk of the loan portfolio of banks, but because it pertains to how banks respond to housing demand (which is a crucial issue) in Namibia. An increase in this ratio implies that banks are engaged in risky mortgage lending behaviour which also means increased credit risks for them. As such, a positive relationship between lending behaviour and NPL is expected as reasoned by Canepa and Khaled (2018).

e) *Net interest margin* (*NIM*): *NIM* is calculated as the ratio of interest income minus interest expense divided by earning assets. It represents the net return on banks' assets, which is inclusive of investment securities, loans, and leases. Radivojevic and Jovovic (2017) contended that NIM serves as a good indicator of how optimal the banks' investments are. Usually, a negative amount of NIM suggests that banks' investment decisions are inefficient. Hence, a negative relationship between NIM and NPL is expected.

f) *Loan to Deposit Ratio* (*LDR*): *LDR* is measured by the ratio of total loans to total deposits. It measures the liquidity of the banking sector. This is achieved by assessing the banking sector's ability to sell its assets within a reasonable period of time and at desirable prices in order to meet the cash requirements for loans and deposit withdrawals of its customers. It is vital that the banking sector manages well its liquidity position as failure to do so is one of the causes of financial instabilities which may result from i.e., a depositors' panic – a situation whereby depositors hurry to withdraw their deposits, causing a crush on the banking sector. A higher[67] LDR denotes that deposits are geared towards loans for revenue generation purposes. On the other hand, a lower LDR implies that resources have not been efficiently allocated. Wood and Skinner (2018) argue that since a rise in LDR entails that more of the deposits are committed towards loans, a positive relationship between LDR and NPL is expected.

[67] *Usually, the ideal loan to deposit ratio is one that runs between 80% to 90%. A loan to deposit ratio of i.e., 80% implies that the banking sector loans 80 cents to its clients for every dollar they receive in deposits.*

g) *Loan growth* (*LG*): *LG* represents the increase in gross loans issued by the entire banking sector in Namibia on a quarterly basis. This variable is considered because over 50% of what constitutes the banking sector assets in Namibia is tied up in the amount of loans issued out. *LG* is herein used as a proxy for the lending behaviour of banks in general. Messai and Jouini (2013) argued that an abrupt credit growth in credit can expose the entire banking sector to a higher credit risk level. It is therefore expected that a positive relationship between credit growth and NPL exists.

Table 4.3 summarises the discussions on the bank specific factors alongside their expected signs and the sources from whence these data were obtained.

Table 4.3: Bank specific indicators

Indicators	Sign	Definition	Source
Non-performing loans (NPL)	(+)	Represents non-performing loans as a % of total gross loans.	BoN
Return on Assets (ROA)	(-)	Represents the banks' net income as a % of total assets.	BoN
Return on Equity (ROE)	(-)	Represents the banks' net income as a % of shareholders' equity.	BoN
Capital Adequacy Ratio (CAR)	(-)	The sum of Tier 1 and 2 capital over the risk-weighted assets of the banks.	BoN
Lending behaviour (LB)	(+)	Represents the ratio between mortgage and real GDP.	Computed using BoN & NSA data
Net interest margin (NIM)	(-)	Represents a ratio of net interest income to total assets.[68]	BoN
Loan to Deposit Ratio (LDR)	(+)	Represents the ratio of total loans to total deposits.	Computed using BoN data
Loan growth (LG)	(+)	Loan growth is expected to be positive.	BoN

Source: Own compilation

Note: BON = Bank of Namibia

[68] $NIM = \left(\frac{Interest\ Income — Interest\ Expenses}{Total\ Assets}\right)$

4.2.2.3.4 The monetary ($MONE$) indicators

The variables used to estimate the isolated effects of the *MONE* indicator on *NPL* are: Narrow money, Broad money, and Net foreign assets. Next is a discussion of each variable featured in the $MONE$ indicator and the rationale for including such variables.

a) *Narrow money* (*M1*): *M1* supply comprises currency in circulation plus overnight deposits, excluding Central Government and depository corporations. M1 also proxies gross domestic product (Vogiazas & Nikolaidou, 2011, p. 9). Since an increase in M1 entails that there is more narrow money in circulation, it is expected to have a negative effect on NPL. This means that as M1 rises, NPL is also bound to fall.

b) *Broad money* (*M2*): *M2* supply includes currency outside depository corporations, transferable and other deposits in the national currency of the resident sectors. It excludes deposits of the Central Government and those of the depository corporations. M2 is widely used in many literatures as a proxy for financial sector development. Likewise, it is expected that as broad money supply rises, the level of NPL is bound to decline. Hence a negative relationship is expected.

c) *Net foreign assets* (*NFA*): *NFA* are used as a proxy to represent the ability of the banking sector to service its foreign debt, by determining whether or not a country is a creditor or a debtor. Simply put, NFA is computed as the difference between a country's external assets and liabilities.[69] That is, the sum of all foreign assets possessed by the central bank's authority and deposit money banks, minus its foreign liabilities. It is expected that as the NFA position rises, NPL fall. Thus, a negative relationship between NFA and NPL is expected. Table 4.4 summarises the discussions on the monetary variables alongside their expected signs and the sources from whence these data were obtained.

[69] *NFA position can also be defined as the cumulative change in a country's current account.*

Table 4.4: Monetary indicators

Indicators	Sign	Definition	Source
Narrow money (M1)	(-)	Consists of currency in circulation plus over-night deposits (Vogiazas & Nikolaidou, 2011).	BoN
Broad money (M2)	(-)	Is defined to include currency outside depository corporations, transferable and other deposits in national currency of the resident sectors. It excludes deposits of the Central Government and those of the depository corporations.	BoN
Net foreign assets (NFA)	(-)	It represents the capability of the banking sector to service the country's foreign debt.	BoN

Source: Own compilation

Note: BON = Bank of Namibia

4.2.2.3.5 The interest rate ($INTER$) indicators

The variables to estimate the individual effects of the *INTER* factors on *NPL* are: Repo rate, Lending rate, Deposit rate, Interest spread, and Treasury bills. Up next is a detailed discussion of each of the $INTER$ variables and the rationale for their inclusion in the model.

a) *Repo rate* (*REPO*): *REPO* is an interest rate that represents the cost borne by banks as they borrow money from the central bank (Bank of Namibia). The REPO is considered to be less prone to credit risks due to collateral backing attached to the lending agreements. In other words, in the event that a particular bank defaults, the bank of Namibia has the right to repossess that bank's assets that are equivalent to the value owned. There are different types[70] of REPO, but the overnight REPO is used in this study as it is the most common form of REPO. The REPO has often been used as a proxy of the monetary policy tool of the Bank of Namibia. Since a rise in the REPO not only implies that the lending rate of commercial banks will rise, but also implies an increase in the cost of debt serving, a positive relationship between the repo rate and NPL is expected.

b) *Deposit Rate* (*DEPO*): *DEPO* refers to the amount of interest that is paid to depositors. It is worth noting that despite the lower rate of return on depositors' savings, Namibia ranked number

[70] *The other type of repo rate is the longer-term arrangements, known as term repos, which is seldom used.*

seven (7) in the world in 2021 amongst the countries with the highest savings[71] ratio. Since higher lending rates encourages depositors to save more, a negative relationship between lending rate and NPL is expected.

c) *Interest Spread* (*IS*)*: IS* represents the spread between lending rate and deposit rate. This study uses *IS* as a proxy of banking sector revenue. Given that Namibia is an open economy which is mostly dominated by foreign banks that are profit driven, the interest rate spread is likely to be higher as these commercial banks are likely to be charging a higher lending rate in order to maximise their profit. A large interest spread may overburden borrowers, thereby increasing the default risk is likely to also increase. Hence a positive relationship between interest rate spread and non-performing loans is expected, just as argued in Koju et al. (2018b, p. 119).

d) *Treasury Bills* (*TB*): *TB* refers to a 91-day short-term liquid asset issued, in this case by the Government of the Republic of Namibia, to finance its deficits. It is a proxy used to capture the dynamics in market interest rate. TB are said to be almost risk-free in the sense that the government, being the issuer of this instrument, is also considered to be "too big to fail". Consequently, anyone that invests in TB can certainly be sure that their principal payments as well as the interest that accrue to it will surely be honoured by the state as promised. This is especially true in countries that are regarded to have a reputation of good governance, such as Namibia. Since a rise in TB contributes to a rise in the level of government debt stock, it is therefore expected that as the government avails more of this instrument, it exacerbates the cost of debt servicing, which makes it harder for the government to easily honour its debt. Consequently, a positive relationship between TB and NPL is expected.

Table 4.5 summarises the discussions on the interest rate indicators together with their expected signs and the sources from whence these data were obtained.

[71] *This is gross savings as a percentage of GDP. For Namibia, it is majorly concentrated in the country's pension and insurance funds.*

Table 4.5: Interest rate indicators

Indicators	Sign	Definition	Source
Repo rate (REPO)	(+)	The cost of credit to the banking sector charged by the BoN.	BoN
Deposit Rate (DEPO)	(-)	Refers to the amount of interest that may be paid to depositors.	BoN
Interest Spread (IS)	(+)	Represents the difference between lending rate and deposit rate.	Computed using BoN data
Treasury Bill Rate (TBR)	(+)	Refers to the yield that investors earn when the T-bill matures.	BoN

Source: Own compilation

Note: BON = Bank of Namibia

4.2.2.3.6 The financial ($FINA$) indicators

The variables used to estimate individual effects of the *FINA* factors on *NPL* are: Real exchange rate, Private sector credit extension, Oil prices, COVID-19, and stock market prices. The following deliberation centres around the *FINA* variables employed in this study as well as the reasoning for including them in this study.

a) *Real exchange rate* (*RER*): The *RER* between two currencies (i.e., N$ and US$) represents the product of the nominal exchange rate and the ratio of prices between Namibia and the United States. It is computed as follows: $RER = \frac{eP^N}{P}$, where e is the nominal US$ to N$ exchange rate, P^N is the average price of a good in Namibia, and P is the average price of the good in the United States. Not only does an exchange rate depreciation impair credit availability, it also limits borrowers' ability to service their debts. Hence, a negative relationship between NPL is expected.

b) *Private sector credit extension* (*PSCE*): *PSCE* refers to the ratio of credit to the private sector to real GDP. Credit to the private sector plays an important role in the economic activity of any country, i.e., through employment creation, infrastructure development, etcetera. As such, it is imperative that an assessment of the influence of private sector credit of NPL is established for policy purposes. In this analysis, PSCE is used as a proxy of financial sector development. Thus, it is expected that as PSCE rises, the financial sector develops even more and more citizens become financially empowered; as a result, a negative relationship between PSCE and NLP is expected.

c) *Oil prices* (*OIL*): *OIL* represents the Brent crude oil prices, measured in US$ per barrel. OIL is an important indicator that is exogenously determined by forces of demand and supply taking place in the global oil market, amongst other factors. Of recent, Namibia has been making historic discoveries of oil deposits for commercial use. Whether or not these discoveries will yield any positive outcomes is yet to be seen. For now, Namibia remains a net importer of Brent crude oil, making it vulnerable to external shocks emanating from the global oil market. This being the case, the effects of oil prices on NPL can be both direct and indirect through various factors. It is thus expected that, any volatility in oil prices, i.e., a rise in oil prices, will negatively affect the domestic economy, and once the economy is affected, the citizens will find it harder to service their debts. Therefore, oil prices are expected to be positively related to NPL in Namibia.

d) *COVID-19*: is a dummy variable[72] meant to capture the impacts of the COVID-19 pandemic on NPL. It is herein also used as a proxy of financial crisis. Considering that unemployment was already a serious challenge prior to the entrance of the COVID-19 pandemic, the entrance of COVID-19 aggravated the situation even further as more workers became retrenched and some companies ceased to exist. This means that workers who were previous employed and had some debts, were no longer in a position of servicing their debts. This means that a positive relationship between the COVID-19 global pandemic and NPL can be expected.

e) *Stock Market prices* ($SHARES$): $SHARES$ represents the market value of listed companies, resulting from a company performance. It is herein used to proxy the role of Namibia's stock market activity. The Namibian Stock Exchange (NSX), is currently home to about 40 firms, with a total market capitalisation of US$ 136,000m. in 2021, and is ranked the second largest exchange in Africa for obvious reasons[73]. Hence, it was imperative to include the stock market prices in order to capture the influence of stock market activities on NPL. Improvements in the performance of stock market causes the share price to rise thereby making the shareholders of the listed companies

[72] *With a value of 0 for the period 1996 - 2019, and 1 for the remainder of the period 2020 - 2021.*
[73] *Mainly due to large number of dual or secondary listings and a sound financial system.*

well off. Therefore, a negative relationship between SHARES and NPL is expected, as found by Mohanty et al. (2018).

Table 4.6 summarises the discussions on the financial indicators alongside their expected signs and the sources from whence these data were obtained.

Table 4.6: Financial indicators

Indicators	Sign	Definition	Source
Real exchange rate (RER)	(-)	The RER between two currencies (i.e., N$ and US$) represents the product of the nominal exchange rate and the ratio of prices between Namibia and the United States.	BoN
Private sector credit extension (PSCE)	(-)	*PSCE* refers to the ratio of credit to the private sector to real GDP.	BoN
Oil prices (OIL)	(+)	OIL represents the Brent crude oil prices, measured in US$ per barrel.	BP
COVID-19	(+)	COVID-19 represents a dummy variable meant to capture the impacts of a pandemic on NPL.	Computed
Stock market prices (SHARES)	(-)	Represent the current market value of a company's shares or stocks (measured in N$).	NSX

Source: Own compilation

Note: BON = Bank of Namibia; BP = British Petroleum; NSX = Namibia Stock Exchange

4.2.2.3.7 The institutional (*INST*) indicators

The variables used to estimate the isolated influences of the *INST* factors on *NPL* are: Voice and accountability, Political stability and absence of violence/terrorism, Control of corruption, Regulatory quality, Government effectiveness, Rule of law, and Anti-corruption commission. After this is a detailed discussion of each of these variables and the rationale for including them in the study.

a) *Voice and Accountability* (*VA*): *VA* represents the extent to which a country's citizens are able to take part in the selection process of their government, as well as being able to exercise their freedom of expression, freedom of association, and a free media. *VA* is used to control governance (or institutional) quality in Namibia. According to Ozili (2018) and Boudriga *et al*. (2010), *VA* has got a positive impact in reducing the level of NPL. Thus, the coefficient of *VA* is expected to be negatively associated with levels of non-performing loans.

b) *Political Stability and Absence of Violence/Terrorism* (*PS*): *PS* measures perceptions for the probability of political instability and/or politically motivated violence, including terrorism. As used in Ozil (2018, p. 470), *PS* is used to control governance quality in Namibia. In contrast to Rachid (2019)' study that found *PS* to be positively related to NPL, in Namibia this is likely to turn out to be negatively associated to NPL for obvious reasons[74].

c) *Control of corruption* (*CC*): *CC* measures perceptions of the extent to which public power is exercised for private gain as well as state capture by elites and private interests. *CC* is also used to control governance quality as propagated by Ozil (2018). Of recent, Namibia witnessed an incremental rise in the levels of corruption scandals which at times involved high profile senior government figures, such as those involved in the so-called "Fishrot"[75] saga, to mention but a few. Against this background, a negative relationship between CC and *NPL* is expected, because it is expected that as the level of corruption control is hastened at both governmental and banking sector levels, *NPL* is bound to diminish just as observed in Arham *et al.* (2020).

d) *Regulatory Quality* (*RQ*): *RQ* measures the perceptions for government to formulate and implement sound policies and regulations that permit and promote private sector development. *RQ* is equally used as a control variable for governance quality in Namibia following Ozil (2018, p. 470)'s approach. Based on both Arham *et al.* (2020) and Boudriga *et al*. (2010), *RQ* helps to positively reduce the levels of *NPL*. For this reason, *RQ* is also expected to be negatively related to *NPL* due to the fact that Namibia has a number of institutions that are meant to serve as regulatory bodies.

[74] *Unlike, Rachid (2019)'s study which was centred on politically unstable MENA countries, Namibia enjoys a sound political atmosphere.*

[75] *Which featured the former Minister of Fisheries and the former Justice Minister.*

e) *Government Effectiveness* (*GE*): *GE* measures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. *GE* will also be used to control governance quality in Namibia, just stipulated used in Ozil (2018, p. 470). Based on Tatarici *et al.* (2020) and Arham *et al.* (2020), improvements in *GE* has got the potential of diminishing the levels of NPL. In this regard, a negative relationship between coefficient of *GE* and NPL is expected as Namibia is considered to be properly governed.

f) *Rule of Law* (*RL*): *RL* measures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. *RL* is used as a proxy for investors and creditors protection as argued in Ozil (2018)'s study. A number of studies (Boudriga et al., 2010; Ozili, 2018, to mention but a few) arrived at the same conclusion that reinforcement/improvements in the rule of law assist in diminishing the undesirable rises of NPL. The same is expected for Namibia, which is known for its well managed rule of law. As such, a negative relationship between *RL* and *NPL* is expected.

g) *Anti-corruption commission* (*ACC*): *ACC* represents a dummy variable with a value of 1 for the beginning period 2006 – 2021, and 0 otherwise. The expectation is that the existence of the Anti-corruption commission (ACC)[76] has enabled the country to combat and prevent corrupt activities in Namibia, thereby reinforcing the *rule of law* and *corruption control*. Therefore, *ACC* is expected to negatively be associated with the levels of *NPL* in Namibia.

The indicators outlined from (a) to (f) are sometimes referred to as the Worldwide Governance Indicators. One of the novelties of this study is the introduction of the *ACC* variable.

Table 4.7 summarises the discussions on the institutional indicators together with their expected signs and the sources from whence these data were obtained.

[76] *The Namibian Anti-corruption commission was established by an Act of Parliament, the Anti-Corruption Act number 8, of 2003 in order to combat and prevent corruption in Namibia, but it only became operational from 2006.*

Table 4.7: Institutional factors

Indicators	Sign	Definition	Source
Voice and Accountability (VA)	(-)	Refers to the extent to which Namibian citizens are able to partake in the election process of their government, and the ability to exercise their freedom of expression, freedom of association, and a free media.	WGI
Political Stability and Absence of Violence/Terrorism (PS)	(-)	It measures perceptions for the probability of political instability and/or politically motivated violence, including terrorism.	WGI
Control of corruption (CC)	(-)	It measures perceptions of the extent to which public power is exercised for private gain as well as state capture by elites and private interests.	WGI
Regulatory Quality (RQ)	(-)	It measures perceptions of the ability for government to formulate and implement sound policies and regulations that permit and promote private sector development	WGI
Government Effectiveness (GE)	(-)	It measures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.	WGI
Rule of Law (RL)	(-)	It measures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	WGI
Anti-corruption commission (ACC)	(-)	Represents a dummy variable for the period since the formation of ACC.	Computed

Source: Own compilation

Note: WGI = Worldwide Governance Indicators[77]

4.2.3 Estimation procedures

In this section, a series of econometrics techniques undertaken to tackle the specific objectives raised in this chapter are outlined. Section 4.2.3.1 provides a discussion on the time series properties of the data utilised in this study, such as the descriptive statistics and the correlation test. Section 4.2.3.2 present a preliminary test for determining the optimal number of lags to be used in the subsequent tests. Section 4.2.3.3 outlines the stationarity tests applied to establish the order of integration of variables. Section 4.2.3.4 details the modelling techniques used to investigate the study's objectives. Lastly, Section 4.2.3.5 briefly outlines the robustness checks for each model adopted in this chapter. The checks include the diagnostics and stability tests.

4.2.3.1 Time series properties of the data

Prior to conducting the ARDL bounds test, the summary (descriptive) statistics[78], correlation analysis and the individual plots of the time series dataset employed in this study are presented. This was done in order to visually have a sense of the behaviour of the dataset used in this study. With regards to the correlation analysis, the correlation matrix test has been used to establish the strength of relatedness of the variables used in this study. The test is based on the Pearson's correlation coefficient formula expressed as:

$$r = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left[n\sum x^2 - \left(\sum x\right)^2\right]\left[n\sum y^2 - (y)^2\right]}} \qquad (4.8)$$

Where $r = Pearson\ Coefficient$; $n = number\ of\ the\ pairs\ of\ the\ stock$; $\sum xy$ = sum of products of the paired stocks; $\sum x$ = sum of the x scores; $\sum y$ = sum of the y scores; $\sum x^2$= sum of the squared x scores and $\sum y^2$ = sum of the squared y scores. The value of the correlation coefficient may range between -1 and $+1$. A correlation coefficient value closer to +1 indicates a strong positive linear correlation between the two variables. Whereas, a correlation coefficient value closer to –1 indicates a strong negative linear correlation between the two variables. Nonetheless,

[77] *For a comprehensive description of the WGI methodology, consult the WGI report on the six broad dimensions of governance for the period 1996 – 2021.*
[78] *Such as, the mean, median, maximum, minimum, standard deviation, Skewness, Kurtosis, Jarque-Bera etc...*

if the correlation coefficient is close to zero it means that the two variables in question are uncorrelated.

4.2.3.2 Lag selection criteria

The next step involves selecting the optimum number of lag(s) to be used in the subsequent tests. The estimation procedure for selecting the optimum number of lag(s) is obtained via the VAR model which contains various selection criteria that recommend their own specific lags. The different criteria are: the sequential modified Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz-Bayesian Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ). Given the relatively smaller dataset considered in this study, the decision of optimum lag is based on the findings suggested by the SC. This is due to the fact that it is considered a more appropriate lag selection tool than the other tests that are useful when the sample size is large enough. This means that the majority selection rule will not apply.

Determining the optimum number of lag(s) is highly recommended in order to prevent the error of using default selection provided by most econometrics software, thereby leading to errors of either selecting very few lag(s) – which can lead to problems of misspecification- or choosing too many lags, which may cause problems of loss of the degrees of freedom and overparameterisation. Put differently, including a large number of lags erodes the degrees of freedom in the specified model while including fewer numbers of lag length could lead to the error of omitting important lag dependencies.

4.2.3.3 Stationarity test

The stationarity test, also known as the unit root test, is a useful test for ascertaining the variables' order of integration (i.e., I [0], I [1], and/or I [2]) when handling time series dataset. The test forms the bases for selecting the appropriate econometric techniques used in this study. Stationarity in the data rids off the estimated models from spuriousness that could result from non-stationary series, thereby preventing an erroneous interpretation of results that would lead to misleading policy implications.

Generally, a time series variable is considered to be stationary when its mean and variance is time-invariant. There are many alternative techniques used to test whether a time series variable is stationary. Historically speaking, the Augmented Dickey Fuller (ADF) and the Philips-Perrons (PP) unit root tests have been extensively used in the many literature works. However, both the ADF and the PP unit root tests are criticised for being prone to under reject the null hypothesis of unit roots. This is mainly due to the massive loss of degrees of freedom under these tests. As a result, some more advanced tests, such as the Dickey-Fuller Generalized Least Squares (DF-GLS) (1992), Ng and Peron (1996), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski et al., 1992) and Clemente-Montañés-Reyes (CMR) (1998) have been developed to address some of these drawbacks, amongst others.

Against this background, two stationarity tests (DF-GLS and CMR) are used in this study. The DF-GLS test is substantially more powerful when compared to both the PP and ADF tests, especially when an unknown mean or trend is present in the data. On the other hand, the CMR test surpasses all of these test as it accounts for possibilities of structural breaks in the data, which is often the case with most time series dataset, including the ones used in this study. The CMR approach has two models namely, an additive outlier model (AO) and an innovative outlier model (IO). The former allows for a sudden change in the mean of a time series whereas the latter allows for a gradual shift in the mean of the time series of the model. The deciding test on which the decision of stationarity for this study is based on the CMR-IA test, due to the fact that some of the dataset involved in this study has at least one structural break in a particular year. This is the case due to sudden changes brought about by the dynamics[79] in the local and/or global economy.

In both the DF-GLS and CMR tests, the decision rule for rejecting the null hypotheses for unit root in favour of the alternative hypothesis of stationarity is when the test statistic is more negative than the MacKinnon's critical values are specified at 1% or 5% or 10% levels of significance. For the DF- GLS unit root test, the results for both the constant and trend are tested.

[79] *Such as, the persistent drought conditions of the past 7 years, the aggressive fiscal consolidation measures which took effect in 2016 as a result of spiraling global economic downturn, to mention but a few.*

4.2.3.4 Cointegration tests: ARDL approach

As with most studies, a dynamic model is used to assess the effects of indicators on NPL in both the long- and short run. The dynamic model employed in this chapter is the ARDL bounds test developed by Pesaran et al. (2001). The ARDL bounds test is preferred over most traditional cointegration techniques[80] due to the following advantages it possesses:

a) It uses time series variables regardless of whether they are integrated of order one [I(1)], order zero [I(0)] or a combination of both I(0) and I(1);
b) It generates suitable results regardless of whether the sample size is small or large.
c) It can simultaneously generate both the short run and long run model estimates, as well as get rid of problems of omitted variable bias and serial correlation (Srinivasan, Kumar & Genesh, 2012).
d) The Wald or F-statistics incorporated under the bounds test has an asymmetrical distribution under the null hypothesis of no cointegrating relationship between the variables under investigation.
e) The ARDL bounds test approach produces unbiased estimates of the long run model as well as plausible t-statistics, in spite of some explanatory variables suffering from endogeneity (Harris & Sollis, 2003, as cited in Srinivasan *et al*., 2012).
f) It accounts for the error correction term which measures the speed of adjustment to long run equilibrium.

In light of the aforementioned advantages and series of Equations previously stipulated, both the isolated and the combined effects of the six categories of indicators have been empirically evaluated to provide an insight to the objectives [(a) and (b)] of this thesis. The three steps involved in the ARDL estimation processes are stated as follows:

Firstly, the ARDL - unrestricted error correction model (UECM), which is measured by means of an ordinary least squares (OLS) estimation, is specified. The purpose of this estimation is to validate whether a long run relationship exists between the variables. The F-test for joint

[80] *Such as the, the Engle-Granger cointegration test, Johansen-Juselius cointegration test, amongst others.*

significance is instrumental in determining in validating cointegration amongst the variables. Pesaran et al. (2001) provides two sets of critical value for different model specifications.

Initially, it assumes the variables in the model to be integrated of order one, I (0), implying the absence of cointegration amongst the underlying variables. Then it assumes that the variables in the model are integrated of order, I (1), implying the existence of cointegration amongst the variables in the model. Due to the nature[81] of the sample data availability, this study presents the critical values as provided by Pesaran *et al.* (2001) together with those provided by Narayan (2005, which were based on a much smaller sample size of between 30 to 80 observations. On the contrary, the critical values presented in Pesaran *et al.* (2001) are best suited for much larger sample sizes ranging from 500 to 40 000 observations.

Secondly, the conditional[82] ARDL long run model for *NPL* is estimated. Finally, the short run coefficients are obtained by means of an ECM extracted from the long run test results.

4.2.3.5 Robustness checks

For the sake of robustness checks, which are indispensable in validating the findings of this study, the error term is subjected to numerous diagnostic tests, namely, the tests of normality, homoscedasticity, and the serial correlation test. Moreover, to scrutinise the robustness of the model, the following tests are also employed: autocorrelation, heteroscedasticity, the CUSUM stability test and the normality test.

The guidelines for rejecting or failing to reject the null hypothesis of the aforementioned tests are hereby stipulated:

a) *Autocorrelation Test*: Under the autocorrelation test, the Breusch-Godfrey LM test is used, the null hypothesis of no serial correlation is rejected when the $p\text{-}value < 0.05$. The desired outcome is to fail to reject the null hypothesis of no serial correction, which conclusion can only be reached

[81] *The sample size considered in this study is relatively smaller.*
[82] *The Schwarz Information Criterion (SIC) was used in all the model.*

when he $p\text{-}value > 0.05$. The Durbin-Watson (DW) statistics by Watson and Durbin (1951) is also used to augment the findings of Breusch-Godfrey LM test regarding autocorrelation in the error term. Under this test, the null hypothesis of no autocorrelation is not rejected when the DW statistics is round about the value of two (2).

b) *Heteroscedasticity Test*: With regards to heteroscedasticity test, the Breusch-Pagan-Godfrey test which was developed by Breusch and Pagan (1979) and Godfrey (1978) is used. Under this test, the null hypothesis of homoscedasticity is not rejected when the $p\text{-}value > 0.05$.

c) *Functional Form Test*: To ascertain whether the model is correctly specified, the Ramsey RESET test is used. The null hypothesis for correctly specifying the model is not rejected when the p-value is greater than 5%. By implication, if the p-value is less than the 5% level of significance, the null hypothesis must be rejected in favour of the alternative hypothesis, which means there is misspecification in the model.

d) *Stability Test*: To test for the model's stability, the cumulative sum of recursive residuals (CUSUM) and cumulative sum of recursive residuals of squares (CUSUMSQ) are used. The null hypothesis for an unstable model is rejected if the plots for both the CUSUM as well as the CUSUMSQ appear to be within the critical bounds of 5% significance level.

e) *Normality Test*: with respect to testing for the normality of the residual, the Jarque–Bera (JB) test was used. This test fails to reject the null hypothesis of normality when the $p\text{-}value > 0.05$. In other words, the JB statistics have to be insignificant for normality of the disturbance term to hold. It is worth noting that since the sample data used in this study is relatively large, the normality assumption is not that crucial, due to the asymptotic assumption of dealing with a large sample.

4.3 Empirical results and discussion

4.3.1 Descriptive statistics and correlations analysis

Prior to carrying out any serious econometric analysis, it was necessary to understand the nature of the data at hand by carrying out a descriptive statistic of each variable as well as a correlation analysis measuring the strength of the variables with each other. The descriptive statistics step, which involves various tests used to describe and summarize data, is a crucial start in data analysis as it helps identify possible problems in the data, i.e., outliers that may require to be removed (which is one of the aspects of data wrangling). The results provided by the correlation analysis form the basis for discarding any variable deemed highly correlated with other variables in the model, thereby avoiding the consequences of spurious results caused by multicollinearity.

The summary statistics for the six indices plus the NPL variables is presented in Table 4.8. The Table contains both descriptive statistics and correlation analysis for all the seven series. The reported descriptive measures include: the mean, median, maximum, minimum, standard deviation (Std. Dev.), skewness, Kurtosis, Jarque-Bera (JB) and the number of observations. The calculations were computed using EViews software.

Table 4.8: Summary statistics for NPL and the six composite indices, 1996Q1 - 2021Q4

	NPL	*MACRO*	*BANK*	*MONE*	*INTER*	*FINA*	*INST*
Mean	3.5	6.7e-16	9.1e-16	3.e7-16	1.4e-16	3.4e-17	-4.2e-16
Median	2.8	0.4	-0.5	-0.3	-0.1	-0.2	0.6
Maximum	11.6	2.2	3.5	3.8	5.9	3.6	2.6
Minimum	1.3	-2.9	-3.5	-2.1	-4.6	-2.2	-3.3
Std. Dev.	2.4	1.4	1.8	1.7	2.6	1.6	1.8
Skewness	1.7	-0.8	0.3	0.6	0.5	0.6	-0.4
Kurtosis	5.6	2.7	2.1	2.3	2.5	2.8	1.7
JB	79.3	10.9	5.0	9.2	5.5	7.2	9.6
Pairwise Correlation							
NPL	1.00	-0.15	0.27	-0.07	0.34	-0.09	-0.36
MACRO		1.00	0.59	-0.73	0.62	-0.68	-0.50
BANK			1.00	-0.86	0.87	-0.85	-0.89
MONE				1.00	-0.90	0.98	0.85
INTER					1.00	-0.91	-0.82
FINA						1.00	0.84
INST							1.00
Observations	104	104	104	104	104	104	104

Source: Own compilation

According to Table 4.8, which reports the summary statistics of all the indices with the ratio of NPL, the ratio of NPL in Namibia's banking sector ranged from 1.3% to 11.6%. The quarterly average for NPL was 3.5% with a standard deviation of 2.4% for the period, 1996Q1 – 2021Q4. For the period of the study, the MACRO index hovered between -2.9 and 2.2 with a standard deviation of 1.4. The BANK index ranged between -3.5 and 3.5 with a standard deviation of 1.8. The MONE index fluctuated between -2.1 and 3.8 with a standard deviation of 1.7. The INTER index oscillated between -4.6 and 5.9 with a standard deviation of 2.6. The FINA index ranged between -2.2 and 3.6 with a standard deviation of 1.6. The INST index fluctuated between -3.3 and 2.6 with a standard deviation of 1.8. The JB statistics for all the indices seem to suggest that the indicators are normally distributed.

The correlation analysis presented on Table 4.8 depicts no high correlations betwixt the regressors and NPL. Nevertheless, the test appears to suggest a high correlation (some negative and others positive) between the indicators. This could be due to how closely related these indicators are to each other, especially the BANK, MONE, INTER and FINA. Notwithstanding, this study also presents more formal tests for detecting multicollinearity in order to ensure the absence of high collinearity and serial correlation in the model's residual.

Following, is the disaggregated summary statistics for each variable embedded in the six compact indicators formulated through the mechanism of the PCA technique. Tables 4.9 to 4.14 present the descriptive statistics and correlation analysis of the compact indicators as well as the individual variables with all their aforementioned descriptive statistics included.

Table 4.9: Summary statistics for NPL and the macroeconomic indicators, 1996Q1 - 2021Q4

	OPEN	*DEBT*	*GAP*	*UN*	*HP*	*INF*	*NPL*
Mean	0.9	30.9	0.0	21.3	9.1	6.2	3.5
Median	0.9	25.8	0.0	21.7	9.3	6.0	2.8
Maximum	1.1	65.6	0.6	24.6	22.2	11.0	11.6
Minimum	0.8	8.2	-0.5	16.6	-3.9	2.1	1.3
Std. Dev.	0.1	16.8	0.3	1.7	6.4	2.4	2.4
Skewness	0.2	1.0	0.2	-0.7	-0.1	0.1	1.7
Kurtosis	2.4	2.7	2.5	3.7	2.4	2.0	5.6
JB	2.3	17.7	1.7	11.7	1.5	4.6	79.3
Pairwise Correlation							
OPEN	1.00						
DEBT	-0.15	1.00					
GAP	0.10	0.09	1.00				
UN	-0.23	-0.19	0.17	1.00			
HP	0.10	-0.50	-0.17	-0.04	1.00		
INF	0.19	-0.56	-0.11	0.16	-0.02	1.00	
NPL	-0.43	0.13	-0.12	0.25	-0.20	0.03	1.00
Observations	104	104	104	104	104	104	104

Source: Own compilation

According to Table 4.9, which reports the summary statistics of the macroeconomic indicators with the ratio of NPL, the ratio of NPL in Namibia's banking sector ranged from 1.3% to 11.6%. The quarterly average for NPL is 3.5% with a standard deviation of 2.4%. For the period of the study, the ratio of Namibia's trade openness (OPEN) averaged 0.9 which indicates that the country's degree of openness in terms of international trade is quite high as its ratio nears the value of one. Trade openness ranged between 0.8 and 1.1 with a standard deviation of 0.1. With regards to debt to GDP ratio (DEBT), the quarterly averaged DEBT was 30.9% with the highest standard deviation of 16.8%. The minimum and maximum quarterly DEBT amount registered was 8.2% and 65.6%, respectively. The JB statistics for DEBT seem to suggest that the variable is normally distributed.

The output gap (GAP) had a mean and standard deviation of 0 and 0.3% respectively with the lowest minimum of -0.5% and a maximum of 0.6%. The average unemployment rate (UN) was registered to stand at 21.3% with the highest standard deviation of 1.7%. The lowest rate of unemployment ever recorded was 16.6% while its highest quarterly unemployment rate stood at

24.6%. Just like the DEBT variable, the JB statistics suggest that the variable UN is also normally distributed. The average house price index (HP) was 9.1% with its standard deviation of 6.4%. Its corresponding minimum and maximum value were -3.9% and 22.2%, respectively. The average rate of inflation (INF) was 6.2% with a standard deviation from the mean of 2.4%. The minimum inflation rate for the period under investigation was 2.1% and the maximum rate of inflation was 11.0%. The JB statistics for inflation suggest that it is normally distributed.

The correlation analysis in Table 4.9 demonstrates no high correlations betwixt the regressors. The low correlation betwixt most macroeconomic indicators are proof of the absence of multicollinearity problems. Because of this, the finding that emanate from the regression analysis of these variable are valid for decision making (policy). Other than the OPEN and GAP variables, whose correlation signs are unconformable to the a priori discussed afore, the correlation signs for DEBT, UN, HP, and INF as per the a priori and economic reasoning postulated in chapter four.

Table 4.10: Summary statistics for NPL and the bank specific indicators, 1996Q1 - 2021Q4

	ROA	*ROE*	*CAR*	*LB*	*NIM*	*LDR*	*LG*	NPL
Mean	2.6	25.9	15.0	17.3	5.0	99.5	10.8	3.5
Median	2.2	22.3	15.1	15.5	4.9	96.8	12.8	2.8
Maximum	4.3	45.1	16.9	41.9	6.8	121.7	17.7	11.6
Minimum	1.2	10.4	12.7	1.6	3.8	81.7	0.0	1.3
Std. Dev.	0.8	10.0	0.9	12.0	0.9	10.7	4.7	2.4
Skewness	0.8	0.8	-0.2	0.4	0.3	0.6	-0.8	1.7
Kurtosis	2.5	2.2	3.0	1.9	1.7	2.3	2.5	5.6
JB	11.7	12.3	0.6	7.2	8.9	8.7	10.9	79.3
Pairwise Correlation								
ROA	1.00	0.97	-0.19	-0.76	0.34	0.56	0.18	0.32
ROE		1.00	-0.22	-0.78	0.29	0.54	0.10	0.28
CAR			1.00	0.34	0.18	0.11	-0.38	-0.17
LB				1.00	0.09	-0.64	-0.34	-0.17
NIM					1.00	0.28	-0.11	0.16
LDR						1.00	0.19	0.29
LG							1.00	-0.29
NPL								1.00
Observations	104	104	104	104	104	104	104	104

Source: Own compilation

Based on Table 4.10, which consists of the summary statistics for the bank specific indicators. During the period of the study, the return on assets (ROA) ratio for Namibia's banking sector ranged from 1.2% to 4.3%. The ROA quarterly average was 2.6%, with a smaller standard deviation of 0.8%. The ratio of the returns on equity (ROE) extended from 10.4% to 45.1%. The average ROE recorded was 25.9% with a standard deviation from the mean of 10.0%. The banking sector's capital adequacy ratio (CAR) varied from 12.7% to 16.9% with its mean and standard deviation being 15.0% and 0.9%, respectively. Evidently, although Namibia's banking sector might have experienced some fluctuations in its levels of profitability, it has fared very well and the sector's capitalisation is generally adequate beyond the national and the Basel Accord criteria.

The mortgage lending behaviour (LB) of the banking sector, which is a proxy of the banking sector's appetite for lending, has varied from as low as 1.6% to a peak of 41.9%. Its average stood at 17.3% with a mean standard deviation of 12.0%. The net interest margin (NIM) ranged between 3.8% and 6.8%. The average net interest margin was 5.0% with a standard deviation from the mean of 0.9%. The loan to deposit ratio (LDR) extended from 81.7% to 121.7% with a mean of 99.5% and a variance of 10.7%. The loan growth (LG) varied ranged from 0.0% to 17.7% with an average of 10.8% and a standard deviation of 4.7%. With regards to the findings of the JB statistics, the variable CAR has a probability less than 5% indicating that the variable is not normally distributed. The rest of the seven bank specific indicators are normally distributed as their probabilities are greater than 5%, which leads to the non-rejection of the null hypothesis of normality.

Based on the correlation analysis depicted on Table 4.10, there is clearly a weaker correlation between the bank specific indicators and NPL. The low correlation is indicative that multicollinearity is not an issue. Consequently, the regression results from these variables are highly reliable. It is also worth stating that the correlation between ROA and ROE is unsurprisingly high as both of these ratios are highly related to each other and they are sometimes interchangeably used as measures of profitability.

Table 4.11: Summary statistics for NPL and the monetary indicators, 1996Q1 - 2021Q4

	M1	*M2*	*NFA*	*NPL*
Mean	23472.1	48023.3	19260.2	3.5
Median	18866.1	37724.5	18206.3	2.8
Maximum	65605.0	125769.6	52547.8	11.6
Minimum	1800.5	4815.5	820.3	1.3
Std. Dev.	18918.2	38847.8	13705.8	2.4
Skewness	0.7	0.6	0.6	1.7
Kurtosis	2.3	2.0	2.5	5.6
JB	10.5	10.4	6.4	79.3
Pairwise Correlation				
M1	1.00			
M2	0.99	1.00		
NFA	0.97	0.97	1.00	
NPL	-0.05	-0.07	-0.09	1.00
Observations	104	104	104	104

Source: Own compilation

Table 4.11 presents the summary statistics for the monetary indicators used in this study. For the period under review, the minimum and maximum amount of narrow money supply (M1) was recorded to be N$1.8 billion and 65.6 billion, respectively. The average amount was registered to be N$ 23.5 billion and standard deviation from the mean was N$18.9 billion. The minimum and maximum amount for the broad money supply (M2) was recorded to range from about N$4.8 billion to N$128.8 billion. The average amount for M2 was recorded to be about N$48.0 billion with a standard deviation from the means of N$38.8 billion. The net foreign assets averaged about N$19.3 billion with a standard deviation of N$13.7 billion as well as a corresponding minimum and maximum value of about N$0.8 billion and N$52.5 billion, respectively. As for the JB statistics, it suggests that all the monetary variables are normally distributed given that their probabilities are greater than 5%.

The correlation matrix for the monetary indicators reported on Table 4.11 indicates that, although there is a strong positive correlation amongst the monetary indicators, the correlation between any of the monetary indicators with NPL is weaker and negative which is in line with the afore discussed a priory reviewed in the preceding chapter. Moreover, the weaker correlation implies that there are not problems of multicollinearity between the monetary indicators and the NPL ratio, which means any regression analysis relating to the monetary indicators and NPL should turn out to be non-spurious.

Table 4.12: Summary statistics for NPL and the interest rate indicators, 1996Q1 - 2021Q4

	REPO	*DEPO*	*IS*	*TBR*	*NPL*
Mean	8.7	6.7	5.4	8.8	3.5
Median	7.1	6.0	4.7	8.1	2.8
Maximum	19.3	14.2	9.1	18.9	11.6
Minimum	3.7	2.6	3.7	4.2	1.3
Std. Dev.	3.9	2.7	1.5	3.5	2.4
Skewness	1.3	1.2	1.1	1.3	1.7
Kurtosis	3.8	3.9	2.9	4.1	5.6
JB	31.7	29.0	19.8	34.3	79.3
Pairwise Correlation					
REPO	1.00	0.98	0.83	0.97	0.37
DEPO		1.00	0.79	0.97	0.41
IS			1.00	0.83	0.55
TBR				1.00	0.42
NPL					1.00
Observations	104	104	104	104	104

Source: Own compilations

The summary statistics reported in Table 4.12 for the interest rate indicators and the ratio of NPL for the period 1996Q1 to 2021Q4 indicate that, the Central Bank's repo rate (REPO) ranged from as low as 3.7% to 19.3%. The average REPO was 8.7%, with a smaller standard deviation from the mean of 3.9%.

The deposit rate (DEPO) varied from as low as 2.6% to a maximum of 14.2% with a recorded average of 6.7% and a standard deviation of 2.7%. The interest rate spread (IS) oscillated between a minimum of 3.7% and a maximum of 9.1|%. The average IS stood at 5.4% with its deviation from the mean of 1.5%. The treasury bill rate (TBR) fluctuated from a minimum of 4.2% to a maximum of 18.9%. The mean TBR during the analysed time period was 8.8% with a deviation from the mean of 3.5%. The JB statistics for all the five interest rate indicators suggest that the variables are normally distributed since their probabilities are greater than 5%.

With respect to the correlation results displayed in Table 4.12, the matrix shows that there is a moderate and positive correlation between the interest rate indicators and NPL. The low correlation is indicative that multicollinearity is not an issue. Consequently, the regression results from these variables are highly reliable. It is worth underlining that the correlation amongst the interest rate indicators is unsurprisingly high as they are closely related to one another.

Table 4.13: Summary statistics for NPL and the financial indicators, 1996Q1 - 2021Q4

	RER	*PSCE*	*OIL*	*SHARES*	*NPL*
Mean	9.2	32.5	56.7	760.6	3.5
Median	8.2	31.1	55.2	833.3	2.8
Maximum	16.6	59.3	116.3	1789.4	11.6
Minimum	4.3	10.6	12.3	166.7	1.3
Std. Dev.	3.5	16.0	30.9	406.2	2.4
Skewness	0.6	0.2	0.4	0.2	1.7
Kurtosis	2.2	1.6	2.0	2.0	5.6
Jarque-Bera	9.4	8.8	6.8	5.1	79.3
Pairwise Correlation					
RER	1.00				
PSCE	0.89	1.00			
OIL	0.19	0.53	1.00		
SHARES	0.79	0.94	0.61	1.00	
NPL	-0.01	-0.20	-0.52	-0.21	1.00
Observations	104	104	104	104	104

Source: Own compilations

Table 4.13 reports the summary statistics for the financial indicators and the ratio of NPL for the period 1996Q1 to 2021Q4. Based on the reported results real exchange rate (RER) ranged from a minimum of 4.3% to a maximum of 16.6%. The average RER was registered to be 9.2% with a standard deviation from the mean of 3.5%. The private sector credit extension ratio (PSCE) extended from a minimum of 10.6% to a maximum of 59.3%. The registered average PSCE was 32.5% with a standard deviation from the mean of 16.0%.

The oil prices (OIL) of a barrel of crude oil ranged from a minimum price of US$12.3 to a maximum price of US$116.3. The quarterly average oil price per barrel of crude oil was US$56.7

and the corresponding standard deviation from the mean was US$30.9. The Namibian stock market index (SHARES) fluctuated between 166.7 and 1789.4. The mean SHARES was 1789.4 with a standard deviation of 406.2. The JB statistics for all the five financial indicators are normally distributed as their probabilities are greater than 5%.

From the correlation findings displayed in Table 4.13, it shows that with the exception of the OIL variable that is negatively and moderately correlated to NPL, the rest of the financial indicators are also negatively but weakly correlated with the NPL ratio. OIL is the most negatively and strongly correlated variable with NPL. The weaker correlation in most, if not all the financial variables, is indicative that there are no problems of multicollinearity. Thus, the findings from any regression analysis based on these variables are considered to be BLUE[83].

Table 4.14: Summary statistics for NPL and the institutional indicators, 1996Q1 - 2021Q4

	VA	*PS*	*CC*	*RQ*	*GE*	*RL*	*NPL*
Mean	60.6	67.4	66.7	58.6	61.1	60.0	3.5
Median	59.7	68.4	65.2	56.8	61.5	60.6	2.8
Maximum	67.6	94.7	77.9	69.3	66.5	69.2	11.6
Minimum	54.0	34.9	58.3	49.2	55.6	49.7	1.3
Std. Dev.	3.5	12.5	5.7	5.2	2.6	3.9	2.4
Skewness	0.4	-0.6	0.6	0.3	-0.1	-0.5	1.7
Kurtosis	2.3	3.6	2.3	1.9	2.7	3.7	5.6
JB	5.1	7.2	8.9	6.4	0.7	7.4	79.3
Pairwise Correlation							
VA	1.00	0.17	0.02	-0.60	0.13	0.57	-0.18
PS		1.00	-0.06	-0.36	0.12	0.28	-0.42
CC			1.00	0.47	0.57	-0.05	0.39
RQ				1.00	0.35	-0.47	0.29
GE					1.00	0.07	-0.20
RL						1.00	-0.13
NPL							1.00
Observations	104	104	104	104	104	104	104

Source: Own compilations

Table 4.14 contains the summary statistics results for the institutional indicators and the ratio of NPL for the period 1996Q1 to 2021Q4. The ranking for voice and accountability (VA) ranged from a low rank of 54.0% to a maximum rank of 67.6%. The average VA rank was 60.6% with a

[83] *Best linear unbiases estimators*.

standard deviation from the mean of 3.5%. The rank of political stability and absence of violence/terrorism (PS) extended from a minimum rank of 34.9% to a maximum of 94.7%. The registered average PS was 67.4% with a standard deviation from the mean of 12.5%.

The control of corruption (CC) index ranged from a minimum of 58.3% to a maximum of 77.9%. The average index of CC was 66.7% with its corresponding standard deviation of 5.7%. The average index of regulatory quality (RQ) stood at 58.6% with a standard deviation of 5.2%. The minimum RQ index was 49.2% and a maximum of 69.3%. The government effectiveness (GE) index fluctuated from a minimum of 55.6% to a maximum of 66.5%. The mean GE index was 61.1% with a standard deviation of 2.6%. The rule of law (RL) index oscillated from a minimum of 49.7% to a maximum of 69.2%. The average RL index was 60.0% with a standard deviation of 3.9%. With exception of GE, the JB statistics for the remaining five institutional indicators show that the variables are normally distributed as their probabilities are greater than 5%.

Table 4.14 also shows that the variables: VA, PS, GE and RL are weakly and negatively correlated with the dependent variable (NPL) just as expected as per the a priori discussed in the previous chapter. The variable PS is the most negatively correlated with NPL with a correlation of -0.42. Conversely, CC was found to be the most positively correlated with NPL with a correlation of 0.39. On the other hand, the variables CC and RQ turned out to be positively and weakly correlated with NPL. More specifically, the findings suggest that improvements in political stability helps to reduce the ratio of NPL, whilst surprisingly the variable CC increases the ratios of NPL. All in all, the variables do not suffer from multicollinearity. As such, the regression findings are non-spurious and suitable for policy making.

4.3.2 Lag length selection test results

The optimum lag length required in all the subsequent estimations has been establish via the VAR estimation model. Table 4.15 presents the test results provided by various information criteria embedded in the EViews software package: such as the sequential modified Likelihood Ratio test statistic (LR), the Final Prediction Error (FPE), the Akaike Information Criterion (AIC), the Hannan-Quinn information criterion (HQ) and finally, the Schwarz-Bayesian Information

Criterion (SC).

Table 4.15: VAR lag order selection criteria for all the models

Category	Lag	LogL	LR	FPE	AIC	SC	HQ
Composite Model	0	-914.16	NA	0.24	18.42	18.61	18.5
	1	248.08	2138.51	0	-3.84	**-2.38***	-3.25
	2	345.84	**166.18***	**1.94e-11***	**-4.81***	-2.08	**-3.70***
	3	360.88	23.47	0	-4.14	-0.13	-2.51
	4	372.96	17.16	0	-3.4	1.89	-1.26
Macroeconomic Model	0	-1223.27	NA	114.47	24.61	24.79	24.68
	1	-216.55	1852.37	0	5.45	6.91	6.04
	2	-45.21	**291.27***	**4.83e-08***	**3.00***	**5.74***	**4.11***
	3	-18	42.45	0	3.44	7.45	5.06
	4	-1.47	23.48	0	4.09	9.38	6.23
Bank specific Model	0	-1663.7	NA	45754.73	33.43	33.64	33.52
	1	-451	2207.13	0	10.46	12.34	11.22
	2	-267.22	**305.07***	**4.51e-07***	**8.06***	**11.61***	**9.50***
	3	-235.95	46.9	0	8.72	13.93	10.83
	4	-212.05	32.03	0	9.52	16.4	12.3
Monetary Model	0	-3275.14	NA	3.57e+23	65.58	65.69	65.63
	1	-2485.83	1499.7	6.85e+16	50.12	50.64	50.33
	2	-2392.49	**169.88***	**1.46e+16***	**48.57***	**49.51***	**48.95***
	3	-2386.54	10.36	1.79e+16	48.77	50.13	49.32
	4	-2384.51	3.37	2.39e+16	49.05	50.82	49.77
Interest rate Model	0	569.1	NA	0	-11.26	-11.11	-11.2
	1	1356.03	1463.68	0	-26.28	-25.19	-25.84
	2	1531.83	**305.90***	**9.58e-21***	**-29.08***	**-27.05***	**-28.25***
	3	1555.09	37.69	0	-28.82	-25.85	-27.62
	4	1578.08	34.48	0	-28.56	-24.65	-26.98
Financial Model	0	-4507.57	NA	6.45e+31	90.27	90.43	90.33
	1	-3490	1892.67	1.92e+23	70.64	71.73	71.08
	2	-3325.75	**285.79***	**1.49e+22***	**68.08***	**70.11***	**68.90***
	3	-3308.03	28.7	2.19e+22	68.44	71.41	69.64
	4	-3300.22	11.71	4.00e+22	69	72.91	70.59
Institutional Model	0	-1870.77	NA	4.82e+07	37.56	37.74	37.63
	1	-890.49	1803.72	0.39	18.93	20.39	19.52
	2	-751.76	**235.84***	**0.07***	**17.14***	**19.87***	**18.24***
	3	-730.49	33.18	0.12	17.69	21.7	19.31
	4	-717.27	18.78	0.26	18.41	23.69	20.55

Source: Own compilations

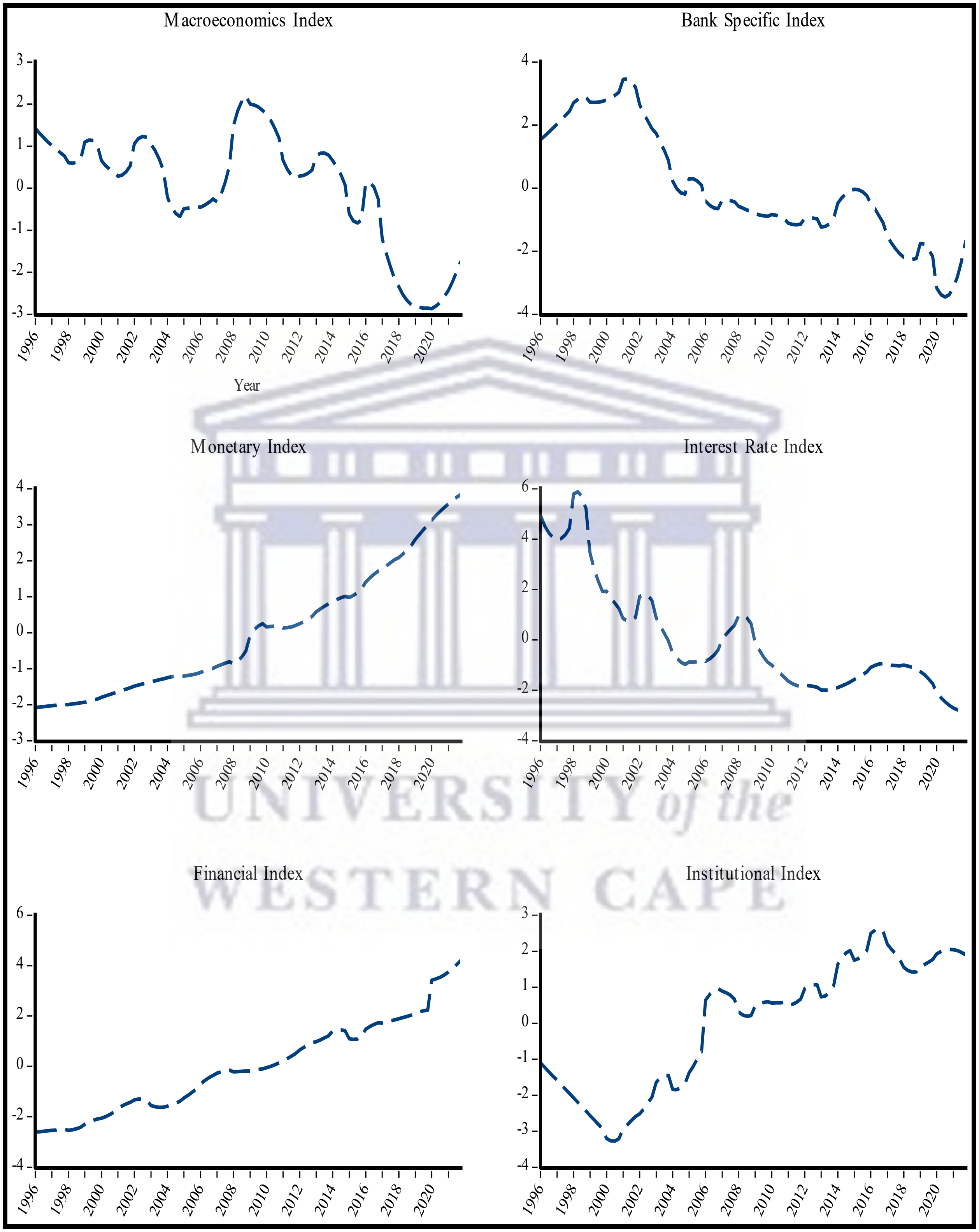
Note: The asterisks (*) appearing in Table 4.15 denotes the lag order selected by the respective criterion.

Based on the VAR lag selection results presented in Table 4.15, the majority of tests chosen in all the seven models chose two lags as the optimum lag. It is worth noting that the SC information criteria in the overall model chose one lag. Given that the ARDL model estimation only takes one specific lag selection test at a time, the SC test is conveniently considered as, unlike the other tests, it works better with relatively smaller sample sizes.

4.3.3 Time Series Patterns

Before formally conducting any econometric analysis on the series, it was necessary to graphically depict the series used in this thesis in order to understand the features of data, such as the trend patterns, the structural breaks in the data and stationarity. Figures 4.2 to 4.7 display the graphical presentation of all the variables contained in the six broad categories of indicators used in this thesis. The plots were produced using the R software package.

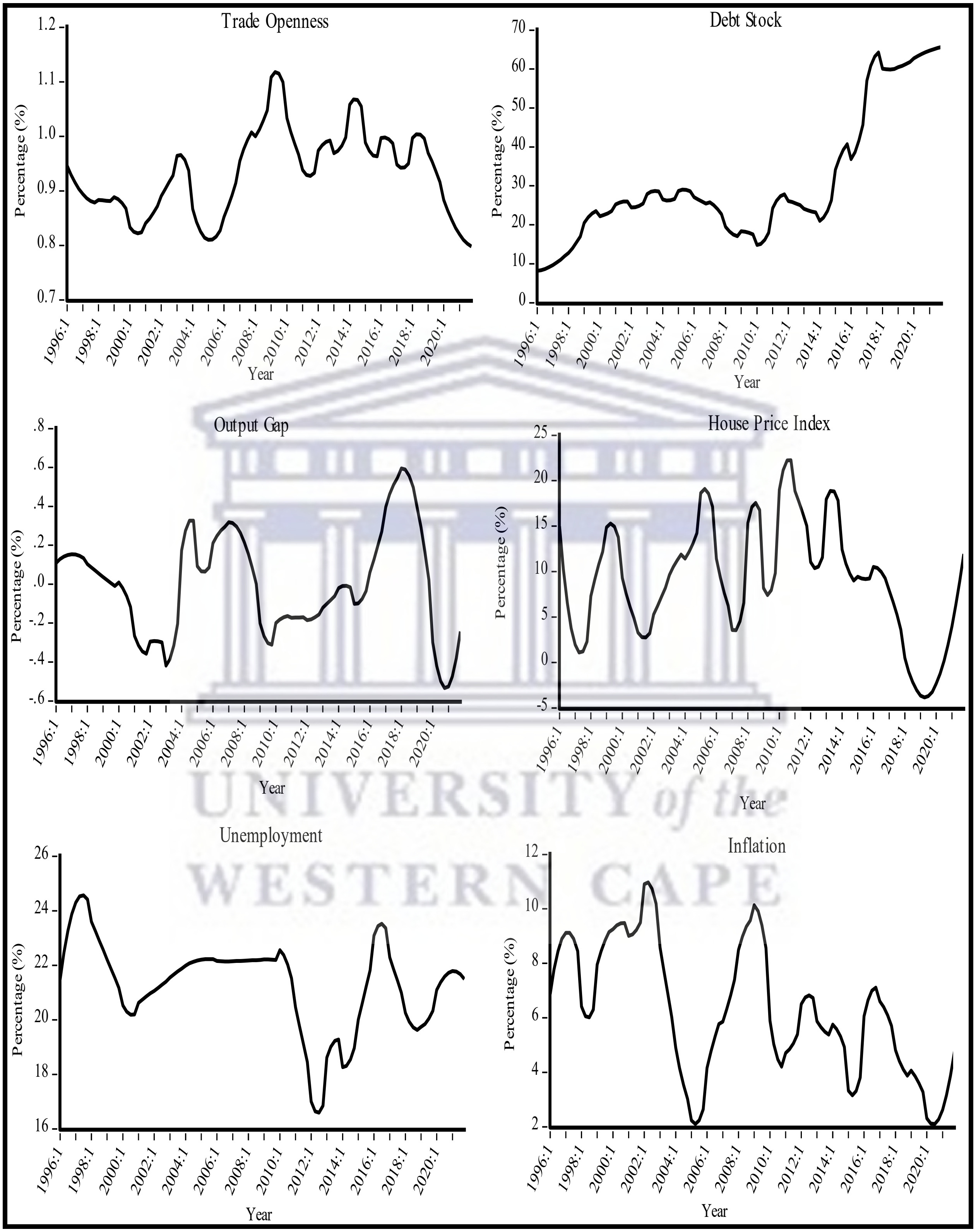
Figure 4.2: Time series plot for the composite indices, 1996Q1–2021Q4



Source: Own compilations

Figure 4.2 shows that the macroeconomic, bank specific, and financial indicators have been downward trending. This unprecedented deterioration of macro factor is also reflected on the quality of the loan portfolio (See the plot trend of NPL plotted in Figure 1.1). Notwithstanding, the monetary, financial, and institutional indicators (index) appear to have fared well. This is not surprising at all, as the country has for years enjoyed both political and economic stability, causing it to become an attractive destination for a number of both local and international investors.

Figure 4.3: Time series plot for the macroeconomic indicators, 1996Q1 – 2021Q4



Source: Own compilations

As can be observed from the individual time series plots of the macroeconomics variables shown in Figure 4.3, all the displayed macroeconomic plots exhibited some forms of fluctuations during the period 1996Q1 to 2021Q4. In particular, trade openness (which measures the degree of openness, in terms of trade, to the rest of the world) appears to be cyclical in nature when considering the irregular rises and falls in the variables over time. The uneven fluctuations could have been brought about by various factors[84] which altogether might bear some influence on the levels of NPL in Namibia's banking sector.

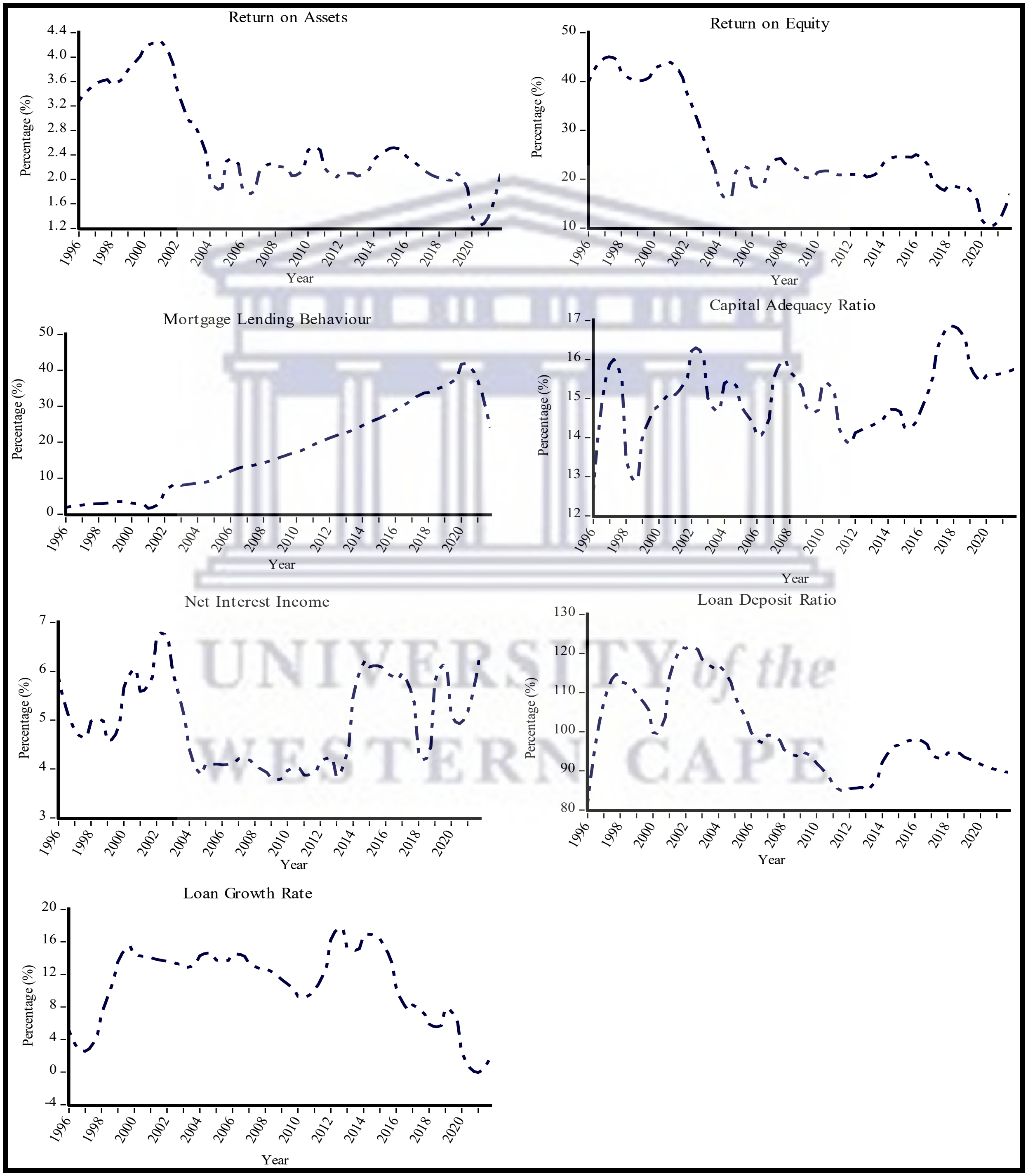
On the other hand, the Debt to GDP ratio exhibit an upward cyclical trend which is in line with the country's continual appetite for borrowed funds intended to finance its fiscal budget. The persistency became so strong beginning in the 2014Q3 and since then, there seems to be no signs of it subsiding in the nearest future. The variations in output gap and unemployment appear to display a cyclical linear and determinist trend which is indicative of the fact that there is still room for the economy to operate at full potential, thereby ameliorate the current pattern of NPL in the banking sectors.

In the same vein, the trend in the house price index appears to show an upward cyclical and deterministic trend in pattern prior to it starting to decline in the 3rd quarter of 2010. Conversely, inflation rate exhibits some downward and deterministic trend pattern which for the most part has below single digits. The stable price environment enjoyed by Namibia since attaining its independence in 1990 is largely attributed to the collective commitment of inflation targeting pursued under the Common Monetary Area (CMA) arrangement of which it is part. Other members being Lesotho, Eswatini and South Africa - the main leader. Under this arrangement, each member state has the authority to issue its own currency; however, only the South African Rand is considered to be a legal tender in these countries. The CMA member state in this regime are in a fixed exchange rate, where their currency is pegged on a 1 to 1 basis. This ensures that member states, like Namibia, import a stable inflation from South Africa, which is a leading implementer of an inflation targeting monetary policy regime.

[84] *Such as the fluctuation in the global commodity prices for minerals, climate change (i.e., drought), the geopolitical instabilities in Europe, the global Coronavirus pandemic, etc.*

All in all, the visual representation of the macroeconomic variables appear to suggest that the data might have unit root problems, hence a formal unit root test is required to ascertain the issues beyond the shadow of a doubt.

Figure 4.4: Time series plot for the bank specific indicators, 1996Q1 – 2021Q4



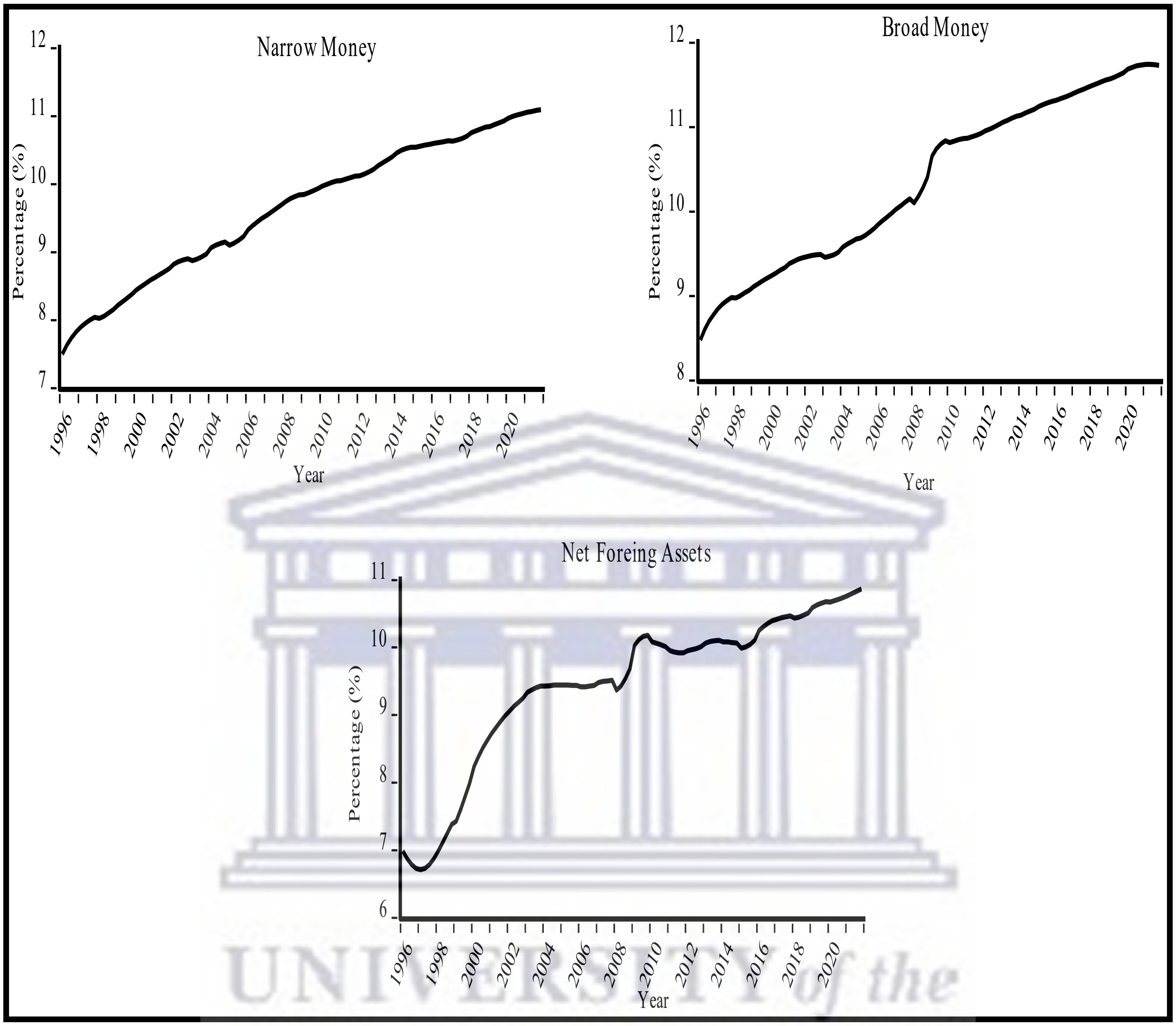
Source: Own compilations

The graphical observation from plots of the bank specific variables displayed in Figure 4.4 illustrate that the time series plots exhibited some forms of fluctuations during the sample period, 1996Q1 to 2021Q4. For instance, looking at the plots of the return on assets as well as that of the returns on equity, it is safe to allege that between the periods 1996Q1 to 2014Q3, both variables experienced a downward linear and deterministic trend. Thereafter, they exhibited cyclicality without a trend. Similarly, the pattern of loans to deposit ratio and loan growth has been cyclical in nature and downward trending overtime.

On the other hand, the capital adequacy ratio (CAR) has visibly experienced persistent cyclical swings that have been trending upwards overtime. It is worth noting that for the period under review, the banking sector in Namibia had a sufficient CAR that is beyond the international required levels of 8% proposed by the Basel III Accord of 2019. Similarly, the lending behaviour of commercial banks with regards to mortgages has been rising upwards. This illustrates the appetite of the banking sector in desiring to profit from the interest income generated through mortgage lending. However, the net interest margin experienced an unpredictable pattern with some sudden high jumps in some years.

All in all, the following bank specific indicators: return on assets, return on equity, mortgage lending behaviour, and loan growth appear to suffer from unit root. For capital adequacy ratio and net interest margin it not easy to tell whether they might be at risk of suffering from unit root. As such, a formal unit root test is required to rule out all these uncertainties.

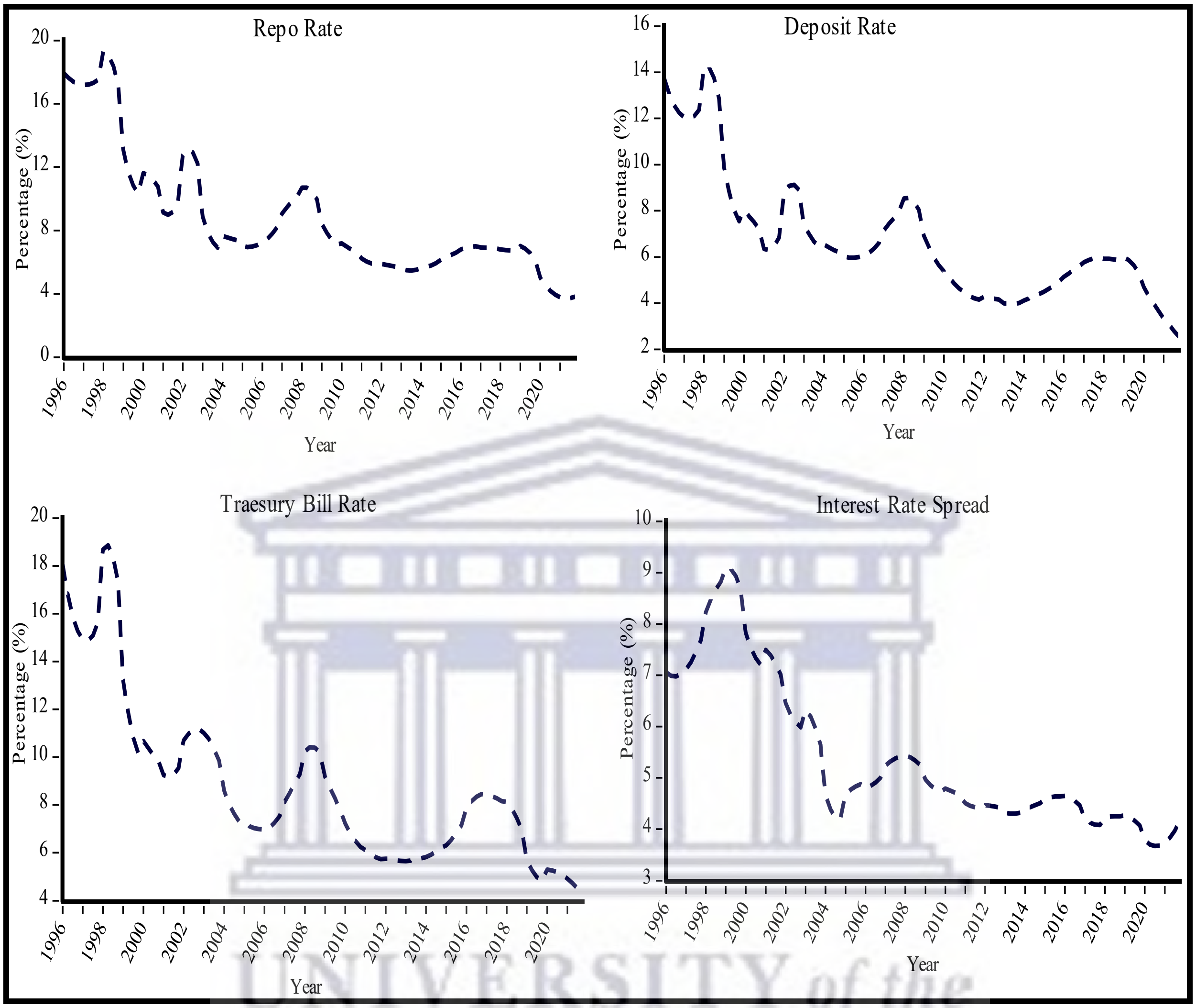
Figure 4.5: Time series plot for the monetary indicators, 1996Q1 – 2021Q4



Source: Own compilations

Figure 4.5 depicts the graphical presentations of the monetary indicators employed in this study. Although the variables have been sourced in their standard units of measurements (N$ Million), it was required that the same be converted into logarithm to make it easier to infer a sensible meaning out of them by means of elasticities. The three variables appear to exhibit an upward trend, even though the net foreign assets slightly experienced more variabilities. By observation, it is safe to surmise that the three variables have a unit root problem.

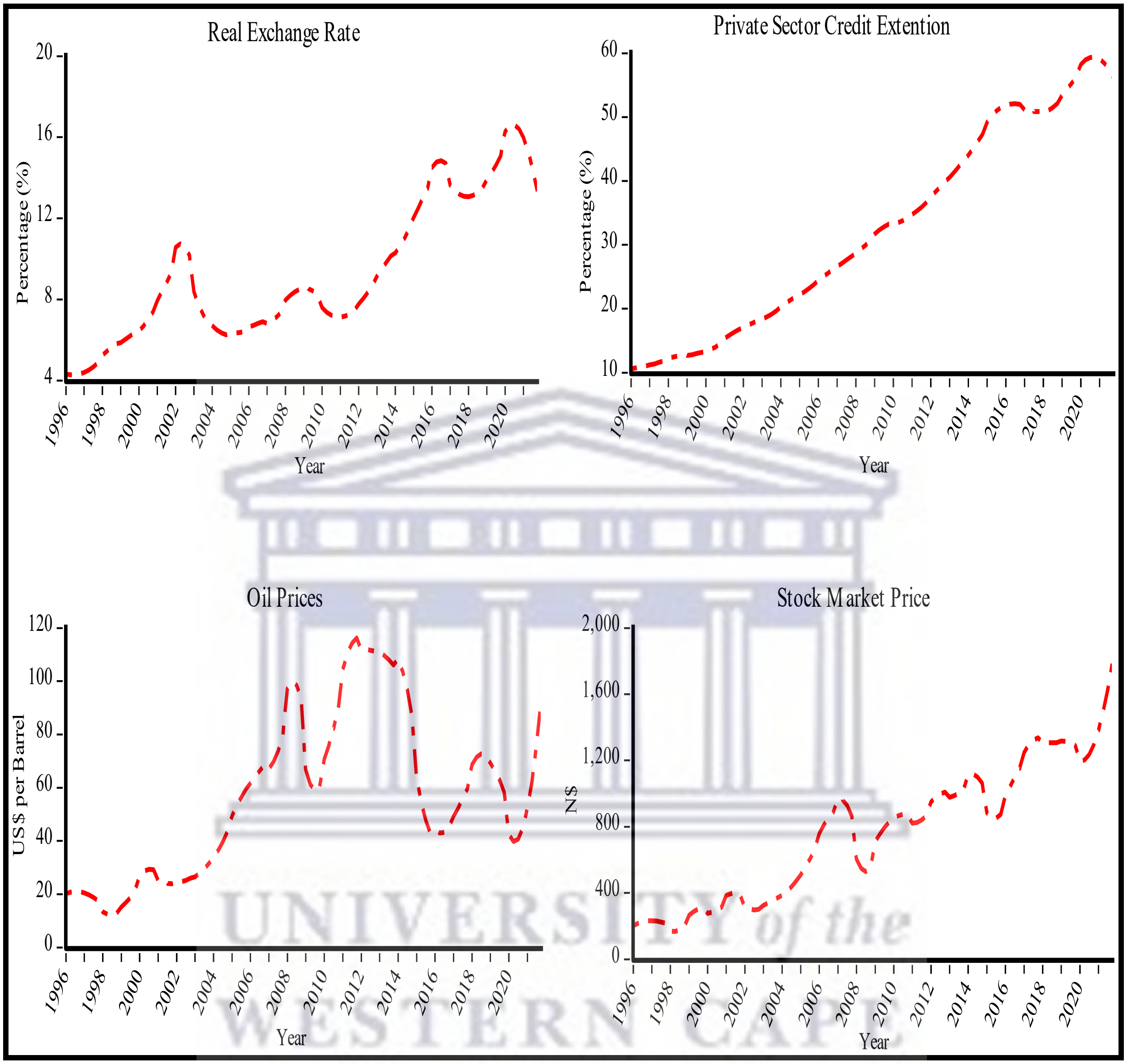
Figure 4.6: Time series plot for the interest rate indicators, 1996Q1 – 2021Q4



Source: Own compilations

Figure 4.4 displays the graphical visualisation of the interest rate indicators examined in this study. Clearly, the plots indicate that the repo rate, deposit rate, interest rate spread, and the treasury bill rate experienced a cyclical downwards trend for the period under study. The patterns appear to be negatively associated with the patterns of NPL and the variables seem to be non-stationarity.

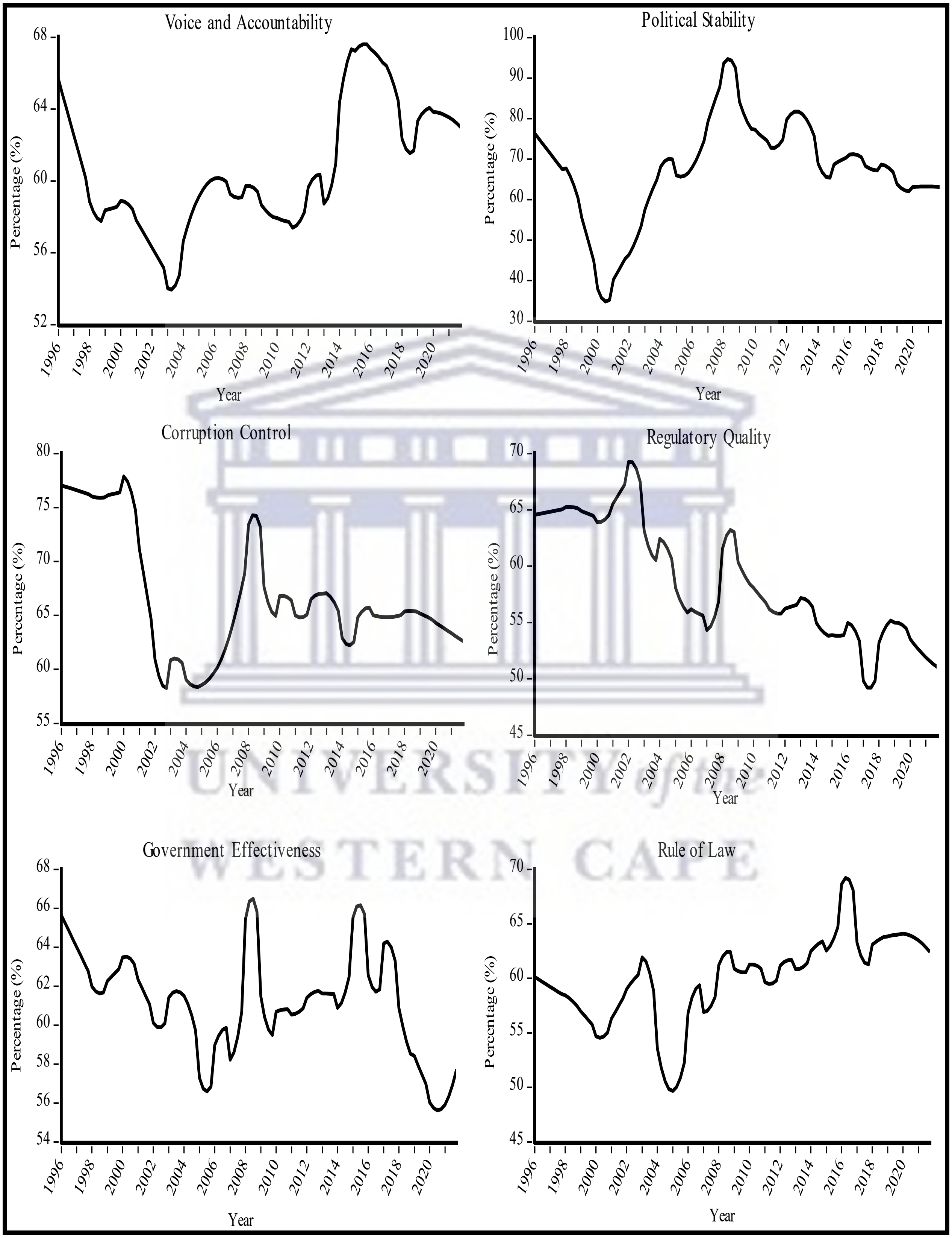
Figure 4.7: Time series plot for the financial indicators, 1996Q1 – 2021Q4



Source: Own compilations

Figure 4.7 shows the time series patterns for all the financial indicators utilised in this study. The plots of real exchange rate, private sector credit extension, market capitalisation, and the stock market index exhibited an upward trend for the period under review, excepting the Brent crude oil prices which at first had an upward cyclical trend up until 2011, followed by a downward cyclical trend. The volatilities in real exchange rate, Brent crude oil and stock market index are characterised by high spikes in some time periods. In summary, the variables appear to suffer from a unit root problem.

Figure 4.8: Time series plot for the institutional indicators, 1996Q1 – 2021Q4



Source: Own compilations

Figure 4.8 shows the time series properties for the institutional indicators investigated in this study. With the exception of the indicators *Government Effectiveness* and *Political Stability* whose oscillatory pattern is unclear and is characterised by high jumps in some years, the rest of the indicators have a clear cyclical pattern. For instance, the indicators *Voice and Accountability* as well as the *Rule of Law* are cyclical in nature and they have an upward trend, which is indicative of the country's improvement in these governance indicators over the years since independence.[85]

On the contrary, the indicators *Corruption Control* and *Regulatory Quality* have a cyclical downward trend. The gradual deterioration of *Corruption Control* may be due to a gradual increase in the level of corruption (in which at times, some high-profile Government officials are also involved). The declines in *Regulatory Quality* are likely caused by the contestation of the land question, which has remained an issue of contention by pressure groups[86] in recent years. If this contestation is not addressed in time, it has been predicted to be a time bomb capable of ruining the sound political stability the country currently enjoys. All in all, the institution indicators seem to suggest that the variables do suffer from non-stationarity problems.

4.3.4 Stationarity Test

Following the graphical presentations of the time series variables are the formal unit root tests on each variable used for this study. The outcomes from both the Dickey-Fuller Generalized Least Squares (DF-GLS) and the Clemente-Montañés-Reyes (CMR) stationarity test results of the six categories of indicators used are presented in Tables 4.15 -4.21. The DF-GLS and the CMR unit root tests have been carried out in EViews and STATA software, respectively.

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[85] *Namibia has on numerous occasions, maintained its 1st position in Africa in terms of the country with the best press freedom. Currently, World Press Freedom Index ranks it at position 18th out of 180 countries, with a global score index of 81.84% as classified by Reporters Without Borders.*

[86] *Such as the Trade unions, Ova Herero/Nama pressure groups, Affirmative Reposition movement, Landless Peoples movements, to mention but a few.*

Table 4.15: Stationarity test for the composite indices

Variable Name	Model Specification	DF - GLS Levels	DF - GLS 1st Diff.	CMR Break Year	CMR Levels	CMR 1st Diff.	Order of Integration
MACRO	Intercept	-1.316 (-1.944)	-4.975^{a} (-2.588)	2015Q3	-3.969^{b} (-3.560)	-	I(0)
	Trend & Intercept	-2.507 (-3.028)	-4.995^{a} (-3.578)				
BANK	Intercept	-1.190 (-1.944)	-3.967^{a} (-2.588)	2005Q4	-3.737^{b} (-3.560)	-	I(0)
	Trend & Intercept	-2.416 (-3.028)	-4.301^{a} (-3.578)				
MONE	Intercept	-2.701^{a} (-2.588)	-	2010Q1 & 2008Q3	-2.262 (-3.560)	-6.737^{b} (-3.560)	I(1)
	Trend & Intercept	-0.555 (-3.578)	-5.523^{a} (-3.578)				
INTER	Intercept	-0.068 (-1.944)	-4.317^{a} (-2.588)	2001Q3 & 1998Q3	-3.268 (-3.560)	-6.201^{b} (-3.560)	I(1)
	Trend & Intercept	-2.212 (-3.028)	-5.220^{a} (-3.578)				
FINA	Intercept	-4.597^{a} (-2.588)	-	2020Q2 & 2019Q3	-1.792 (-3.560)	-8.929^{b} (-3.560)	I(1)
	Trend & Intercept	-0.742 (-3.027)	-8.956^{a} (-3.578)				
INST	Intercept	-0.462 (-1.944)	-5.687^{a} (-2.587)	2006Q2 &2005Q3	-3.520 (-3.560)	-7.251^{b} (-3.560)	I(1)
	Trend & Intercept	-1.759 (-3.028)	-6.344^{a} (-3.578)				

Source: Own compilation

Note: a) ^{a}, ^{b}, ^{c} denotes the rejection of the null hypothesis of non-stationarity at 1%, 5%, and 10% critical levels, respectively. b) The values not in parenthesis are the t-statistics whilst those in parenthesis are the critical values based on MacKinnon's critical value. c) In instances where the t-statistics value is not with asterisks, the 5% critical values is selected. d) In instances where all the variable is stationary at all the levels of significance, the 5% critical value is by default selected.

Table 4.15 shows that the DF-GLS unit root test strongly rejects the null hypothesis of unit root (at 1% significant level) after first difference at trend and intercept levels. The CMR unit root test results, which evaluates the null hypothesis of unit root at 5% significant level and serves as the ultimate deciding test for the order of integration, reveals different structural breaks years for each variable. The unit test results show that except for NPL, MACRO and BANK indicator which were found to be stationary in level, the rest of the variables only became stationary after first difference. This integration mix is considered in the next section that establishes whether cointegrating relationships exist amongst the variables in the model.

Table 4.16: Stationarity test for the macroeconomic indicators

Variable Name	Model Specification	DF - GLS Level	DF - GLS 1st Diff.	CMR Break year	CMR Level	CMR 1st Diff.	Order
OPEN	Intercept	-2.392^{b} (-1.944)	-	2008Q3	-3.324 (-3.560)	-5.026^{b} (-3.560)	I(1)
	Trend & Intercept	-2.399 (-3.021)	-5.206^{b} (-3.028)				
DEBT	Intercept	0.524 (-1.994)	-5.800^{b} (-1.944)	2018Q1	-4.605^{a} (-3.560)	-	I(0)
	Trend & Intercept	-1.604 (-3.028)	-5.893^{b} (-3.028)				
GAP	Intercept	-3.252^{b} (-1.944)	-	2004Q4	-3.723^{b} (-3.560)	-	I(0)
	Trend & Intercept	-3.255^{b} (-3.028)	-				
UN	Intercept	-3.241^{b} (-1.944)	-	2012Q4	-5.314^{b} (-3.560)	-	I(0)
	Trend & Intercept	-4.031^{b} (-3.029)	-				
HP	Intercept	-3.055^{b} (-1.994)	-	2018Q2	-4.215^{b} (-3.560)	-	I(0)
	Trend & Intercept	-3.535^{b} (-3.028)	-				
INF	Intercept	-3.065^{b} (-1.944)	-	2004Q3	-4.192^{b} (-3.560)	-	I(0)
	Trend & Intercept	-4.217^{b} (-3.029)	-				

Source: Own compilations

Note: a) ^{a}, ^{b}, ^{c} denotes the rejection of the null hypothesis of non-stationarity at 1%, 5%, and 10% critical levels, respectively. b) The values not in parenthesis are the t-statistics whilst those in parenthesis are the critical values based on MacKinnon's critical value. c) Wherever the t-statistics value is not denoted with plus signs, the 5% critical level is selected by default. d) Wherever the variable is stationary at all the levels of significance, the default critical value selected is also the 5% critical level.

Based on the stationarity test results for the macroeconomic indicators presented in Table 4.16, the DF-GLS unit root test reveals that only two variables (trade openness and debt stock) are integrated of order one, while the rest of the macroeconomic variables are of order zero. On the other hand, the CMR unit root test reaffirms that indeed the variable trade openness is integrated of order one whilst the rest of the variables are order zero. The fact that there is a variable mix in the order of integration of both I (0) and I (1) makes the employments of the ARDL bounds test approach possible. The mixture is also suggestive of the existence of cointegration relationships amongst the macroeconomic variables.

Table 4.17: Stationarity test for the bank specific indicators

Variable Name	Model Specification	DF - GLS Levels	DF - GLS 1st Diff.	CMR Break year	CMR Level	CMR 1st Diff.	Order
NPL	Intercept	-3.027^{b} (-1.944)	-	1997Q3	-4.801^{b} (-3.560)	-	I(0)
	Trend & Intercept	-3.131^{b} (-3.021)	-				
ROA	Intercept	-1.464 (-1.994)	-4.368^{b} (-1.944)	2005Q1	-4.701^{b} (-3.560)	-	I(0)
	Trend & Intercept	-2.398 (-3.028)	-4.847^{b} (-3.028)				
ROE	Intercept	-1.001 (-1.944)	-3.207^{b} (-1.944)	2005Q4	-5.128^{b} (-3.560)	-	I(0)
	Trend & Intercept	-2.345 (-3.028)	-4.091^{b} (-3.028)				
CAR	Intercept	-1.759^{c} (-1.615)	-	2017Q2	-5.216^{b} (-3.560)	-	I(0)
	Trend & Intercept	-3.502^{b} (-3.028)	-				
LB	Intercept	-1.929^{c} (-1.614)	-	2020Q3	-2.484 (-3.560)	-6.419^{b} (-3.560)	I(1)
	Trend & Intercept	-3.170^{b} (-3.029)	-				
NIM	Intercept	-2.287^{b} (-1.944)	-	2014Q4 & 2017Q3	-3.452 (-3.560)	-5.591^{b} (-3.560)	I(1)
	Trend & Intercept	-2.509 (-3.028)	-5.526^{b} (-3.028)				
LDR	Intercept	-3.098^{b} (-1.944)	-				
	Trend & Intercept	-3.369^{b} (-3.028)	-	2011Q3	-6.450^{b} (-3.560)	-	I(0)
LG	Intercept	-1.615^{b} (-1.615)	-				
	Trend & Intercept	-1.888 (-3.028)	-	2018Q3	-3.637^{b} (-3.560)	-	I(0)

Source: Own compilations

Note: a) ^{a}, ^{b}, ^{c} denotes the rejection of the null hypothesis of non-stationarity at 1%, 5%, and 10% critical levels, respectively. b) The values not in parenthesis are the t-statistics whilst those in parenthesis are the critical values based on MacKinnon's critical value. c) In instances where the t-statistics value is not with asterisks, the 5% critical values is selected. d) In instances where all the variable is stationary at all the levels of significance, the 5% critical value is by default selected.

Table 4.17 contains the stationarity test results for the bank - specific indicators. With respect to the DF-GLS unit root test, it reveals that the variables return on asset (ROA), return on equity

(ROE) and net interest margin (NIM) are integrated of order one, and the rest of the bank specific variables are order zero. The results from the CMR unit root test indicate that with the exception of the variables banks' lending behaviour (LB) and the net interest margin (NIM) which have been tested of being integrated of order one, the rest of the variables are order zero. Since there is a variable mix in the order of integration (I [0] and I [1]), it is possible to implement the ARDL bounds test approach, and be able to verify if indeed there is a cointegrating relationship in the variables.

Table 4.18: Stationarity test for the monetary indicators

Variable Name	Model Specification	DF - GLS		CMR			Order
		Levels	1st Diff.	Break year	Level	1st Diff.	
M1	Intercept	-2.089^{b} (-1.944)	-	2015Q1 & 2016Q3	-2.664 (-3.560)	-4.072^{b} (-3.560)	I(1)
	Trend & Intercept	-0.543 (-3.028)	-4.783^{b} (-3.028)				
M2	Intercept	-1.529 (-1.944)	-4.100^{b} (-1.944)	2008Q3 & 2010Q1	-2.240 (-3.560)	-4.151^{b} (-3.560)	I(1)
	Trend & Intercept	-1.097 (-3.028)	-4.601^{b} (-3.028)				
NFA	Intercept	-1.988^{b} (-1.944)	-	2010Q1	-2.619 (-3.560)	-4.845^{b} (-3.560)	I(1)
	Trend & Intercept	-1.724 (-3.028)	-5.602^{b} (-3.028)				

Source: Own compilations

Note: a) ^{a}, ^{b}, ^{c} denotes the rejection of the null hypothesis of non-stationarity at 1%, 5%, and 10% critical levels, respectively. b) The values not in parenthesis are the t-statistics whilst those in parenthesis are the critical values based on MacKinnon's critical value. c) Wherever the t-statistics value is not denoted with a plus sign, the 5% critical level is selected by default. d) Wherever the variable is stationary at all the levels of significance, the default critical value selected is also the 5% critical level.

Table 4.18 consists of the stationarity test results for the monetary indicators. The outcomes provided by the DF-GLS unit root test found the intercept specification model for both the narrow money (M1) and net foreign assets (NFA) to be integrated of order zero. However, the model factoring in both the intercept and trend reveals all the three monetary variables to be of order one. Similarly, the CMR unit root test attests that the three indicator variables are integrated of order one. Therefore, the ARDL bounds test is still a relevant approach in establishing whether variables move along in the long run.

Table 4.19: Stationarity test for the interest rate indicators

Variable Name	Model Specification	DF - GLS		CMR			Order
		Levels	1st Diff.	Break year	Level	1st Diff.	
REPO	Intercept	-0.358 (-1.994)	-6.178^{b} (-1.944)	2000Q1	-3.928^{b} (-3.560)	-	I(0)
	Trend & Intercept	-2.431 (-3.028)	-6.301^{b} (-3.028)				
DEPO	Intercept	-0.153 (-1.944)	-4.603^{b} (-1.944)	2000Q1	-3.696^{b} (-3.560)	-	I(0)
	Trend & Intercept	-2.345 (-3.028)	-5.393^{b} (-3.028)				
IS	Intercept	-0.808 (-1.944)	-5.389^{b} (-1.944)	2005Q1	-4.180^{b} (-3.560)	-	I(0)
	Trend & Intercept	-2.331 (-3.028)	-5.393^{b} (-3.028)				
TBR	Intercept	-0.808 (-1.944)	-5.389^{b} (-1.944)	2001Q1	-3.637^{b} (-3.560)	-	I(0)
	Trend & Intercept	-2.331 (-3.028)	-5.393^{b} (-3.028)				

Source: Own compilations

Note: a) ^{a}, ^{b}, ^{c} denotes the rejection of the null hypothesis of non-stationarity at 1%, 5%, and 10% critical levels, respectively. b) The values not in parenthesis are the t-statistics whilst those in parenthesis are the critical values based on MacKinnon's critical value. c) Wherever the t-statistics value is not denoted with plus signs, the 5% critical level is selected by default. d) Wherever the variable is stationary at all the levels of significance, the default critical value selected is also the 5% critical level.

Table 4.19 contains the stationarity test results for the interest rate indicators. Based on the DF-GLS unit root test results, the interest rate indicator variables are all integrated of order one. On the other hand, the CMR unit root test reveals that variables are integrated of order zero. Given this, it possible to employ the ARDL bounds test approach to assess the respective objectives of this study.

Table 4.20: Stationarity test for the financial indicators

Variable Name	Model Specification	DF - GLS Levels	DF - GLS 1st Diff.	CMR Break year	CMR Level	CMR 1st Diff.	Order
RER	Intercept	-1.134 (-1.994)	-3.656[b] (-1.944)	2017Q1	-4.010[b] (-3.560)	-	I(0)
	Trend & Intercept	-2.862[c] (-2.738)	-				
LnPSCE	Intercept	-0.132 (-1.944)	-2.726[b] (-1.944)	2009Q3 & 2014Q3	-2.186 (-3.560)	-3.610[b] (-3.560)	I(1)
	Trend & Intercept	-0.421 (-3.028)	-3.165[b] (-3.028)				
OIL	Intercept	-1.115 (-1.944)	-4.421[b] (-1.944)	2009Q1	-3.805[b] (-3.560)	-	I(0)
	Trend & Intercept	-2.345 (-3.028)	-4.353[b] (-3.028)				
SHARES	Intercept	-0.938 (-1.994)	-5.039[b] (-1.944)	2007Q3	-2.646 (-3.560)	-5.326[b] (-3.560)	I(1)
	Trend & Intercept	-4.293[b] (-3.029)	-				

Source: Own compilation

Note: a) [a], [b], [c] denotes the rejection of the null hypothesis of non-stationarity at 1%, 5%, and 10% critical levels, respectively. b) The values not in parenthesis are the t-statistics whilst those in parenthesis are the critical values based on MacKinnon's critical value. c) Wherever the t-statistics value is not denoted with plus signs, the 5% critical level is selected by default. d) Wherever the variable is stationary at all the levels of significance, the default critical value selected is also the 5% critical level.

Based on the stationarity test results presented in Table 4.20, the DF-GLS and CMR unit root test results reveal that there is a mixture integration of both order zero and order one amongst the financial indicator variables. For this reason, this study applies the ARDL bounds test approach to examine the specific aims pertaining to the financial indicators.

Table 4.21: Stationarity test for the institutional indicators

Variable Name	Model Specification	DF - GLS		CMR			Order
		Levels	1st Diff.	Break Year	Levels	1st Dif.	
VA	Intercept	-1.442 (-1.994)	-3.876^b (-1.944)	2015Q1	-4.142^b (-3.560)	-	I(0)
	Trend & Intercept	-1.749 (-3.028)	-4.816^b (-3.028)				
PS	Intercept	-1.983^b (-1.944)	-	1999Q3 & 2007Q3	-3.384 (-3.560)	-4.354^b (-3.560)	I(1)
	Trend & Intercept	-2.128 (-3.028)	-4.304^b (-3.028)				
CC	Intercept	-1.117 (-1.944)	-5.312^b (-1.944)	2003Q1	-4.250^b (-3.560)	-	I(0)
	Trend & Intercept	-2.634 (-3.028)	-2.225 (-3.028)				
RQ	Intercept	-0.905 (-1.944)	-6.032^b (-1.944)	2004Q1	-3.640^b (-3.560)	-	I(0)
	Trend & Intercept	-3.751^b (-3.028)	-				
GE	Intercept	-1.975^b (-1.944)	-	2019Q1	-4.633^b (-3.560)	-	I(0)
	Trend & Intercept	-3.271^b (-3.028)	-				
RL	Intercept	-2.669^b (-1.944)	-	2009Q1	-4.378^b (-3.560)	-	I(0)
	Trend & Intercept	-3.236^b (-3.028)	-				

Source: Own compilation

Note: a) ^{a}, ^{b}, ^{c} denotes the rejection of the null hypothesis of non-stationarity at 1%, 5%, and 10% critical levels, respectively. b) The values not in parenthesis are the t-statistics whilst those in parenthesis are the critical values based on MacKinnon's critical value. c) Wherever the t-statistics value is not denoted with plus signs, the 5% critical level is selected by default. d) Wherever the variable is stationary at all the levels of significance, the default critical value selected is also the 5% critical level.

Table 4.21 contains the stationarity test results for the institutional indicators. Based on the DF-GLS unit root test results, there is an integration mixture of order zero and order one in the institutional indicators. In contrast, the CMR unit root test shows the political stability (PS) variable of being integrated of order one, while the rest of the variables are order zero. Therefore, the ARDL bounds test approach is conducted to analyse the effects of the institutional indicators on NPL.

4.3.5 Cointegration test results

The ARDL bounds test is applied to examine the impacts that the macroeconomic indicators, bank specific indicator, monetary indicator, interest rate indicators, financial indicators and institutional indicators have on NPL ratios of Namibia's banking sector. Tables 4.23 to 4.30 presents the results of the ARDL bounds test for cointegration based on Equations 4.0, 4.2, 4.5, 4.8, 4.11, 4.14, 4.14 and 4.17, respectively. In each case, the optimal lag length was based on the Schwarz-Bayesian Information criterion:

Table 4.22: ARDL bounds test results for all the models

Model	Level of Significance	Critical Value		F-Statistics	*k*
		Lower Bound	Upper Bound		
Composite	1%	3.15	4.43	4.00^{b}	6
	5%	2.45	3.61		
	10%	2.12	3.23		
Macroeconomic	1%	3.15	4.43	8.75^{a}	6
	5%	2.45	3.61		
	10%	2.12	3.23		
Bank specific	1%	2.96	4.26	10.37^{a}	7
	5%	2.32	3.5		
	10%	2.03	3.13		
Monetary	1%	4.29	5.61	7.15^{a}	3
	5%	3.23	4.35		
	10%	2.72	3.77		
Interest rate	1%	3.74	5.06	12.43^{a}	4
	5%	2.86	4.01		
	10%	2.45	3.52		
Financial	1%	2.25	3.86	18.77^{a}	5
	5%	2.06	3.24		
	10%	1.83	2.94		
Institutional	1%	2.79	4.1	4.04^{a}	7
	5%	2.22	3.39		
	10%	1.95	3.06		

Source: Own compilation

Note: a) ^{a}, ^{b}, ^{b} means the rejection of null hypothesis of no cointegration at 1%, 5%, and 10% levels of significance, respectively. b) The critical values presented are the ones provided by Pesaran et al. (2001). Case III, which is based on the unrestricted constant without a trend is used. c) k is the number of independent variables present under each model.

The results contained in Table 4.22 reveal that the computed F-Statistics value of the macroeconomics, bank specific, monetary, interest rate, financial and institution model is greater than the upper critical bound at all levels of significance. As a result, the null hypothesis of no cointegration is safely refuted, which implies that there is a stable long run cointegrating relationship among the six categories of indicators and the ratio of NPL in Namibia.

4.3.6 Unravelling the determinants of NPL and the causal dynamics variables

The establishment of cointegration in each of the seven models forms the basis for estimating the long- and short run effects that the regressors exert on NPL. The outcomes, presented on Tables 4.23 to 4.36, are the basis upon which the first two objectives pertaining to this study are premised, as well as the test for causality. The discussions for both the long- and short run estimations are presented beneath each table.

4.3.6.1 Analysis of the overall NPL model with the composite indices

The empirical estimations for the composite model (consisting of the *macroeconomic, bank specific, monetary, interest rate, financial, and institutional indices*) is estimated to provide a more comprehensive insight of the indicators influencing NPL. Through the ARDL framework the first and second specific objective spelt out in chapter one is assessed. In specific terms, this means that the long- and short run effects, causality effects, as well as the diagnostic tests, are evaluated. The results are presented in Table 4.23.

Table 4.23: ARDL results for the impact of the composite indices on NPL

A. Short run dynamics. Regressand:			ΔlnNPL	B. Long run dynamics. Regressand:			*ln*NPL
Regressors	Coeff	Std. Error	Prob.	Regressors	Coeff.	Std. Error	Prob.
ΔlnNPL(-1)	1.301[a]	0.141	0.000	*ln*MACRO	-0.626	0.239	0.010[a]
ΔlnMACRO	-0.130[a]	0.047	0.000	*ln*BANK	-0.231	0.297	0.438
ΔlnMACRO(-1)	0.135b	0.046	0.027	*ln*MONE	-0.050	0.629	0.936
ΔlnBANK	0.039	0.055	0.472	*ln*INTER	1.026[a]	0.304	0.001[a]
ΔlnMONE	-0.103	0.161	0.791	*ln*FINA	0.534	0.776	0.494
ΔlnINTER	0.210[c]	0.071	0.062	*ln*INST	-0.065	0.392	0.868
ΔlnINTER(-1)	-0.189[a]	0.084	0.027				
ΔlnFINA	-0.043	0.161	0.791				
ΔlnINST	0.112[a]	0.051	0.008				
ECT(-1)	-0.721[a]	0.198	0.000				
C	0.006	0.012	0.593				
Short run diagnostic tests		Statistics	F-Stats	LM	JB	HET	RESET
Adjusted R^2	0.667	F-Stats	21.234	0.902	245.674	7.345*	0.008
DW-Stats.	2.154	*p*-value	0.000	0.410	0.000	0.000	0.928

Source: Own compilation

*Note: a) The term Δ denotes the first difference; ln = natural logs; [a, b, c] denotes the 1%, 5%, and 10% significant levels, respectively. b) DW = Durbin-Watson; Stats. = Statistics; LM=Breusch-Godfrey Serial Correlation LM Test; JB=Jarque-Bera statistics; HET=Breusch-Pagan-Godfrey' test for Heteroskedasticity; *implies that heteroskedasticity has been accounted for by the White-Hinkley heteroskedasticity test which provides consistent standard errors and covariance; RESET=Ramsey' test for functional misspecification.*

According to Table 4.23, the long run estimation tests show that a 1% rise in the *macroeconomic (MACRO) index* is estimated to lead to a 0.63% fall in NPL, other factors being constant. The fact that the *MACRO index* is inversely related to NPL underscores the importance of ensuring a sound and stable macroeconomic environment. On the other hand, a 1% rise in the *interest rate (INTER) index* is found to cause an increase in NPL by 1.02%, ceteris paribus. The findings for the *MACRO* and *INTER index* are statistically significant and consistent with the logical arguments of Vogiazas and Nikolaidou (2011) and Ranjan and Dhal (2003).

The outcome of the *MACRO index* (which according to loadings presented in Table B1.2 of Appendix B is influenced by debt stock, *inflation*, *unemployment*, and *trade openness*) is as expected. The result shows that previous economic gains are indeed useful in safeguarding the present assets' quality of the loan portfolios of not only the banking sector, but the financial system as a whole. In the same vein, it is worth stressing that although previous macroeconomic conditions have been key in stabilising the Namibian banking sector, it has not been entirely successful in reducing the country's appetite for debt accumulation nor has it been able to reverse the course of unemployment or ameliorate the degree of trade openness.

In the short run, the results of the Error Correction Term (ECT) is recorded to bear the correct negative sign which is also statistically significant at 1% level; implying that a short run disequilibrium caused by a shock in the system will cause the system to realign itself back into a long run equilibrium, at a fast speed of about 72.1%. The short run coefficient estimation results reveal that the previous quarter NPL, present quarter MACRO index, previous quarter MACRO index, previous quarter INTER index and present quarter INST index are statistically significant in influencing the ratio of NPL in the present quarter.

More specifically, the result indicates that a 1% rise in the previous quarters of NPL causes NPL in the present quarter to rise by 1.30%, ceteris paribus. This result suggests that NPL was persistent during the period of this study. This finding is not unique to this study as it has also been confirmed by numerous studies undertaken in the same area at hand including Rosenkranz and Lee (2019), Radivojevic and Jovovic (2017), and Rajha (2017), to mention but a few. Similarly, a 1% rise in the MACRO index was estimated to causes a 0.21% rise in NPL, other factors being constant. The values of both the present and past quarter of the macroeconomic (MACRO) index are found to have a symmetrical effect. In particular, the result shows that a 1% rise in the past MACRO index, a representative of the current macroeconomic environment, leads to a rise in about 0.135% in NPL. However, this is almost reversed in the current quarter, as a 1% rise in MACRO is said to improve the quality of the loan portfolio by 0.13.%.

The previous INTER index is found to inversely influence NPL. The result shows that a 1% rise in INTER leads to a 0.19% decline in NPL, ceteris paribus. In other words, an increase in the prevailing rate of interest causes the quality of the banking sectors' loan portfolio to appreciate. This is possibly due to the fact that both the new and old borrowers become a bit more cautious in not wanting to indebt themselves at unnecessarily costly interest rates. On the financial institutions' side, they will make sure that their credit standards are beefed up to the point where bad debtors are barred from accessing the loans. Ultimately, it causes the quality of their loan portfolio to rise. The outcome of the INTER index is in alignment with those gotten by Arham

(2020), but they are not in line with the outcomes of Ranjan and Dhal (2003) and Ćurak et al. (2013), who, respectively, concluded that changes in the expected higher interest rate causes NPL to rise.

The *institutional (INST) indicator*, in its current quarter, was found to be directly related to NPL in the current quarter. Specifically, the finding shows that a 1% rise in the institutional indicator is associated with a 0.11% rise in NPL. This result is quite interesting as it contradicts the a priori of what would normally be expected. The findings seem to suggest that a rise in the INST index endanger the successful operation of banks, thereby dampening the asset quality of the loan portfolios of banks in Namibia. The result also insinuates that there could be a number of policies that could be proving to be ineffective in regulating the banking sector, thereby endangering the quality of the loan portfolios in the country's banking system.

Zooming into the results of the principal components of the institutional index (See Table G1 in Appendix G), it is evident that the inefficiency of the indicator is being mainly dominated by the control of corruption, followed by the regulatory quality, anti-corruption commission, and government effectiveness measures. Despite Namibia being ranked the 8th (out of a total of 54 African countries) in terms of overall governance, its overall performance has declined (Mo Ibrahim Foundation, 2023). Therefore, there is still much room for improvement, especially in areas such as those just mentioned. Therefore, the finding that the improvements in institutional factors lead to rising NPL contradicts Bayar (2019) and Tanasković and Jandrić (2015)'s results, in which they concluded that the more institutionally developed a country's banking system is, the lower NPL should be maintained within reasonable bounds.

With regards to the long run causal relationship, it is firstly inferred through the coefficient of the Error Correction Term (ECT) found in Table 4.23. Since the coefficient of the ECT is negative and statistically significant at 1% level, it is safe to conclude that the statistically significant variables estimated using the model Equation 4.0*b* are causally related with NPL in the long run. On the other hand, the short run causality is evaluated through the regressors' *t*-statistics, that are statistically significant. Since the probability values of NPL(-1), MACRO, MACRO(-1), INTER(-1), and INST are statistically significant at 5% level, it is right to conclude that in the short run, there is a strong causal effect running from these variables to NPL. Tables 4.18 contains the pairwise Granger causality test results obtained through the VAR model, using Equation 4.1a and 4.1b.

With regards to the long run causal relationship, it can be inferred through the coefficient of the Error Correction Term (ECT) presented in Table 4.23. Since the coefficient of the ECT is negative and statistically significant at 1% level, it is safe to conclude that there is a long run causal effect between the variables in the long run. On the other hand, the short run causality, evaluated through the significance of the regressors' *t*-statistics, shows that the null hypothesis of no causality going from NPL(-1), MACRO, MACRO(-1), INTER(-1), and INST to NPL is rejected. On this basis, it is safe to concluded that in the short run, there is a strong causal effect running from the NPL(-1), MACRO, MACRO(-1), INTER(-1), and INST to NPL.

Table 4.24 contains the pairwise Granger causality test results required to validate the direction of causality reached using the ECM framework. The test results are obtained using the VAR model Equation 4.1a and 4.1b.

Table 4.24: Pairwise Granger causality test results for the composite model

Null hypothesis:	*Lag: 1 Quarter*		
	Obs.	*F-Stat.*	*P-value*
*ln*MACRO does not GC *ln*NPL	103	5.465	0.021[b]
*ln*NPL does not GC *ln*MACRO		1.378	0.243
*ln*BANK does not GC *ln*NPL	103	0.509	0.477
*ln*NPL does not GC *ln*BANK		0.174	0.678
*ln*MONE does not GC *ln*NPL	103	2.004	0.160
*ln*NPL does not GC *ln*MONE		1.165	0.283
*ln*INTER does not GC *ln*NPL	103	0.159	0.691
*ln*NPL does not GC *ln*INTER		6.247	0.014[b]
*ln*FINA does not GC *ln*NPL	103	1.969	0.164
*ln*NPL does not GC *ln*FINA		0.637	0.427
*ln*INST does not GC *ln*NPL	103	1.726	0.192
*ln*NPL does not GC *ln*INST		3.419	0.067[c]

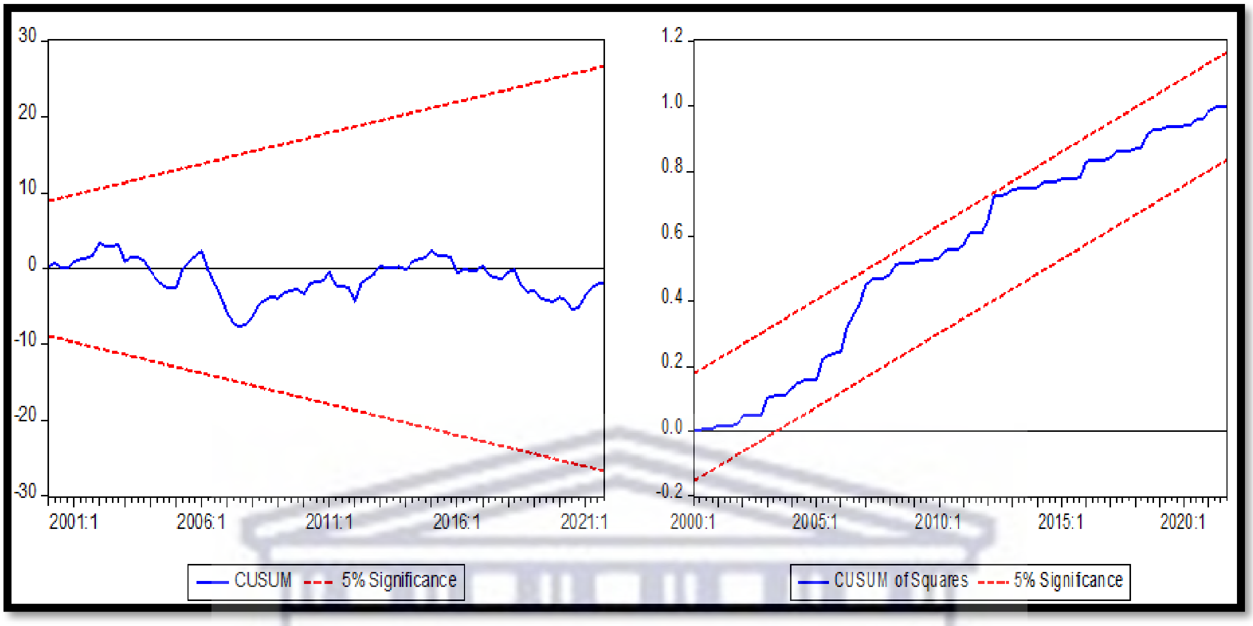
Source: Own compilation

Note: a) ln = natural logs; [a], [b], and [c] denote the 1%, 5% and 10% significant levels, respectively.

The results in Table 4.24 complements those obtained through the ECM framework and they are used to determine the nature and direction of short run causality in the model. The results relate to the causality that might exist between the credit risk (NPL) variable and indicators employed in the composite model. The results confirm a unidirectional causal relationship ranging from the macroeconomic (MACRO) indicators to NPL. The rest of the indicators are not helpful in predicting NPL. Therefore, just as in Sheefeni (2015b), the macroeconomic environment is a crucial factor for the performance of NPL in Namibia. For this reason, the variables reported to exert a greater loading in the constructed MACRO index must be cautiously monitored. This vigilance is necessary to ensure the quality of the Namibian banking sector loan portfolio. There is also a unidirectional causality running from NPL to the INTER index, as well as from NPL to the INST index.

The diagnostic checks based on the residual of the short run model indicates that the F-statistic of about 21.2% is statistically significant, entailing the model in use is robust. This result is further supported by the Ramsey RESET test results which ascertains that the model's functional form is correctly specified as the null hypothesis of functional form is not rejected, since the p-value is greater than 5% significant level. On the other hand, the Durbin-Watson (DW) statistics is close to two (2.15), which is an indication that the model does not suffer from first order autocorrelation. The conclusion of not autocorrelation is further augmented by the Breusch-Godfrey LM test results, which indicate a non-rejection of the null hypothesis of no serial correlation as its p-value (0.410) is greater than the 5% level of significance. The estimated model accounted for Heteroskedasticity by employing robust standard errors. Considering that the sample size utilised was relatively large, the asymptotic property for normality is relevant. Finally, to ensure that the estimated model is valid and reliable, the model's stability is evaluated through the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ) tests. The test results are presented in Figure 4.9.

Figure 4.9: Stability tests: CUSUM and CUSUMSQ



Source: Own compilations

Results from Figure 4.9 show that the short run model is stable as the critical bands in both plots are within the bounds of the 5% significance level. Hence, the results presented in these models are valid and reliable.

4.3.6.2 Analysis of the NPL model with the macroeconomic indicators

In this section, Equation 4.4*a* is estimated in order to obtain the long run coefficient, short run coefficients, diagnostic tests using the ARDL technique. The optimal lag length for the selected error correction representation of the ARDL (1, 1, 1, 0, 1, 1, 1, 0) model has been determined by the Schwarz-Bayesian Information Criterion (SC). Table 4.25 presents the long- and short run effects of the macroeconomic indicators on the ratio of NPL in Namibia. The diagnostic tests for the short run model are also presented in the bottom panel of the table.

Table 4.25: ARDL results for the effects of the macroeconomic indicators on NPL

A. Short run Dynamics. Regressand: ΔlnNPL				B. Long run Dynamics. Regressand: lnNPL			
Regressors	Coeff.	Std. Error	Prob.	Regressors	Coeff.	Std. Error	Prob.
ΔlnNPL(-1)	0.976[a]	0.089	0.000	lnOPEN	-1.371	1.145	0.316
ΔlnOPEN	1.983[a]	0.537	0.000	lnDEBT	0.018	0.352	0.948
ΔlnOPEN(-1)	-2.162[a]	0.433	0.000	lnGAP	1.556[b]	0.754	0.019
ΔlnDEBT)	0.303[b]	0.103	0.004	lnUN	3.358[b]	0.960	0.025
ΔlnDEBT(-1)	-0.263[b]	0.080	0.001	lnHP	-0.649[a]	0.170	0.000
ΔlnGAP	0.080	0.079	0.312	lnINF	0.324	0.258	0.281
ΔlnUN	-1.088[a]	0.449	0.018				
ΔlnUN(-1)	1.601[a]	0.353	0.000				
ΔlnHP	0.128[a]	0.043	0.004				
ΔlnHP(-1)	-0.178[a]	0.037	0.000				
ΔlnINF	-0.290[a]	0.113	0.012				
ΔlnINF(-1)	0.372[a]	0.089	0.000				
ECT(-1)	-0.425[a]	0.107	0.000				
C	0.001	0.006	0.830				

Short run diagnostic tests		Statistics	F-Stats	LM	JB	HET	RESET
Adjusted R^2	0.774	F-Stats	27.593	0.146	37.325	1.036	3.874
DW- Stats	1.893	p-value	0.000	0.863	0.000	0.424	0.052

Source: Own compilation

Note: a) The term Δ denotes the first difference; ln = natural logs; [a, b, c] denotes the 1%, 5% and 10% significant levels, respectively. b) DW = Durbin-Watson; Stats. = Statistics; LM=Breusch-Godfrey Serial Correlation LM Test; JB=Jarque-Bera statistics; HET=Breusch-Pagan-Godfrey' test for Heteroskedasticity; RESET=Ramsey' test for functional misspecification.

The results from Table 4.25 show that in the long run the output gap (GAP), unemployment rate (UN) and house price index (HP), all in their natural logarithm, are statistically significant. More precisely, in the long run the GAP and UN were found to positively affect the levels of NPL ratio in Namibia's banking sector, while HP had a negative effect on NPL. This simply means that a 1% increase in GAP, causes the ratio of NPL to increase by 1.55% over the long run, ceteris paribus. This implies that when the country's economy is not operating at full capacity of the factors of production, the output gap tends to rise.

Thus, it is in the country's economic interest to narrow the output gap so that the ratio of NPL is suppressed. Likewise, the results also insinuate that a 1% rise in UN leads to a 3.35% rise in the ratio of NPL over the long run, ceteris paribus. For this reason, any governmental effort aimed at combatting unemployment should be perceived as a noble duty that can safeguard the financial stability of the country. On the other hand, a 1% increase in HP is expected to cause a decline of 0.64% in the ratio of NPL over the long run, ceteris paribus. These findings are all in line with the a priori expectations and the empirical findings advocated by some researchers (Alrfai et al., 2022; Canepa & Khaled, 2018; Radivojevic & Jovovic, 2017) as discussed in Section 4.3.2.

In the short run, except for the output gap, the rest of the macroeconomic indicators are statistically significant in influencing the ratio of NPL in Namibia's banking sector. The macroeconomic variables found to have a positive effect on the ratio of NPL were the: ratio of NPL in the previous quarter (NPL (-1)), trade openness (OPEN), debt to GDP ratio (DEBT), UN from the previous quarter (UN (-1)), HP, and the rate of inflation from previous quarter (INF (-1)). On the contrary, previous quarter OPEN (-1), previous quarter DEBT (-1), UN, HP (-1) and INF were found to bear a negative effect on the ratio of NPL.

More specifically, a 1% increase in the past ratio of NPL in the previous quarter leads to a 0.97% increase in the ratio of NPL in the present period, an indication that credit risk is persistent and habitual. The fact that the lagged logarithm value of NPL is statistically significant and is positively related to the ratios of NPL in the present period is evidence that the occurrence of NPL has a prolonged effect on Namibia's banking sector. This outcome is supported by numerous studies (Gaur et al., 2022; Koju et al., 2018; Radivojevic & Jovovic, 2017, amongst others) on the subject matter at hand.

A 1% increase in trade openness (OPEN) in the previous quarter, ceteris paribus, is reported to lead to a 2.16% decline in NPL in the current quarter. However, in the current quarter, a 1% increase in OPEN is reported to lead to a 1.98% rise in the ratio of NPL levels. Despite the undesirability of the second outcome, it is not such a big concern as its increase does not completely offset the gains of the previous quarter. In other words, the margin of appreciation in the quality of the loan portfolio in the previous quarter is higher than the depreciations experienced in the present quarter. The latter outcome is nevertheless in line with what Mpofu and Nikolaido (2018) found, when they argued that a country with a higher degree of openness has a large degree of exposure to credit risk.

Normally, it is expected that as a country's degree of openness rises, the economic opportunities for its citizens increase, which enables them to be in a better position to service their debt obligation. However, this appears not to be the case for Namibia, partly because for many years the country has recorded unfavourable imbalances in terms of trade as it heavily relies on imports from South Africa (over 60% imports of goods and services), which imports also exceed the level of exports.

A 1% increase in the ratio of debt to GDP (DEBT) in the previous quarter is recorded to decrease the ratio of NPL by 0.26%. However, the appreciation is reversed in the current quarter, as the results indicate that a rise in DEBT causes the ratio of NPL to rise by 0.30%. Clearly, the increase in the present quarter is of much larger effect, which highlights how important the issues of debt accumulation is to a country's financial stability. This result is very plausible as it suggests that a rise in sovereign debt levels increases NPL and if care is not exercised it can destabilise the solidity of a country's financial system over the short run. The results are comparable with those obtained by Gashi (2021) and Us (2017) using the data from Poland and Turkey respectively.

With regards to the output gap (GAP), despite it being statistically significant in the long run, it was found to be statistically insignificant in the short run. This is indicative of the fact that it is not much of an issue over the short run horizon.

A 1% rise in the past rate of unemployment (UN) causes the ratio of NPL to rise by 1.60%, holding other factors constant. In the current period, a 1% rise in it is found to decrease the levels of NPL by 1.08%. The appreciation experience in the current quarter is considered insufficient to offset the deteriorations caused in the previous period. Hence it is safe to conclude that overall, a rise in UN is found to deteriorate the quality of the loan portfolio. This outcome is congruent with the a *priori* and the findings of researchers, such as Gashi (2021), Kjosevski et al., (2019), Canepa and Khaled (2018), and Radivojevic and Jovovic (2017), to mention but some..

Similarly, a 1% rise in the housing price index (HP) in the previous quarter is reported to be associated with a decline in the NPL by 0.18%, ceteris paribus. However, in the current quarter an increase in HP causes NPL to rise by 0.13%. The latter outcome, which correlates with Canepa and Khaled (2018)'s findings, is not surprising considering that over the years, Namibia has experienced a high credit demand for mortgage financing. The surge in this demand, if not tamed, may lead to serious credit risk for the banking and financial system. Looking forward, housing prices are expected to ease down, especially with the looming election campaigns in 2024.

Concerning the rate of inflation, just as expected, the outcomes of the previous quarter and the current quarter are ambiguous. The result indicates that, in the short run, a 1% rise in the rate of inflation of the previous quarter causes NPL to rise by 0.37%, all factors being the same. However, in the present quarter, a 1% rise in NPL leads to a decline of 0.29% in current NPL ratios. Despite the decline experienced in NPL in the current quarter, it is not sufficient to override the deterioration caused in the previous period. For this reason, it is safe to surmise that a rise in inflation has a negative implication on the asset quality of Namibia's loan portfolio. This outcome is not unique to Namibia, as Wood and Skinner (2018) and AlizadehJanvisloo and Muhammad (2013) found similar results while using data from Barbados and Malaysia, respectively.

Regarding the long run causal relationship, it is primarily inferred through the coefficient of the Error Correction Term (ECT) presented in Table 4.25. Since its coefficient is negative and statistically significant at 1% level, it is concluded that the statistically significant variables, examined using the model Equation 4.4*a* are causally related with NPL in the long run. On the other hand, the short run causality test results, evaluated through the significance of the regressors' *t*-statistics, show that the null hypothesis of no causality going from NPL(-1), OPEN, OPEN(-1), DEBT, DEBT(-1), UN, UN(-1), HP, HP(-1), INF and INF(-1) to NPL is rejected at 1% significant level. On this basis, it is safe to conclude that in the short run, there is a strong causal effect running the listed variables to NPL.

Table 4.26 contains the pairwise Granger causality test results required to authenticate the direction of causality obtained through the ECM framework. The test results are obtained by employing the VAR model Equations 4.4*b* and 4.4*c*.

Table 4.26: Pairwise Granger causality test results for the model with macroeconomic indicators

Null Hypothesis:	*Lags: 2 Quarters*		
	Obs.	*F-Stat.*	*P-value*
*ln*OPEN does not GC *ln*NPL	102	1.902	0.155
*ln*NPL does not GC *ln*OPEN		3.019	0.054[c]
*ln*DEBT does not GC *ln*NPL	102	0.159	0.853
*ln*NPL does not GC *ln*DEBT		0.196	0.823
*ln*GAP does not GC *ln*NPL	102	1.448	0.240
*ln*NPL does not GC *ln*GAP		0.906	0.408
*ln*UN does not GC *ln*NPL	102	4.040	0.021[b]
*ln*NPL does not GC *ln*UN		0.282	0.755
*ln*HP does not GC *ln*NPL	102	5.462	0.006[a]
*ln*NPL does not GC *ln*HP		0.238	0.789

Source: Own compilation

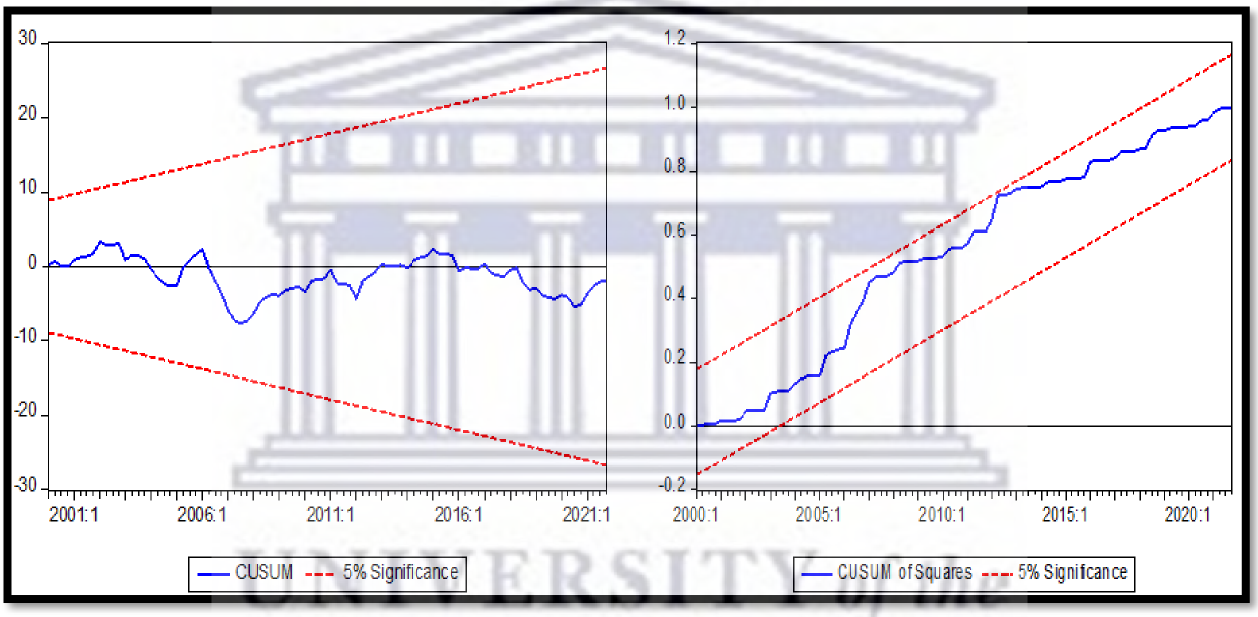
Note: a) ln = natural logs; [a, b, c] denotes the 1%, 5% and 10% significant levels, respectively. GC stands for Granger cause.

The results contained in Table 4.26, which simply complement those obtained through the ECM framework show that, a very strong unidirectional causal relationship springing from the housing prices index (HP), a proxy for the Namibian housing market, to NPL and from unemployment rate (UN) to NPL. On the contrary, NPL is reported to mildly Granger cause trade openness (OPEN) in Namibia. The rest of the indicators do not help predict the behavioural patterns of NPL.

The diagnostics test results presented in the bottom section of Table 4.25, show that the error correction term (ECT) of the short run model reaffirms the existence of a cointegrating relationship between NPL and the macroeconomics variables employed. Put simply, the ECT value of -0.425 implies that the adjustment process to equilibrium process in the long run is approximately 42.5%. The adjusted R-squared of 0.774, implies that 77.4% of the variations in the ratios of NPL is explained by the macroeconomic variables used in the specified model equation.

The F-statistic of about 27.6%, which is statistically significant, indicates that the specified model is robust and this is further supported by the results of the Ramsey RESET test, which ascertains that the model's functional form is correctly specified. On the other hand, the Durbin-Watson (DW) statistics (1.893) are close to two, which means that the model does not suffer from first-order autocorrelation. The conclusion of no autocorrelation in the model is further supported by the Breusch-Godfrey LM test results, which rule out that there is no serial correlation in the model since the p-value (0.863) is greater than 5% significant level, causing one to fail to reject the null hypothesis of autocorrelation. The estimated model does not suffer from heteroskedasticity since the p-value (0.424) is greater than the 5% significant level. Given that the sample size utilised was relatively large, the asymptotic property for normality was applied. Lastly, to ascertain the robustness of the estimated model, Figure 4.10 presents the model stability test conducted through the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ) tests.

Figure 4.10: Stability Tests: CUSUM and CUSUMSQ



Source: Own compilations

Results from Figure 4.10 show that the short run model is stable as the critical bounds in both plots are within the bound of the 5% significance level. Hence, the results presented in these models are reliable and robust.

4.3.6.3 Analysis of the NPL model with the bank specific indicators

In this section, Equation 4.7*a* is estimated in order to obtain the long- and short run coefficients using the ARDL technique. The optimal lag length for the selected error correction representation of the ARDL (1, 1, 1, 1, 0, 1, 0, 0) model has been determined by the Schwarz-Bayesian Information Criterion (SC). Table 4.27 presents the long- and short run effects of the bank specific indicators on the ratio of NPL in Namibia. The diagnostic tests for the short run model are also presented in the bottom panel of the Table.

Table 4.27: ARDL results for the effects of the bank specific indicators on NPL

A. Short run dynamics. Regressand:			ΔNPL	B. Long run dynamics. Regressand:			NPL
Regressors	Coeff.	Std Error	Prob.	Regressors	Coeff.	Std. Error	Prob.
ΔNPL(-1)	1.127[a]	0.120	0.000	ROA	-22.942[c]	11.921	0.057
ΔROA	1.383	0.934	0.142	*ROE*	2.234[c]	1.105	0.046
ΔROA(-1)	-2.599[a]	0.536	0.000	CAR	-1.726	1.105	0.103
ΔROE	-0.165[c]	0.091	0.072	LB	0.701	0.336	0.044
ΔROE(-1)	0.267[a]	0.053	0.000	*ln*NIM	-12.296	7.958	0.126
ΔCAR	-1.105[a]	0.307	0.001	LDR	0.496[b]	0.220	0.027
ΔCAR(-1)	1.255[a]	0.233	0.000	LG	-0.370[b]	0.176	0.038
ΔLB	0.269[a]	0.082	0.001				
ΔLB(-1)	-0.294[a]	0.103	0.005				
Δ*ln*NIM)	-0.359	0.896	0.689				
ΔLDR	0.097[a]	0.026	0.000				
ΔLDR(-1)	-0.080[a]	0.025	0.002				
ΔLG	0.004	0.042	0.924				
ECT(-1)	-0.657[a]	0.115	0.000				
C	0.021	0.029	0.481				
Short run diagnostic tests		Statistics	F-Stats	LM	JB	HET	RESET
Adjusted R^2	0.782	F-stats	26.879	0.938	439.064	44.899*	1.836
DW- Stats.	2.160	*p*-value	0.000	0.396	0.000	0.000	0.069

Source: Own compilation

*Note: a) The term Δ denotes the first difference; ln = natural logs; [a, b, c] denotes the 1%, 5%, and 10% significant levels, respectively. b) DW = Durbin-Watson; Stats. = Statistics; LM=Breusch-Godfrey Serial Correlation LM Test; JB=Jarque-Bera statistics; HET=Breusch-Pagan-Godfrey' test for Heteroskedasticity; *implies that heteroskedasticity has been accounted for by the White-Hinkley heteroskedasticity test which provides consistent standard errors and covariance; RESET=Ramsey' test for functional misspecification.*

The results presented in Table 4.27 reveal that, over the long run, the return on assets (ROA), return on equity (ROE), lending behaviour (LB), loan-to-deposit ratio (LDR), and loan growth (LG) were found to be statistically significant. More specifically, in the long run the ROE, LB, and LDR were found to be positively related to the ratios of NPL, while ROA, CAR and LG were obtained to be negatively related to NPL.

In definite terms these results indicate that in the long run, a 1 unit rise in ROE is estimated to cause an increase of 2.23 units in NPL, ceteris paribus (cp). This finding implies that banks whose aim is to increase the returns on owners' equity tend to engage into riskier investment opportunities, that ends up destabilising the quality of the loan portfolio for Namibia's banking sector. A 1 unit increase in LB is projected to lead to a rise of 0.70 units in NPL, cp. This outcome suggests that risky lending behaviours of banks are associated with rising NPL in Namibia. This finding is in alignment with moral hazard hypothesis and confirms what Canepa and Khaled (2018) obtained when carrying out a similar investigation on a panel of twenty three countries. A 1 unit increase in LDR is found to causes a rise of approximately 0.50 units in the levels of NPL, cp. This result contradicts Koju *et al*.(2018a)'s stance in which the researchers contend that as banks extend more credit to the public, their interest earnings increase, which ends up increasing their profitability. This finding, along with that of LB, is not surprising considering the large concentration of banks' assets is largely made up of mortgages (Bank of Namibia, 2022; Bank of Namibia & NAMFISA, 2021). The finding that banks LDR exacerbates NPL is in alignment with the *a priori* expectation and the result obtained by Wood and Skinner (2018).

On the other hand, the results in Table 4.27 also show that in the long run, a 1 unit rise in ROA (a measure of banks' profitability) causes NPL to decline by 22.94 units, ceteris paribus (cp). Albeit, its influence is found to be statistically weaker, at 10% significance levels, when compared to that of the ROE (the other alternative measure of banks' profitability) at 5% significance levels. Thus, the outcome of ROA suggests that a strong banking sector performance minimises the tendency for banks to engage themselves in riskier investment adventures that end up minimising the phenomenon of NPL. A 1 unit rise in the rate of loan growth (LG) is found to cause an approximate decline of 0.04 units in NPL, cp. The finding is in accordance with what Rifat (2016) who argued that LG tends to exert a negative influence on NPL when the demand of loans subsides.

The ambiguity in the findings of the two profitability measures (ROA and ROE) can be dispelled even without using an interaction between the two measures. Considering that the ROA is weakly significant, the sign of the outcome of the interaction term is likely to be positive. The finding that ROE positively influences NPL contradicts the finding of an earlier study by Sheefeni (2015a) in Namibia. The contrast is likely due to the methodological differences, time frame of the series and the fact that author evaluated the two measures of banks' profitability in two separate models. Nevertheless, the finding of ROA is consistent with the a *priori* as well as the finding of previous empirical studies (Azar & Maaliki, 2018; Ghorbani & Jakobsson, 2019; Sheefeni, 2015a; Wood & Skinner, 2018).

In the short run, except for the ROA in the current quarter, the logarithm of net interest margin (NIM) and the loan growth (LG), the rest of the bank specific indicators were found to strongly (at the 1% significance level) influence the levels of NPL in Namibia's banking sector. Amongst them were the levels of NPL in the previous quarter, ROE in the previous quarters, capital adequacy ratio (CAR) in the previous quarter, banks' lending behaviour (LB) in the current quarter, and LDR in current quarter that were found to positively influence the levels of NPL. In more specific terms, a 1 unit rise in NPL in the previous quarter is estimated to cause an increase of 1.13 units in NPL itself, ceteris paribus (cp). A 1 unit increase in ROE in the previous quarter is estimated to cause a rise of 0.27 units in NPL, cp. A 1 unit rise in CAR in the previous quarter is expected to cause an increase of 1.26 units in NPL, cp. A 1 unit rise in LB in the current quarter is estimated to lead to a rise of 0.27 units in NPL, cp. Lastly, a 1 unit increase in LDR in the current quarter is projected to cause a rise of 0.10 units in NPL, cp.

Conversely, the bank specific indicators found to negatively influence on NPL over the short run include ROA in the previous quarter, ROE in the current quarters, CAR in the current quarter, LB in the previous quarter, and LDR in the previous. In particular, the findings indicate that a 1 unit rise in ROA in the previous quarter is estimated to cause a decline of 2.60 units in NPL, ceteris paribus (cp). A 1 unit rise in CAR in the current quarter is projected to cause a decline of 1.11 units in NPL, cp. A 1 unit rise in LDR in the prvious quarter is expected to cause a decline of 0.08 units in NPL, cp.

The aforementioned short-run results validate the fact that credit risk is a recurring, which could have a prolonged effect on the country's banking sector. This outcome is supported by past empirical studies (Gaur et al., 2022; Koju et al., 2018; Radivojevic & Jovovic, 2017, amongst others) on the subject of determinants of NPL. The finding that ROA in the previous quarter negatively influence NPL still supports the view that having a strong banking sector performance decreases the chance for banks to lured by risky investment activities. The fact that magnitude of CAR, a regulatory measure, in the previous quarter is larger than the CAR in the current quarter, indicates that, in Namibia, highly capitalised banks are more likely to heap up riskier investment that engender credit risk. The propensity for banks to engage in risky activities is mainly fuelled by issues pertaining to information asymmetric and moral hazards. LDR in the current quarter is found to destabilise NPL more than in the previous quarter, which is indicative of the fact that the consequences of rising NPL are expected to persist over the long run, as seen by the outcomes of the long run result.

Regarding the long run causal relationship, it is primarily inferred through the coefficient of the Error Correction Term (ECT) presented in Table 4.27. Since its coefficient is negative and statistically significant at 1% level, it is safe to conclude that the statistically significant variables evaluated using the model Equation 4.7*a* are causally related with NPL in the long run. On the other hand, the short run causality test results, evaluated through the significance of the regressors' *t*-statistics, show that there is causality going from the NPL(-1), ROA(-1), ROE, ROE(-1), CAR, CAR(-1), LB, LB(-1), LDR and LDR(-1) to NPL.

The results in Table 4.28 contains the pairwise Granger causality test results intended to affirm the direction of causality established by the ECM framework. The test results are estimated via the VAR model Equations 4.7*b* and 4.7*c*.

Table 4.28: Pairwise Granger causality test results for the model with the bank specific indicators

	Lags: 2 Quarters		
Null Hypothesis:	*Obs.*	*F-Stat.*	*P-value*
ROA does not GC NPL	102	0.739	0.480
NPL does not GC ROA		2.147	0.122
ROE does not GC NPL	102	1.609	0.205
NPL does not GC ROE		1.296	0.278
CAR does not GC NPL	102	4.329	0.016[b]
NPL does not GC CAR		0.201	0.818
LB does not GC NPL	102	0.138	0.872
NPL does not GC LB		2.658	0.075[c]
*ln*NIM does not GC NPL	102	0.303	0.739
NPL does not GC *ln*NIM		0.352	0.704
LDR does not GC NPL	102	1.613	0.205
NPL does not GC LDR		0.314	0.731
LG does not GC NPL	102	5.571	0.005[a]
NPL does not GC LG		0.038	0.963

Source: Own compilation

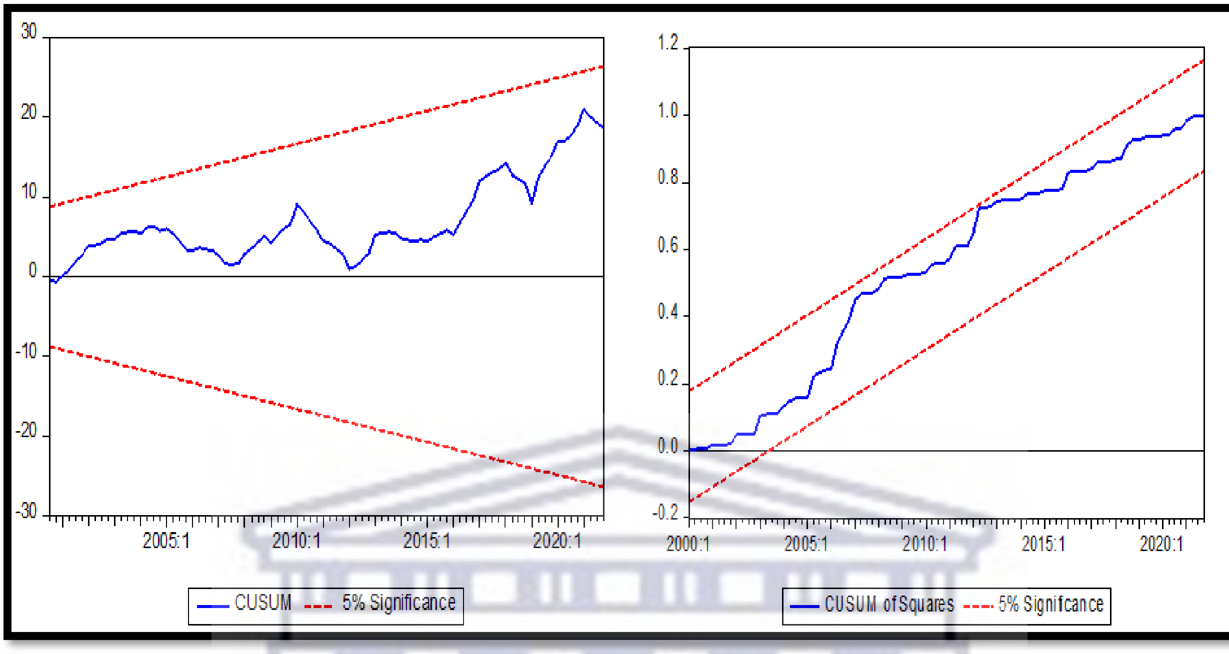
Note: a) ln = natural logs; [a, b, c] denotes the 1%, 5% and 10% significant levels, respectively. GC stands for Granger Cause.

The results contained in Table 4.28, simply complement those obtained through the ECM framework and they show that there is a strong unidirectional causal relationship running from the CAR, a proxy for measuring the capital strength of Namibia's banking system, to NPL and from LG to NPL. On the other hand, a weak unidirectional relationship running from NPL to LB is reported. The rest of the variables are found to be independent from predicting the futurist behavioural patterns of NPL.

The diagnostics test results provided in the bottom section of Table 4.27, show that the error correction term (ECT) of the short run model reaffirms the existence of a cointegrating relationship between NPL and the bank specific variables employed. Put simply, the ECT value of -0.657 implies that the adjustment process to equilibrium process in the long run is approximately 65.7%. The adjusted R-squared of 0.782, implies that 78.2% of the variations in the ratios of NPL is explained by the bank specific variables used in the specified model equation. The F-statistic of about 26.9%, which is also statistically significant, indicates that the specified model is robust and is further supported by the results of the Ramsey RESET test, which ascertains that the model's functional form is correctly specified.

The DW statistics (2.16) is around 2, which implies that the model does not suffer from first order autocorrelation. The conclusion of no autocorrelation in the model is further supported by the Breusch-Godfrey LM test results, which rule out that there is no serial correlation in the model since the p-value (0.396) is greater than 5% significant level, causing one to fail to reject the null hypothesis of autocorrelation. The error terms suffer from heteroskedasticity as the p-value (0.000) is found to be less than the 5% significant level, nevertheless the estimated model accounted for Heteroskedasticity by employing robust standard errors. Since the sample size used in this investigation is relatively large, the asymptotic property for normality is implied. Finally, Figure 4.11 presents the stability test results of the estimated model using both the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ) tests.

Figure 4.11: Stability tests: CUSUM and CUSUMSQ



Source: Own compilation

The results from Figure 4.11 show that the short run model used in this study is stable as the critical bounds in both plots are within the bound of the 5% significance level. Hence, the results presented in these models are reliable and robust.

4.3.6.4 Analysis of the NPL model with the monetary indicators

In this section, Equation 4.10*a* is estimated in order to obtain the long- and short run coefficients using the ARDL technique. The optimal lag length for the selected error correction representation of the ARDL (1, 1, 0, 0, 0, 0) model has been determined by the Schwarz-Bayesian Information Criterion (SC). Table 4.29 presents the long- and short run effects of the monetary indicators on the ratio of NPL in Namibia. The diagnostic tests for the short run model are also presented in the bottom panel of the Table.

Table 4.29: ARDL results for the effects of the monetary indicators on NPL

A. Short run Dynamics. Regressand:			ΔNPL	B. Long run Dynamics. Regressand:			NPL
Regressors	Coeff.	Std Error	Prob.	Regressors	Coeff.	Std. Error	Prob.
ΔNPL(-1)	1.125[a]	0.337	0.001	*ln*M1	28.966[c]	16.192	0.077

ΔlnM1	-10.811[b]	5.148	0.038	lnM2	-15.638[c]	9.026	0.086
ΔlnM1(-1)	13.735[b]	6.449	0.036	lnNFA	-16.286[c]	9.671	0.095
ΔlnM2	-1.556	2.038	0.447				
ΔlnNFA	-0.890	1.017	0.383				
ECT(-1)	-0.597[b]	0.253	0.020				
C	-0.023	0.079	0.429				
Short run diagnostic tests		Statistics	F-Stats	LM	JB	HET	RESET
Adjusted R^2	0.540	F-Stats	20.755	0.905	1784.736	14.445*	0.314
DW- Stats	2.088	p-value	0.000	0.408	0.000	0.009	0.314

Source: Own compilation

*Note: a) The term Δ denotes the first difference; ln=natural logs; [a], [b], [c] denotes the 1%, 5% and 10% significant levels, respectively. b) DW=Durbin-Watson; Stats. =Statistics; LM=Breusch-Godfrey Serial Correlation LM Test; JB=Jarque-Bera statistics; HET=Breusch-Pagan-Godfrey' test for Heteroskedasticity; * implies that heteroskedasticity has been accounted for by the White-Hinkley heteroskedasticity test which provides consistent standard errors and covariance; RESET=Ramsey' test for functional misspecification.*

The long run results presented on Table 4.29 illustrate that the monetary indicators employed in the model have been found to influence NPL, however their influence is weaker since they are statistically significant at 10% level. More distinctively, the findings reveal that a 1% rise in the narrow money supply is projected to cause a 0.29 units rise in NPL, ceteris paribus (cp). This usually happen whenever there is a wider gap between the repo rate and the interest rate (Asiama & Amoah, 2019), which is often the case in Namibia. This particular finding contradicts the result obtained by Vogiazas and Nikolaidou (2011) using data from Romania.

On the other hand, the M2 and the NFA are reported to exert a negatively influence on the ratio of NPL. More precisely, a 1 % rise in M2 causes a decline in NPL of 0.16 units, ceteris paribus (cp). This finding is consistent with Rifat (2016)'s finding and it could imply that whenever an expansionary monetary policy is effected, the levels of NPL of the banking sector is bound to decline due to a fall in the interest rate. Similarly, a 1% increase in NFA leads to a decline of 0.16 unit in NPL, cp. This finding insinuates that as the level of NFA rise, it leads to credit risk minimisation of the banking sector.

In the short run, NPL of previous quarter and M1 in both previous and current quarter were reported to be statistically significant in influencing the levels of NPL at 5% significance level. Notably, NPL (-1) was reported to be positively associated with NPL in the current period as a 1 unit rise in NPL in the previous quarter causes NPL to rise by 1.13 units, ceteris paribus (cp). Although M1 in the current quarter is found to negatively influence NPL, the fact that its magnitude in the previous quarter exceeds that of the current quarter, causes one to conclude that the influence of narrow money strongly positive which is bound to persist in the long run. The same conclusion was also reached by Gaur et al.(2022), Hajja (2022) and Koju et al. (2018b), to mention but a few.

At the same time, a 1% rise in M1 in the current quarter is estimated to reduce NPL by 0.11 units, ceteris paribus (cp). This is encouraging but not satisfying as its magnitude does not completely offset the deterioration incurred in NPL in the previous quarter which persists over the long run. The coefficient of NFA is negative as expected, however it is statistically insignificant. All in all, the monetary indicators are statistically significant in influencing NPL in Namibia's banking system.

Concerning the long run causal relationship, it is initially inferred through the coefficient of the Error Correction Term (ECT) presented in Table 4.29. Since its coefficient is negative and statistically significant at 5% level, it is safe to conclude that the statistically significant variables analysed using the model Equation 4.10*a* are causally related with NPL in the long run. In reference to the short run causality test, estimated through the significance of the regressors' *t*-statistics, the results show that there is a strong causal relationship going from NPL(-1), M1, and M1(-1) to NPL exist.

Tables 4.30 contains the pairwise Granger causality test results required to affirm the direction of causality conclusions obtained through the ECM framework. The test results have been obtained using the VAR model Equations 4.10*b* and 4.10*c*.

Table 4.30: Pairwise Granger causality test results for the model with monetary indicators

Null Hypothesis:	*Lags: 2 Quarters*		
	Obs.	*F-Stat.*	*P-value*
*ln*M1 does not GC *ln*NPL	102	1.15763	0.3185
*ln*NPL does not GC *ln*M1		0.2923	0.7472
*ln*M2 does not GC *ln*NPL	102	0.59698	0.5525
*ln*NPL does not GC *ln*M2		0.07188	0.9307
*ln*NFA does not GC *ln*NPL	102	0.71493	0.4918
*ln*NPL does not GC *ln*NFA		0.06884	0.9335
*ln*RGDP does not GC *ln*NPL	102	2.28768	0.107
*ln*NPL does not GC *ln*RGDP		1.88162	0.1579

Source: Own compilation

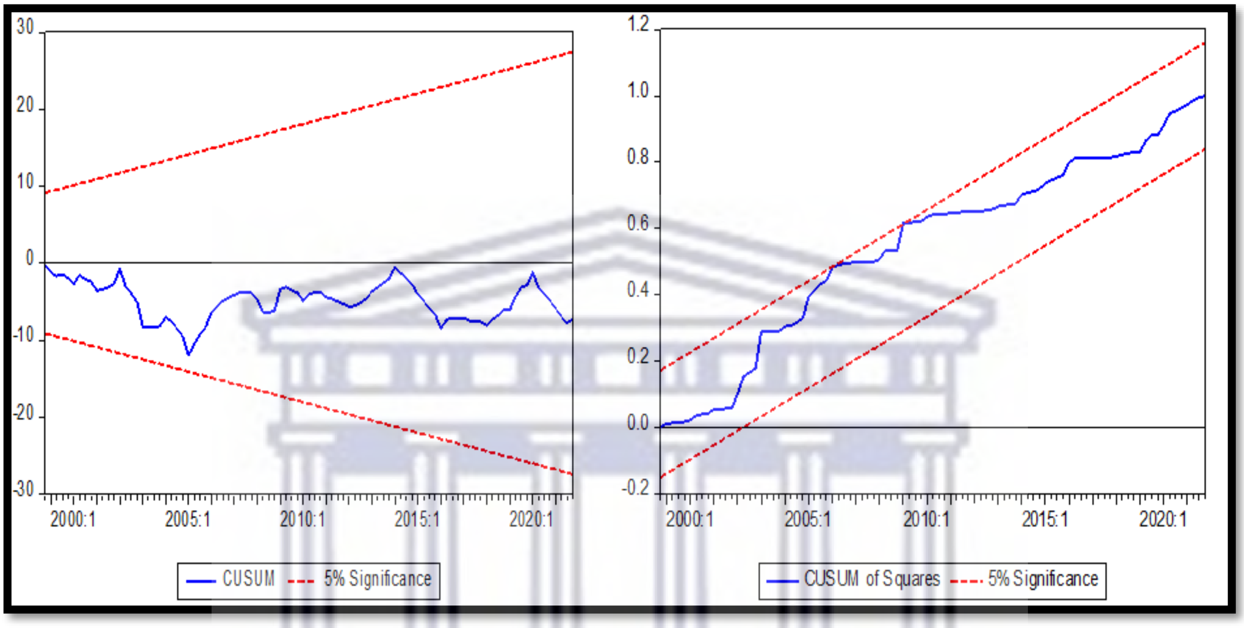
Note: a) ln = natural logs; [c] denotes the 10% significant levels, respectively. GC stands for Granger Cause.

The results contained in Table 4.30, simply show that monetary indicators do not Granger cause NPL and vice versa. Put differently, the monetary indicators are statistically independent from NPL.

The diagnostics test results availed in the bottom section of Table 4.29, show that the error correction term (ECT) of the short run model reaffirms the existence of cointegrating relationship between NPL and the monetary indicators. More precisely, the result of ECT indicates a speed of adjustment to equilibrium in the long run of about 60%. The adjusted R-squared of 0.540, entails that about 54% of the variations in the NPL ratios can be explained by the monetary variables used in the specified model equation. The *F*-statistic of about 20.76%, which is statistically significant, indicates that the specified model is robust, and this is furthermore supported by the results of the Ramsey RESET test, which ascertains that the model's functional form is correctly specified.

Moreover, the DW statistics is closer to 2, which means that the model does not suffer from first order autocorrelation. The conclusion of no autocorrelation in the model is further supported by the Breusch-Godfrey LM test results, which rule out that there is no serial correlation in the model since the p-value (0.408) is greater than 5% significant level, which enables one to fail to reject the null hypothesis of autocorrelation. The estimated model, although the initial estimations indicate that the model suffers from heteroskedasticity, since the p-value (0.009) is lesser than the 5% significant level, yet the estimated model accounted for Heteroskedasticity by using robust standard errors. Given that the utilised sample size is relatively large, the asymptotic property for normality holds. Ultimately, to ensure that the estimated model is valid and reliable, Figure 4.12 presents the models stability test results conducted through the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ) tests.

Figure 4.12: Stability Tests: CUSUM and CUSUMSQ



Source: Own compilations

Results from Figure 4.12 show that the short run model is stable as the critical bounds in both plots are within the bands of the 5% significance level. Hence, the results presented in these models are reliable and robust.

4.3.6.5 Analysis of the NPL model with the interest rate indicators

In this section, Equation 4.13a is estimated in order to obtain the long- and short run coefficients using the ARDL technique. The optimal lag length for the selected error correction representation of the ARDL (1, 1, 1, 1, 0, 0) model has been determined by the Schwarz-Bayesian Information Criterion (SC). Table 4.31 presents the long- and short run effects of the interest rate indicators on the ratio of NPL in Namibia. The diagnostic tests for the short run model are also presented in the bottom panel of the table.

Table 4.31: ARDL results for the effects of the interest rate indicators on NPL

A. Short run Dynamics.	Regressand:		ΔNPL	B. Long run Dynamics.	Regressand:		NPL
Regressors	Coeff.	Std Error	Prob.	Regressors	Coeff.	Std. Error	Prob.
ΔNPL(-1)	1.101[a]	0.152	0.000	REPO	-1.276[b]	0.540	0.020
ΔREPO	-1.624[a]	0.304	0.000	DEPO	0.661	0.703	0.349
ΔREPO(-1)	1.642[a]	0.319	0.000	IS	3.335[a]	0.686	0.000
ΔDEPO	3.103[a]	0.556	0.000	TBR	-0.352	0.421	0.405
ΔDEPO(-1)	-3.093[a]	0.589	0.000				
ΔIS	0.382	0.356	0.286				
ΔIS(-1)	-0.558[b]	0.177	0.011				
ΔTBR	-0.020	0.177	0.878				
ECT (-1)	-0.441[a]	0.124	0.004				
C	-0.005	0.020	0.820				
Short run diagnostic tests		Statistics	F-Stats	LM	JB	HET	RESET
Adjusted R^2	0.862	F-Stats	70.202	1.448	58.274	9.524*	20.140
DW-Stats	2.111	p-value	0.000	0.240	0.021	0.000	0.000

Source: Own compilation

Note: a) The term Δ denotes the first difference; [a] and [b] denote the 1% and 5% significant levels, respectively. b) DW = Durbin-Watson; Stats.=Statistics; LM=Breusch-Godfrey Serial Correlation LM Test; JB=Jarque-Bera statistics; HET=Breusch-Pagan-Godfrey' test for Heteroskedasticity; RESET=Ramsey' test for functional misspecification.

The long run results demonstrated on Table 4.31 show that the repo rate (REPO) and the interest spread (IS) are statistically significant in affecting NPL in Namibia. Notably, the results show that, over the long run, a 1unit rise in REPO causes a decrease of 1.28 units in NPL, ceteris paribus (cp). This finding insinuates that a tighter monetary policy (i.e., an increase in the repo rate) contributes to a reduction in credit risk. This is due to the fact that commercial banks in Namibia tend to be cautious in how they handle the borrowed funds from the Central Bank of Namibia in the face of higher repo rates, thereby improving the asset quality of the loan portfolio. Meanwhile, a 1 unit increase in interest spread is projected to cause a rise of 3.35 units in NPL, cp. This finding is congruent with what Koju et al. (2018b) concluded when examining the determinants of NPL in Nepal.

In the short run, the results reveal that, except for the interest spread and the treasury bill rate, the rest of the variables turned out to be statistically significant. More precisely, the findings show that a 1 unit rise in the levels of NPL in the previous quarter causes a rise of 1.10 units in NPL itself, ceteris paribus (cp). This result demonstrates that the build-up of NPL in Namibia habitual and persistent in nature. Likewise, a 1 unit increase of the REPO in the previous quarter, has a devastating effect of increasing NPL by 1.64 units, cp. Despite the improvements in the levels of NPL in the current quarter, brought about by a 1 unit rise in the REPO in the current quarter, it still does not completely undo the devastation of the previous quarter. A 1 unit increase in the DEPO in the previous quarter causes a decline of 3.09 units in NPL in the current quarter, ceteris paribus. The decline in NPL is short lived as a unit rise of DEPO in the current quarter appears to reverse the gains. The effect of DEPO on NPL in the previous quarter agrees with what Zheng et al. (2020) obtained using Bangladesh banking data. Finally, a 1 unit rise in interest rate spread in the previous quarter is recorded to cause a decline of 0.55 units in NPL in the current quarter, cp.

As for the long run causal relationship, it is first inferred through the coefficient of the Error Correction Term (ECT) presented in Table 4.31. Since the coefficient is found to be negative and statistically significant at 1% significance level, it is therefore right to conclude that the statistically significant variables evaluated using the model Equation 4.13*a* are causally related with NPL in the long run. On the other hand, the short run causality test results evaluated through the significance of the regressors' *t*-statistics, show that there is causal relationship going from NPL(-1), REPO, REPO(-1), DEPO, DEPO(-1), and IS(-1) to NPL.

Table 4.32 contains the pairwise Granger causality test results that are necessary to ascertain the direction of causality found by the ECM framework. The test results are obtained through the VAR model Equations 4.13*b* and 4.13*c*.

Table 4.32: Pairwise Granger causality test results for the model with the interest rate indicators

Null Hypothesis:	*Lags: 2 Quarters*		
	Obs.	*F-Stat.*	*P-value*
REPO does not GC NPL	102	3.098	0.050[b]
NPL does not GC REPO		2.414	0.095[c]
DEPO does not GC NPL	102	3.114	0.049[b]
NPL does not GC DEPO		4.856	0.010[a]
IS does not GC NPL	102	0.736	0.482
NPL does not GC IS		0.689	0.504
TBR does not GC NPL	102	2.491	0.088[c]
NPL does not GC TBR		4.318	0.016[b]

Source: Own compilation

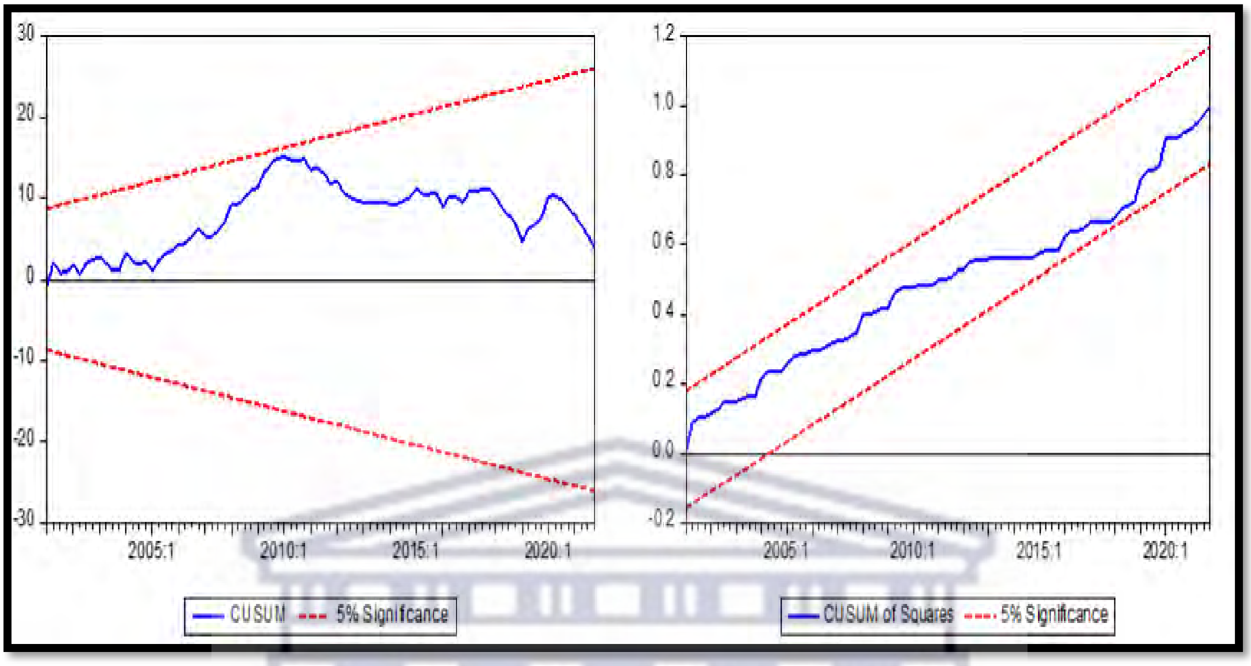
Note: a) [a, b, c] denotes the 1%, 5% and 10% significant levels, respectively. GC stands for Granger Cause.

The results contained in Table 4.32, are complementary to those obtained through the ECM framework. The results show that a bidirectional causal relationship exist between REPO and NPL, DEPO and NPL, as well as TBR and NPL. three bidirectional causalities in NPL with LEND, DEPO and TBR. This means that in Namibia, NPL is predicted by the REPO, DEPO and TBR. Therefore, the only variable found not to have any predictive capacity for the future patterns of NPL is the IS variable.

The diagnostics test results illustrated on the bottom section of Table 4.31, show that the error correction term (ECT) of the short run model reaffirms the existence of cointegrating relationship between NPL and the bank specific variables employed. Put simply, the ECT value of -0.441 indicates that the adjustment process to equilibrium process in the long run is approximately 44.1%. The adjusted R-squared of 0.862, implies that about 86.2% of the variations in the ratios of NPL is explained by the interest rate variables employed in the specified model equation. The F-statistic of about 70.20%, which is statistically significant, shows that the specified model is robust.

On the other hand, the DW statistics (2.110) is close to 2, which simply means that the model does not suffer from first order autocorrelation. The conclusion of no autocorrelation is further supported by the Breusch-Godfrey LM test results, which rule out the possibility of serial correlation in the model as its p-value (0.240) is greater than 5% significant level. The model accounted for heteroskedasticity by making use of robust standard errors. Since the sample size utilised in this analysis is relatively large, the asymptotic property for normality holds. Finally, Figure 4.13 presents the models stability test results conducted through the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ) tests.

Figure 4.13: Stability Tests: CUSUM and CUSUMSQ



Source: Own compilations

Results from Figure 4.13 show that the short run model is stable as the critical bounds in both plots are within the bound of the 5% significance level. Hence, the results presented in these models are reliable and robust.

4.3.6.6 Analysis of the NPL model with the financial indicators

In this section, Equation 4.16*a* is estimated in order to obtain the long- and short run coefficients using the ARDL technique. The optimal lag length for the selected error correction representation of the ARDL (1, 0, 1, 0, 1) model has been determined by the Schwarz-Bayesian Information Criterion (SC). Table 4.33 presents the long- and short run effects of the financial indicators on the ratio of NPL in Namibia. The diagnostic tests for the short run model are also presented in the bottom panel of the same table.

Table 4.33: ARDL results for the effects of the financial indicators on NPL

A. Short run Dynamics. Regressand: ΔNPL				B. Long run Dynamics. Regressand: NPL			
Regressors	Coeff.	Std Error	Prob.	Regressors	Coeff.	Std. Error	Prob.
Δ*ln*NPL(-1)	0.979[a]	0.100	0.000	RER	-0.055	0.192	0.775
ΔRER	0.024	0.031	0.439	PSCE	-0.269[a]	0.096	0.006
ΔPSCE	0.097	0.060	0.109	OIL	-0.024[c]	0.013	0.078
ΔPSCE (-1)	-0.129[a]	0.046	0.007	COVID-19	-4.485[b]	1.754	0.012
ΔOIL	0.000	0.003	0.911	SHARES	0.005[a]	0.002	0.002
ΔCOVID-19	0.201[a]	0.066	0.003				
ΔCOVID-19(-1)	-0.330[a]	0.095	0.001				
ΔSHARES	0.000	0.000	0.147				
ECT (-1)	-0.593[a]	0.128	0.000				
C	-0.003	0.030	0.924				

Short run diagnostic tests		Statistics	F-Stats	LM	JB	HET	RESET
Adjusted R^2	0.794	F-Stats.	20.350	0.213	0.811	2.445*	7.669
DW- Stats	1.973	p-value	0.000	0.807	0.666	0.003	0.007

Source: Own compilation

*Note: a) The term Δ denotes the first difference; ln = natural logs; [a, b, c] denotes the 1%, 5% and 10% significant levels, respectively. b) DW = Durbin-Watson; Stats. =Statistics; LM=Breusch-Godfrey Serial Correlation LM Test; JB=Jarque-Bera statistics; HET=Breusch-Pagan-Godfrey' test for Heteroskedasticity; *implies that heteroskedasticity has been accounted for by the White-Hinkley heteroskedasticity test which provides consistent standard errors and covariance; RESET=Ramsey' test for functional misspecification.*

The results from Table 4.33 illustrate that over the long run, with the exception of real exchange rate (RER), the rest of the regressors presented in the model were found to statistically influence the ratios of NPL in Namibia. Specifically, the results suggest that a 1 dollar rise in the private sector credit extension (PSCE) will lead to a decline of approximately 0.27 units in the NPL, ceteris paribus (cp). This implies that an increase in PSCE has a potential of drastically reducing the incidence of NPL in Namibia's banking system. The finding PSCE is similar with the result obtained by Petkovski et al. (2021), using Polish commercial bank dataset. However, it contradicts the finding of Mpofu and Nikolaidou (2018), in which they investigated the determinants of credit risk in the banking system of twenty-two Sub-Saharan African countries.

The global oil prices (OIL) is estimated to negatively relate to non-performing loans, although its significance is weak. The estimations suggest that a 1 dollar rise in global oil prices results in a decline of about 0.02 units in NPL, ceteris paribus. This outcome contradicts the result of Kalirai and Scheicher (2002) in which they assessed the vulnerability of the Australian banking system to credit risk.

Furthermore, the COVID-19 pandemic has been found to negatively amplify non-performing loans in Namibia's banking system. The finding suggests that on average, the levels of NPL are 0.04 units lower during the period of the pandemic period as opposed to the period without any pandemic. This outcome is unconventional, as it is normally expected that during the periods of crises, like the COVID-19 pandemic, NPL are normally supposed to rise with the crisis. The unconventionality of this outcome can partly be attributed to various policy interventions[87] implemented by the Namibian government alongside other industry players of the economy. This finding is also in conformity with Zunić et al. (2021)'s study, in which the researchers equally concluded that the pandemic had a delayed effect on NPL.

On the other hand, the price of market shares (SHARES) were found to positively influence the level of non-performing loans in both the long- and short run period, but with a very small magnitude (close to zero). In the long run the results appear to suggest that increased competition in the financial market has the possibility of amplifying non-performing loans. This is likely due to risky ventures undertaken by some firms in hopes of maximising profits. Normally, one would expect that as the value of stocks appreciate, NPL are expected to decline (Klein, 2013). One particular study that found an opposite outcome to the current study is that of Beck et al. (2015), in which a panel dataset consisting of seventy-five countries was used to, amongst other reasons, assess the effect of the shares on NPL. Unlike this present study, their study concluded that an increase in share price tends to be associated with lower NPL in countries with large and small stock markets. However, the authors underlined that the magnitude of the coefficient is larger in countries with a large stock market as opposed to countries with a smaller stock market.

The short run results presented on the left side of Table 4.33 indicate that the log of NPL in the previous quarter also turned out to positively influence the ratio of NPL in the current quarter. This

[87] *The social and macroeconomic interventions (social distancing, mandatory wearing of masks in public places, getting vaccinated, curfews, reduction in the repo rate, etc…) implemented aimed not only at curbing the further spread of the COVID-19 virus but also to mitigate the undesirable effects on the economy.*

means that the effects of past levels of NPL accumulations are still felt in the following period ahead. With regards to the specific financial indicators, the results show that only the private sector credit extension (PSCE) in the previous quarter is statistically significant in influencing NPL.

Amongst the control variables that were of interest, the COVID-19 pandemic was found to be statistically significant in both the current as well as the previous quarter, however, the conclusion is still maintained that in Namibia, the COVID-19 pandemic had an immediate effect on NPL as shown by the result of the short run in the current quarter. This assertion is because the magnitude of the COVID-19 coefficient in the previous quarter diminished the propensity for NPL to rise than it did in the current quarter. Thus, the appreciation in the asset quality in the previous quarter outweighed the depreciation in the present quarter by about 0.13 units.

The coefficient of the NPL(-1) entails that a 1 unit increase in the lagged value of NPL leads to an approximate rise 0.98 units in current NPL. This finding also maintains that NPL in Namibia is persistent in nature. This means, previous levels of NPL continue to influence NPL in the current quarter. In addition, the coefficient of PSCE (-1) indicates that a unit increase in the lagged value of PSCE is associated with an approximate decrease of about 0.13 units in NPL, ceteris paribus.

The coefficient of COVID-19 suggests that, in the short run, the ratio of NPL of Namibia's banking sector was about 0.20 higher when compared to periods without the pandemic, ceteris paribus. This result seems to suggest that banking institutions should carefully reconsider issuing loans during periods of crises as well as monitor the debtors in order to minimise losses. The negative coefficient of COVID-19 (-1) suggests that on average, past quarters of COVID-19 pandemics had a 0.33 decrease in the level of NPL when compared to periods where there was no crisis. This suggests that the short-term interventions taken by the Government, through its ministry of finance, as well as the Bank of Namibia, helped in curbing the credit risk exposure of its banking sector.

In relation to the long run causal relationship, it is primarily inferred through the coefficient of the Error Correction Term (ECT) presented in Table 4.33. Since the coefficient is negative and statistically significant at 1% level, it can be concluded that the statistically significant variables assessed using the model Equation 4.16*a* are causally related with NPL in the long run. Meanwhile, the short run causality test results related to the financial variables, evaluated through the significance of the regressors' *t*-statistics, indicate that a causal relationship running from the NPL(-1), PSCE(-1), COVID-19, and COVID-19(-1) to NPL exist.

Table 4.34 consists of the pairwise Granger causality test results required to establish direction of causality reached through the ECM framework. The results are evaluated through the VAR model Equations 4.16*b* and 4.16*c*.

Table 4.34: Pairwise Granger causality test results for the model with financial indicators

Null Hypothesis:	*Lags: 2 Quarters*		
	Obs.	*F-Stat.*	*P-value*
RER does not GC NPL	102	0.085	0.919
NPL does not GC RER		0.677	0.511
PSCE does not GC NPL	102	1.368	0.259
NPL does not GC PSCE		1.750	0.179
OIL does not GC NPL	102	3.857	0.024^{b}
NPL does not GC OIL		0.087	0.917
COVID-19 does not GC NPL	102	0.142	0.868
SHARES does not GC NPL	102	0.389	0.679
NPL does not GC SHARES		0.420	0.658

Source: Own compilation

Note: a) ^{b} and ^{c} denotes the 5% and 10% significant levels, respectively. GC stands for Granger Cause.

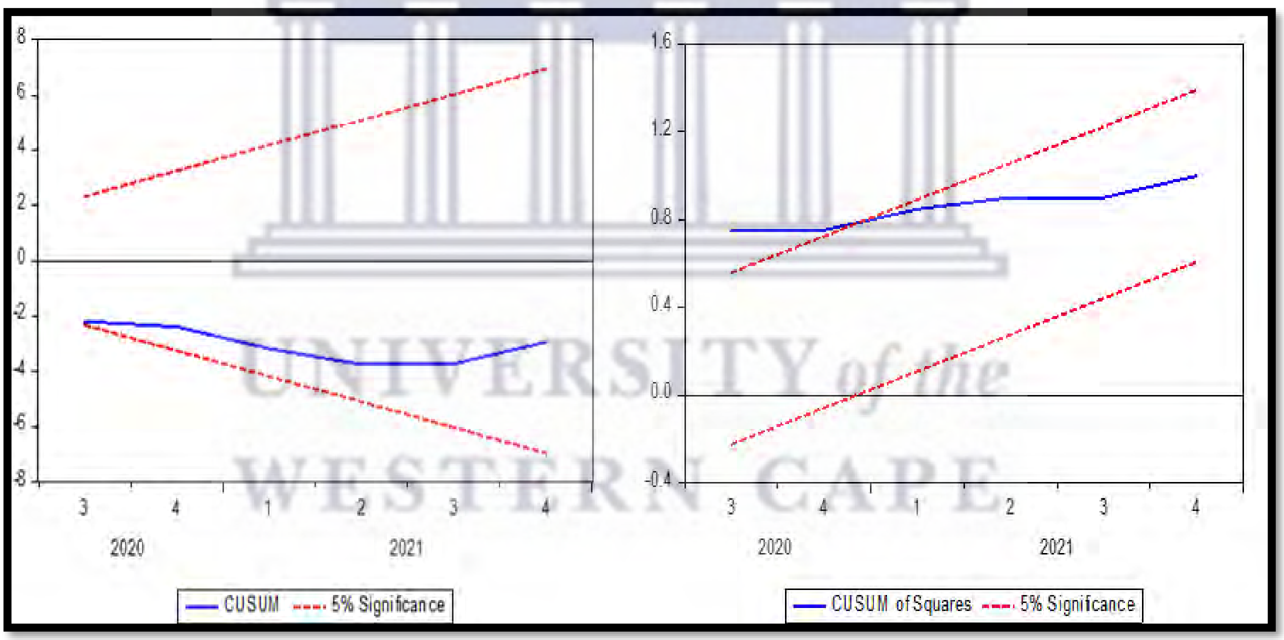
The results contained in Table 4.34, which complement the results obtained through the ECM framework, show a very strong unidirectional causal relationship running from the OIL to NPL. The rest of the variables of interest (the financial variables, excluding the control variables) were found to be independent in predicting the future values of NPL.

The diagnostics test results illustrated on the bottom section of Table 4.33, show that the error correction term (ECT) of the short run model reaffirms the existence of cointegration between NPL and the variables contained in the estimated model. Put differently, the ECT value of -0.593 indicates that the adjustment process to equilibrium process in the long run is approximately 59.3%. The adjusted R-squared of 0.794, implies that about 79.4% of the variations in the ratios of NPL is explained by the variables in the estimated model. The F-statistic of about 50.35%, which is statistically significant, shows that the specified model is robust.

The DW statistics (1.973) is very close to two, which means that the model does not suffer from first order autocorrelation. The conclusion of no autocorrelation in the model is further supported by the Breusch-Godfrey LM test results, which rule out the possibility of serial correlation in the model as its p-value (0.807) is greater than the 5% significant level. The estimated model accounted for Heteroskedasticity by employing robust standard errors. The JB test results showed that the residuals are normally distributed as its p-value (0.666) was found to be greater than the 5% significance level.

Figure 4.14 presents the models stability test results conducted through the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ) tests.

Figure 4.14: Stability Tests: CUSUM and CUSUMSQ



Source: Own compilations

Results from Figure 4.14 show that the short run model is stable under the CUSUM test, as the critical bounds fall within the bound of the 5% significance level. On the basis of CUSUM, the results emanating from the specified model can be reliably considered.

4.3.6.7 Analysis of the NPL model with the institutional indicators

In this section, Equation 4.19a is estimated in order to obtain the long- and short run coefficients using the ARDL technique. The optimal lag length for the selected error correction representation of the ARDL (1, 0, 1, 0, 1, 0, 1, 1) model has been determined by the Schwarz-Bayesian Information Criterion (SC). Table 4.35 presents the long- and short run effects of the institutional indicators on the ratio of NPL in Namibia. The diagnostic tests for the short run model are also presented in the bottom panel of the same table.

Table 4.35: ARDL results for the effects of the institutional indicators on NPL

A. Short run dynamics. Regressand:			ΔlnNPL	B. Long run dynamics. Regressand:			lnNPL
Regressors	Coeff.	Std. Error	Prob.	Regressors	Coeff.	Std. Error	Prob.
ΔlnNPL(-1)	1.221[a]	0.156	0.000	lnVA	-12.082	8.817	0.174
ΔlnVA	-0.921	0.615	0.138	lnPS	-1.573	1.862	0.400
ΔlnPS	0.989[b]	0.378	0.011	lnCC	-4.674	5.885	0.429
ΔlnPS(-1)	-1.058[a]	0.303	0.001	lnRQ	-20.766[b]	10.302	0.047
ΔlnCC	-0.667	0.517	0.201	lnGE	-12.377[a]	4.156	0.004
ΔlnRQ	-2.992[a]	0.683	0.000	lnRL	11.323[a]	5.480	0.042
ΔlnRQ(-1)	2.820[a]	0.707	0.000	ACC	-0.022	1.102	0.984
ΔlnGE	0.149	0.704	0.833				
ΔlnRL	1.561[a]	0.430	0.001				
ΔlnRL(-1)	-1.270[a]	0.399	0.002				
ACC	-0.017	0.017	0.310				
ECT (-1)	-0.632[a]	0.177	0.001				
C	0.016	0.015	0.315				
Short run diagnostic tests		Statistics	F-Stats	LM	JB	HET	RESET
Adjusted R^2	0.721	F-Stats	17.024	0.991	118.561	3.585*	11.076
DW- Stats	2.178	p-value	0.000	0.375	0.000	0.000	0.001

Source: Own compilation

*Note: a) The term Δ denotes the first difference; ln = natural logs; [a, b, c] denotes the 1%, 5% and 10% significant levels, respectively. b) DW = Durbin-Watson; Stats. = Statistics; LM=Breusch-Godfrey Serial Correlation LM Test; JB=Jarque-Bera statistics; HET=Breusch-Pagan-Godfrey' test for Heteroskedasticity; *implies that heteroskedasticity has been accounted for by the White-Hinkley heteroskedasticity test which provides consistent standard errors and covariance; RESET=Ramsey' test for functional misspecification.*

The long run results from Table 4.35 show that the logarithm of the regulatory quality (RQ), government effectiveness (GE), and the rule of law (RL) are statistically significant. In particular, the *RQ* and *GE* are found to negatively affect the levels of NPL ratio, while *RL* is obtained to be positively related to NPL.

Simply put, a 1% rise in the *regulatory quality* variable causes the level of NPL to decline by about 20.8%, ceteris paribus. This particular finding is consistent with what Rachid (2019) obtained when analysing the dynamics of NPL in Central and Eastern European (CEE) countries. This finding implies that institutional soundness benefits the quality of Namibia's loan portfolio. Similarly, a 1% rise in *government effectiveness* is estimated to cause a 12.4% decline in NPL levels, holding all other factors constant. This result also suggests that efficiency in government boosts the asset qualities of the loan portfolio. This particular finding conforms with the results obtained by Tatarici et al. (2020).

Conversely, a 1% rise in the rule of law variable is reported to have a positive effect on NPL. This is an interesting finding, though not surprising, especially when considering the series of corruption scandals that have unfolded without there being any amount of money recovered back to the state coffers. One such scandalous case is the so-called "Fishrot" saga[88] which involved high-level government officials and unveiled alarming corruption levels that for years have plagued the Namibian fishing industry. This specific case simply reinforces the fact that the perception of corruption activation in Namibia has for some time now been on the rise.

Moving on with the interpretation of the short run result, as with other models, the past values of NPL are found to positively influence the values of NPL in the current quarter. The institutional indicators found to influence the present level of NPL include: the past and present values of the political stability (PS), regulatory quality (RQ), past and present rule of law (RL).

Specifically, the result shows that in the short run, a 1% rise in the previous quarter values of NPL leads to a 1.22% rise in the current quarter values of NPL. This result suggests that, since the previous quarter's values of NPL are statistically significant, the present values of NPL are time-persistent. This means that past values of NPL in the previous periods tend to accumulate and

[88]*The name "Fishrot" came about after the notorious 2019 Wikileaks documentary known as the "Fishrot Files".*

brought forward in the present periods. The finding can be comparable with the results obtained by Gaur et al. (2022) and Koju et al. (2018a) using Indian banking data.

A 1% rise in the past values of *political stability* is estimated to cause a 1.06% fall in the present values of NPL, other factors being the same. However, this appreciation is almost completely reversed in the current period as a 1% rise in it is expected to cause a depreciation in the quality of the loan portfolio. Clearly, the finding that previous political stability in the previous quarter improved the quality of the loan portfolio is a testament to the undeniable fact that Namibia is a country that enjoys political stability and this helps it to stabilise the banking and financial system. This finding is similar to what Ozili (2018) obtained when investigating the determinants of banking stability in Africa, but it contradicts the results obtained by Rachid (2019) in MENA countries.

A 1% increase in the past quarter value of *regulatory quality* is found to be associated with a 2.82% rise in the NPL of the current quarter. Nevertheless, this depreciation in the loan portfolio is immediately reversed when a 1% increase in the regulatory quality is recorded to cause a 2.99% decline in the present quarter values of NPL. This outcome implies that, as the governance (or institutional) quality improves, the quality of bank loans also improves. This finding resonates with those that had been obtained by Boudriga et al. (2010) using the datasets of twelve MENA countries, as well as with Ozili (2018)'s findings, using the datasets of forty-eight African countries.

A 1% improvement in the past quarter value of the *rule of law* variable is found to decrease the value of NPL in the current quarter by 1.27%. Unfortunately, this appreciation is depreciated in the current quarter as the estimation shows that a 1% rise in the same causes NPL to decline by 1.56%. The deterioration is 0.29% more than the appreciation in the quality of the loan estimated in the previous quarter. This finding is clearly detached from those obtained by Boudriga et al. (2010),

In connection with the long run causal relationship, it is firstly assumed through the coefficient of the Error Correction Term (ECT) presented in Table 4.35. Since the coefficient of the ECT is negative and statistically significant at 1% level, it is safe to conclude that the statistically significant variables estimated using the model Equation 4.19*a*, are causally related with NPL in the long run. Conversely, the short run causality test results, evaluated through the significance of the regressors' *t*-statistics, show a strong causal relationship going from NPL(-1), PS, PS(-1), RQ, RQ(-1), RL, and RL(-1) to NPL exist.

Table 4.36 comprises of the pairwise Granger causality test results required to validate the direction of causality obtained through the ECM framework. The test results are found using the VAR model Equations 4.19*b* and 4.19*c*.

Table 4.36: Pairwise Granger causality test results for the model with institutional indicators

Null Hypothesis:	*Lags: 2 Quarters*		
	Obs.	*F-Stat.*	*P-value*
*ln*VA does not GC *ln*NPL	102	1.431	0.244
*ln*NPL does not GC *ln*VA		0.450	0.639
*ln*PS does not GC *ln*NPL	102	0.839	0.435
*ln*NPL does not GC *ln*PS		3.593	0.031[c]
*ln*CC does not GC *ln*NPL	102	1.157	0.319
*ln*NPL does not GC *ln*CC		0.185	0.831
*ln*RQ does not GC *ln*NPL	102	0.993	0.374
*ln*NPL does not GC *ln*RQ		0.288	0.751
*ln*GE does not GC *ln*NPL	102	0.802	0.452
*ln*NPL does not GC *ln*GE		0.491	0.614
*ln*RL does not GC *ln*NPL	102	0.028	0.972
*ln*NPL does not GC *ln*RL		1.197	0.307
ACC does not GC *ln*NPL	102	1.537	0.220
*ln*NPL does not GC ACC		0.573	0.566
*ln*PS does not GC *ln*VA	102	0.981	0.379
*ln*VA does not GC *ln*PS		0.310	0.734

Source: Own compilation

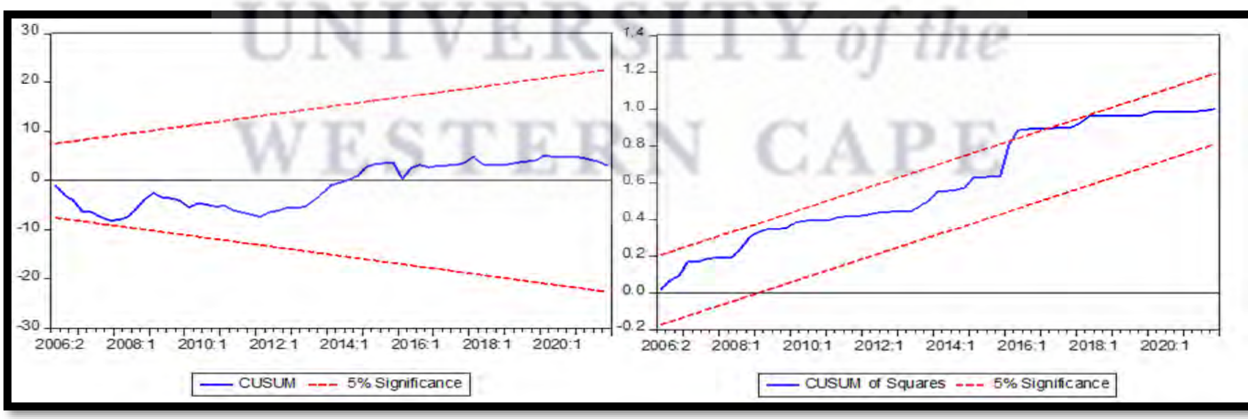
Note: a) ln = natural logs; [a, b, c] denotes the 1%, 5% and 10% significant levels, respectively. GC stands for Granger Cause.

The results contained in Table 4.36, are complementary to those obtained through the ECM framework. The results show that, besides there being a strong unidirectional causality running from NPL to political stability (PS), the rest of the governance (institutional) variables are found to be powerless in predicting the occurrence of NPL in the future.

The diagnostics test results illustrated on the bottom section of Table 4.35, show that the error correction term (ECT) of the short run model reaffirms the existence of a cointegrating relationship between NPL and the bank specific variables employed. Meaning, the ECT value of -0.632 indicates that the adjustment process to equilibrium process in the long run is approximately 63.2%. The adjusted R-squared of 0.721, implies that about 72.1% of the variations in the ratios of NPL is explained by the variables in the estimated model. The F-statistic of about 17.024%, which is statistically significant, shows that the specified model is robust.

On the other hand, the Durbin-Watson (DW) statistics (2.178) hovers close to two, which is indicative of the fact that the model does not suffer from first order autocorrelation. The conclusion of no autocorrelation in the model is further supported by the Breusch-Godfrey LM test results, which rule out the possibility of serial correlation in the model as its p-value (0.375) is greater than 5% significant level. The estimated model accounted for Heteroskedasticity by employing robust standard errors. Given that the sample size utilised was relatively large, the asymptotic property for normality holds. Lastly, the Figure 4.15 presents the models stability test results conducted through the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ) tests.

Figure 4.15: Stability Tests: CUSUM and CUSUMSQ



Source: Own compilations

The results from Figure 5.15 show that the short run model is stable under the CUSUM test as the blue line falls within bounds of 5% significance level.

4.4 Summary

This chapter investigated the underlying indicators responsible for influencing and Granger causing non-performing loans (NPL) in Namibia's banking sector. The empirical estimation was conducted in stages. The initial stage evaluated the control variables pertaining to this study simultaneously. Thereafter, six reduced form models were also analysed in order to gain insight into the individual indicators likely to influencing NPL. The summary results of all the estimations are herein reported.

The findings from the model consisting of the composite measures reveal that in the long run, ceteris paribus, only the macroeconomics (MACRO) and interest rate (INTER) indices significantly affect NPL. Meanwhile, the results from the short run dynamics, other things being equal, show that NPL is influenced by the levels of NPL in the previous quarter and the MACRO index in both the previous and current quarter, the INTER indicators in the previous quarter as well as the institutional (INST) indicators in current quarter. In terms of the causal effects, the results reveal that in the long run, causality only exists between NPL, the macroeconomic and interest rate indicators. In the short run however, a strong causal effect running from the influence of past quarter values of NPL, the MACRO and INST indicator to NPL exist.

The findings from the model containing the macroeconomic indicators indicates that in the long run, NPL is mainly determined by the following macroeconomic indicators: the output gap (GAP), unemployment rate (UN) and the housing price index (HP). However, in the short run, with the exception of the GAP variables, the levels of NPL are influenced by all the macroeconomic variables featured in the model estimation. In terms of causality, the result shows that in the long run, NPL is mainly Granger caused by output gap, unemployment, and the housing price index. Conversely, in the short run, NPL is found to be strongly caused by its own past value, unemployment, and the housing price index.

The results from the model consisting of the bank specific variables obtained that over the long run, NPL is influenced by the return on assets (ROA), return on equity (ROE), lending behaviour (LB), loan-to-deposit ratio (LDR), and loan growth (LG). Albeit, in the short run the results show that the past values of NPL itself, the return on assets (ROA), return on equity (ROE), lending behaviour (LB), loan-to-deposit ratio (LDR), and loan growth (LG) were found to influence NPL. As for the causal relationships, it is found that over the long run period, the ratios of NPL are mostly Granger caused by ROA, ROE, LB, LDR and LG; meanwhile, in the short run period, the NPL is strongly Granger causes by the past values of NPL, ROA, ROE, CAR, LB, LDR and LG. In terms of the direction of causality, a strong unidirectional causality running from CAR and LG to NPL is found. NPL is reported to mildly Granger cause LB.

The outcomes of the model consisting of the monetary indicators reveal that over the long-term, NPL is strongly determined by the narrow money supply (M1), broad money supply (M2), and net foreign assets (NFA). Nevertheless, in the short run, NPL is strongly determined by its own past accumulated values, and the narrow money supply. In relation to the causal relationships, over the long run a causal relationship running from the monetary indicators to NPL was established. But, over the short run NPL was found to be influenced by its own past values, and narrow money supply.

The findings from the model made up of the interest rate indicators illustrated that, over the long run period, NPL is mildly determined by the following interest rate indicators: the repo rate (REPO), and interest spread (IS). Notwithstanding, in the short run horizon, NPL is strongly determined by its own past accumulations, REPO, and DEPO. With reference to causality, the findings show that over the long run REPO and IS are found to Granger cause NPL. But then, over the short run period, the accumulations of NPL in the previous quarter, REPO and IS are found to influenced NPL. A bidirectional causality between REPO and NPL, DEPO and NPL, as well as TBR and NPL is also confirmed.

The outcomes from the model composed of the financial indicator prove that over the long run period, NPL is strongly determined by four financial variables (private sector credit extension (PSCE), oil prices, (OIL), a dummy variable of COVID-19 pandemic, and the stock market prices (SHARES)). However, in the short run period, NPL is strongly determined by its own past accumulations, the real exchange rate, private sector credit extension, oil prices, the COVID-19 pandemic, and SHARES. With regards to causality, the findings show that over the long run, the estimated variables are expected to be causally related with NPL. On the other hand, over the short run period, NPL is estimated to be strongly influenced only by its own past values and OIL.

The outcome of the model made up of the institutional indicators demonstrate that over the long run period, NPL is strongly determined by three variables (the regulatory quality (*RQ*), government effectiveness (*GE*), and the rule of law (*RL*)). But, in the short run period, the results show that NPL is strongly determined by its own past accumulations, political stability (PS), regulatory quality (RQ), past and present rule of law (RL). With regards to causality, the results reveal that over the long run, the variables are expected to be causally related with NPL. In contrast, over the short run period, NPL is solely found to be strongly Granger caused by its own past values.

As seen in the summary results, the empirical findings from the six models (excluding the overall model that includes the composite indices) highlights that there exists an array of factors that underlie the NPL phenomenon. Considering that in the real economy the factors influencing NPL are multifaceted and happen simultaneously, the finding from the composite model, which is regarded as being more realistic and of utmost importance for policy implications is herein considered. The appropriateness of the PCA also lies in the fact that it easily collapses a vast array of indicators into a much smaller number of parameters of choice that is easy to work with and much more comprehensive to draw unambiguous conclusions.

CHAPTER V: A FACTOR-BASED FRAMEWORK FOR STRESS-TESTING THE NAMIBIAN BANKING SECTOR

5.1 Introduction

Following a series of global financial crises[89], which at times have been triggered by impairments in the banking industry assets, efforts to assess the qualities of the loan portfolios as measured by non-performing loans (NPL) have intensified (Alrfai et al., 2022; Henry & Kok, 2013). In particular, a number of policymakers, regulators, and bank managers have been so keen in examining the vulnerabilities of the banking systems as they are subjected to stressful shocks of various nature. The risks of financial instability of many countries have thus been looming, owing to the ongoing geopolitical instabilities, fluctuations in the oil market prices, rising debt crises as well as the uncertainties of financial markets experienced across the world. The collapse of the Chinese biggest "shadow banking" [90] system as well as those of some banks in the United State of America (USA) have posed a significant risk to the stability of the global financial system which is enjoyed by a number of countries around the world. More specifically, the shutdown of the Silicon Valley Bank (VBS) and the First Republic Bank (FRB) in the USA (Dinh, 2023) as well as the financial troubles of Zhongrong International Trust Co, a Chinese state-backed bank with a major stake in the US$ 2.9 trillion trust industry, which has caused enormous challenges to its reeling economy.

The Chinese and USA economies[91] are not only interdependent, but they are also interconnected with the economies of most countries around the world. As such, any disequilibrium in their banking or financial systems has serious repercussions for the global economy. The domino effect resulting from such economies have the potential to rapidly spill-over to the global financial system, especially if such instabilities are not rapidly contained (Kjosevski et al., 2019). It is

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[89] *Such as, the global recession of 1990/93, Asian financial crisis of 1997/98, the 2008/09 global financial crises, the European debt crisis of 2009/18, the financial crisis brought about by the COVID-19 pandemic crisis of 2020/21, to mention but a few.*

[90] *Shadow banks are non-banking financial institutions that are loosely regulated, whose loans are not guaranteed, and there is less transparency of activities operated by such unconventional banking systems (Shah et al., 2023).*

[91] *China ranks as the second leading economy in the world after the US economy.*

therefore not far-fetched that a crisis in any of these leading economies, can have a devastating effect on the global economy. For instance, there is a high likelihood that if the Chinese "shadow banking" system, dominated by entities that are considered to be too-big-to-fail, were to crash, this would automatically lead to a global recession. Thus, the spill-over effects from such crises could have serious repercussions for many economies around the world, especially in developing countries.

With the help of stress-testing[92] techniques, the vulnerability of financial systems have been evaluated in the body of literature (Henry & Kok, 2013). Stress-testing is a process of evaluating the stability of an entity, like a bank or an entire system like a financial system, to withstanding any kind of a shock while still maintaining an adequate level of liquidity. The assessment is based on a set of plausible hypotheses of what could happen, rather than what is likely to happen in the event of a shock. According to Llorent., et al. (2013) and Cihak (2005) stress-testing is commonly used by regulators and supervisory authorities as a risk management tool to gauge the sensitivity of an institution or a system to common shocks, i.e., economic crisis. Proponents of stress-testing argue that, the test is crucial in strengthening the resilience of institutions by build-up an adequate capital base, that can be used to counter the risks of the worst-case scenario whilst identifying the exposure to risk that are latent.

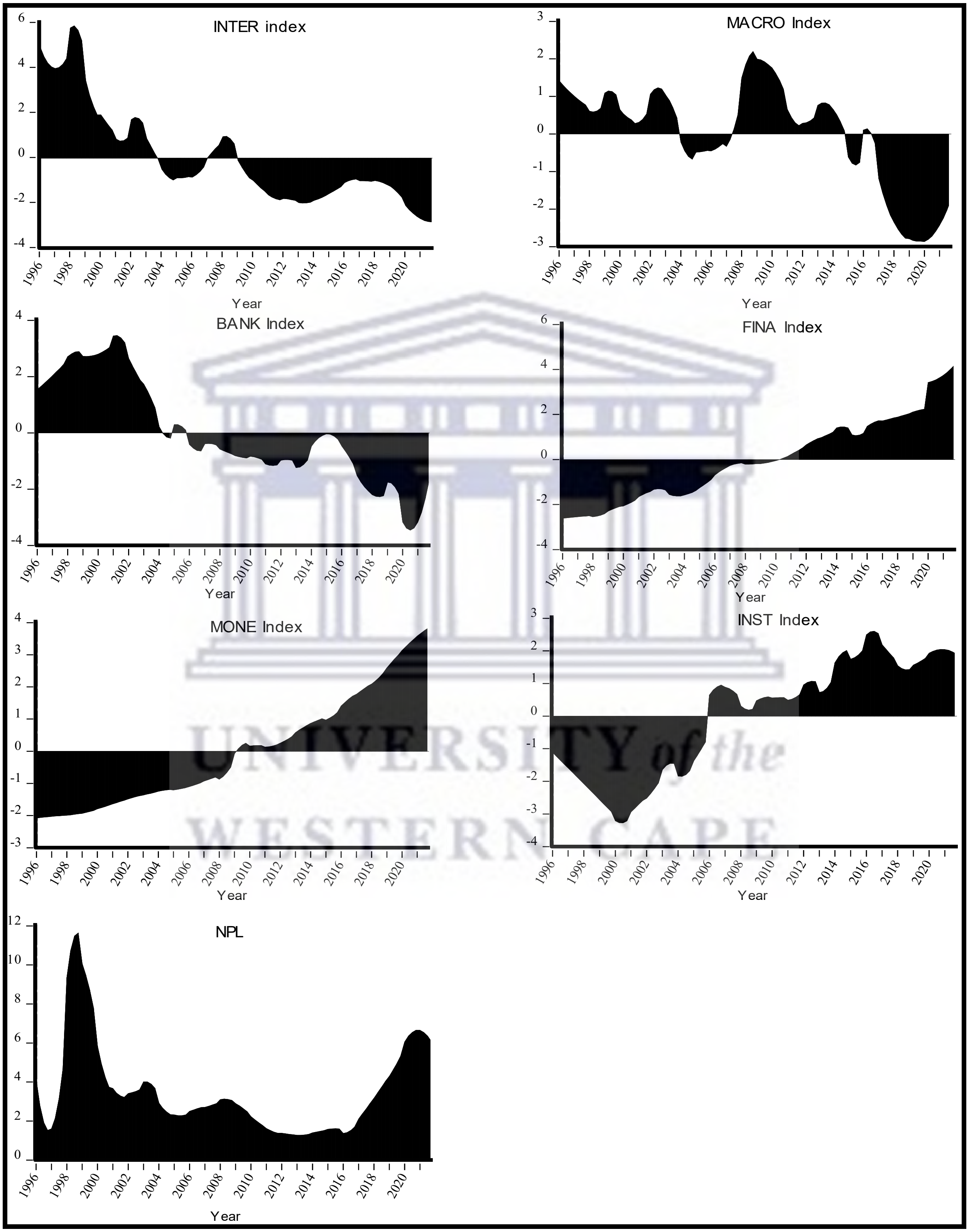
Kalirai and Scheicher (2002) identify two main approaches to applying stress-testing on an aggregate level. The first approach involves the usage of microprudential industry specific factors while the second one involves the usage of aggregated macroprudential data. According to Kanas and Molyneux (2018) the latter approach is rooted in the Internal Models Approach of Basel II which focus on the systemic and credit risks. The second approach, on which this study is premised, accounts for systemic factors that can cause deterioration in NPL. In fact, Gavin and Hausman (1998) argued that systemic shocks destabilise the viability of banks by reducing their asset quality. For this reason, one of the aims of this study is focused on creating a forecast of the quality of Namibia's banking sector's loan portfolio.

[92] *The term "stress test" has its root in the medical field and it is used to refer to a medical procedure for cardiovascular fitness. However, in the financial field it relates to risk assessment by for instance interrogating whether an institution is able to withstand an economic crisis.*

Since a number of major banking crises are linked to systemic shock (Banerjee & Murali, 2017), it is imperative to scrutinise the key indicators that influence not only the stability of the banking sector but also of the entire financial system as a whole. This entails a thorough investigation of the transmission channels through which this kind of shock is most likely to be transmitted, thereby devising workable countermeasures against them. Four[93] of the six determinants of NPL used in this study have been deteriorating as can be seen in Figure 5.1.

[93] *Financial (FINA), Bank-specific (BANK), Macroeconomics (MACRO), and Institutional (INST) indicators.*

Figure 5.1: Time series plot of the endogenous variables



Source: Own computation

Figure 5.1 shows that in recent years there has been an unprecedented decline in interest rates, the macroeconomic conditions, banking, and the institutional environment. The banks' loan portfolio has equally been deteriorating as seen by the NPL plot of Namibia's banking sector. The decline in NPL signals deterioration in the asset quality of banks. In recent years, the levels of NPL have been precarious as it rose beyond the 4% threshold established by the Central Bank of Namibia. The deterioration in NPL has been exacerbated by several shocks, namely the persistence of the drought conditions caused by the negative effects of climate change, the effects of the aftermath of the COVID-19 pandemic as well as the ongoing geopolitical instabilities experienced around the world thus far.

Since the resilience of the banking sector is dependent on many factors, especially those outside the banking sector space, six composite measures [94] whose time-series patterns are presented in Figure 5.1, have been considered in this study to probe the resilience of Namibia's banking system. In doing so, the broader objective of assessing the overall stability of the banking sector is achieved using an array of systemic factors. In the literature of macro-stress-testing, aside from the standard regression analysis that is used to assess the associations amongst the variables, the vector autoregression (VAR) model is widely considered as a stress-testing tool (Amediku, 2006; Kamati et al., 2022; Kanas & Molyneux, 2018). Its usage lies in its capability to capture the dynamic interactions and feedback effects between variables as well as its capability to forecast the effects of a one standard deviation shock of a variable on another variable (Banerjee & Murali, 2017; Tracey, 2007).

In Namibia, both the Bank of Namibia (BoN) as well as the Namibia Financial Institutions Supervisory Authority (NAMFISA) are responsible for regulating and supervising the activities of the banking sector and the financial institutions. Moreover, the two institutions play a pivotal role in guaranteeing the overall stability of the financial system, amongst other mandates. According to Alessandi., et al. (2009), central banks, including the BoN, have long relied upon econometrics modelling to guide their policy decisions. In general, models pertaining to financial stability and

[94] *The six indicators in Figure 5.1 were constructed using the Principal Component Analysis (PCA) technique which is extensively discussed under Appendix A to G.*

systemic risk are poorly developed and quite rare, especially in developing countries, like Namibia.

It is thus not surprising that Namibia lacks studies that thoroughly and analytically assess the fragility of the banking sector. By means of an array of indicators that are purported to offer a more realist view on the matter, this study elucidates what would happen in the event that both the banking sector and the financial systems are subjected to a varying degree of stress. The only available study that attempted to shade some light on the vulnerability of the Namibian banking sector is that of Kamati et al. (2022). Their stress-testing results, which are merely based on four macroeconomic variables, concluded that the asset quality of Namibia's banking sector is resilient. More specifically, their results revealed that the ratio of NPL rose when the real growth rate and the house prices deteriorated by more than two standard deviations over four quarter horizons. Besides this, the joint financial stability reports periodically published by the BoN and NAMFISA also provide a useful risk-assessment of the county's financial condition from a qualitative perspective. Nevertheless, their reports are more of a descriptive statistic in nature, falling short of an analytical and quantitative rigour.

Clearly, a literature gap exists, especially in Namibia, where independent studies are required to thoroughly examine the fragility of the banking sector quantitatively and analytically by means of a robust framework that assesses a varying degree of stress to the banking sector. Therefore, this present study bridges the existing gap by conducting a stress-testing for the Namibian banking sector as well as develop a forecast of the quality of the Namibian banking sectors loan portfolio to credit risk shocks. Thus, the main goal of this chapter is to assess the vulnerability of Namibia's banking sector in the context of key systemic risk factors. More specifically, the study aims to a) perform a sensitivity stress-test to analyse the vulnerability of Namibia's banking sector to systemic factors, and b) create a forecast for the asset quality of the loan portfolio for the Namibian banking sector. The findings from this study raise serious policy implications that, if implemented, can assist lenders to hedge themselves against potential systemic risk factors.

The rest of the chapter proceeds as follows: Section 5.2 outlines the methodology. Section 5.3 presents the empirical results, and Section 5.4 summarises and draws conclusions.

5.2 Methodology

5.2.1 Model Specification

The Vector Autoregression (VAR) framework developed by Sims (1980) has been a useful econometric tool for analysing dynamic linear models. The technique is considered to be an extension of the univariate autoregressive or simultaneous structural models. It symmetrically considers all the variables entered in its system as endogenous, which are impacted by contemporaneous and past values of other variables (Banerjee & Murali, 2017). The VAR framework disregards any aprioristic knowledge of variables utilised in its system. Enders (2015) considers this as one of the weaknesses of the VAR model. Conversely, Banerjee and Murali (2017) emphasised that the attractiveness of the VAR models, as it related to stress-testing analysis, lies in its flexibility, compactness and simplicity of summarising the set of variables responsible for influencing the ability of another variable to withstand shocks.

The important work of Lee and Rosenkranz (2019), Radivojevic and Jovovic (2017) and Vogiazas and Nikolaidou (2017; 2011), amongst others, point to the fact that endogenous variables used to investigate the fragility of the banking sector have the potential of affecting each other. Accordingly, the VAR(p) model is used to circumvent the problems of endogeneity and stress-test the resilience of the Namibian banking sector to a number of factors that have been considered in this study. The VAR model is specified in its compact form as:

$$Y_t = \lambda_0 + \sum_{i=1}^{p} \lambda_i Y_{t-1} + v_t \tag{5.0}$$

Where Y_t is a $(n \text{ x } 1)$ vector of endogenous variables; such as, NPL, $MACRO$, $BANK$, $MONE$, $INTER$, $FINA$ and $INST$ observed in period t; λ_0 is a $(n \text{ x } 1)$ vector of constants, λ_i is a $(n \text{ x } p)$ vector of the coefficients of the lagged endogenous variables (Y_{t-1}) with $i = 1, 2, 3, \dots, p$; where p represents the optimal number of lag length of each variable in the system.[95] v_t is a $(n \text{ x } 1)$ vector

[95] *The selection of lag length in the VAR model is sensitive to different information criteria (which include the sequential modified Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz-Bayesian Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ)). For this reason, it is imperative that an appropriate lag length is selected so as to avoid problems of misspecification which could lead to*

of the white noise processes which are contemporaneously uncorrelated with the set of endogenous variables but is correlated across the system of equations. Since the model employed consists of seven endogenous variables, the actual VAR model is expressed in matrix notation as follows:

$$NPL_t = \alpha_{10} + \beta_{11}NPL_{t-1} + \beta_{12}MACRO_{t-1} + \beta_{13}BANK_{t-1} + \beta_{14}MONE_{t-1} + \beta_{15}INTER_{t-1} + \beta_{16}FINA_{t-1} + \beta_{17}INST_{t-1} + e_t^{NPL} \quad (5.1)$$

$$MACRO_t = \alpha_{20} + \beta_{21}NPL_{t-1} + \beta_{22}MACRO_{t-1} + \beta_{23}BANK_{t-1} + \beta_{24}MONE_{t-1} + \beta_{25}INTER_{t-1} + \beta_{26}FINA_{t-1} + \beta_{27}INST_{t-1} + e_t^{MACRO} \quad (5.2)$$

$$BANK_t = \alpha_{30} + \beta_{31}NPL_{t-1} + \beta_{32}MACRO_{t-1} + \beta_{33}BANK_{t-1} + \beta_{34}MONE_{t-1} + \beta_{35}INTER_{t-1} + \beta_{36}FINA_{t-1} + \beta_{37}INST_{t-1} + e_t^{BANK} \quad (5.3)$$

$$MONE_t = \alpha_{40} + \beta_{41}NPL_{t-1} + \beta_{42}MACRO_{t-1} + \beta_{43}BANK_{t-1} + \beta_{44}MONE_{t-1} + \beta_{45}INTER_{t-1} + \beta_{46}FINA_{t-1} + \beta_{47}INST_{t-1} + e_t^{MONE} \quad (5.4)$$

$$INTER_t = \alpha_{50} + \beta_{51}NPL_{t-1} + \beta_{52}MACRO_{t-1} + \beta_{53}BANK_{t-1} + \beta_{54}MONE_{t-1} + \beta_{55}INTER_{t-1} + \beta_{56}FINA_{t-1} + \beta_{57}INST_{t-1} + e_t^{INTER} \quad (5.5)$$

$$FINA_t = \alpha_{60} + \beta_{61}NPL_{t-1} + \beta_{62}MACRO_{t-1} + \beta_{63}BANK_{t-1} + \beta_{64}MONE_{t-1} + \beta_{65}INTER_{t-1} + \beta_{66}FINA_{t-1} + \beta_{67}INST_{t-1} + e_t^{FINA} \quad (5.6)$$

$$INST_t = \alpha_{70} + \beta_{71}NPL_{t-1} + \beta_{72}MACRO_{t-1} + \beta_{73}BANK_{t-1} + \beta_{74}MONE_{t-1} + \beta_{75}INTER_{t-1} + \beta_{76}FINA_{t-1} + \beta_{77}INST_{t-1} + e_t^{INST} \quad (5.7)$$

Where e_t^{NPL}, e_t^{MACRO}, e_t^{BANK}, e_t^{MONE}, e_t^{INTER}, e_t^{FINA}, and e_t^{INST} are uncorrelated white-noise disturbances, with their usual properties of a zero mean and constant variance. Equation 5.1 is the equation of interest which relates to stress-testing of the Namibian banking system.

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erroneous forecasts and impulse response functions. Considering that the data used in this study is relatively smaller, the optimum lag length selection used in all the various specifications is based on the findings suggested by the SC.

The coefficient matrix, $Y_t' = [\Delta NPL \quad \Delta MACRO \quad \Delta BANK \quad \Delta MONE \quad \Delta INTER \quad \Delta FINA \quad \Delta INST]$, is thus represented as:

$$\begin{bmatrix} \Delta NPL \\ \Delta MACRO \\ \Delta BANK \\ \Delta MONE \\ \Delta INTER \\ \Delta FINA \\ \Delta INST \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \\ \alpha_{30} \\ \alpha_{40} \\ \alpha_{50} \\ \alpha_{60} \\ \alpha_{70} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} & \beta_{16} & \beta_{17} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} & \beta_{26} & \beta_{27} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} & \beta_{35} & \beta_{36} & \beta_{37} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} & \beta_{45} & \beta_{46} & \beta_{47} \\ \beta_{51} & \beta_{52} & \beta_{53} & \beta_{54} & \beta_{55} & \beta_{56} & \beta_{57} \\ \beta_{61} & \beta_{62} & \beta_{63} & \beta_{64} & \beta_{65} & \beta_{66} & \beta_{67} \\ \beta_{71} & \beta_{72} & \beta_{73} & \beta_{74} & \beta_{75} & \beta_{76} & \beta_{77} \end{bmatrix} \begin{bmatrix} \Delta NPL_{t-1} \\ \Delta MACRO_{t-1} \\ \Delta BANK_{t-1} \\ \Delta MONE_{t-1} \\ \Delta INTER_{t-1} \\ \Delta FINA_{t-1} \\ \Delta INST_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^{NPL} \\ e_t^{MACRO} \\ e_t^{BANK} \\ e_t^{MONE} \\ e_t^{INTER} \\ e_t^{FINA} \\ e_t^{INST} \end{bmatrix}$$

In general, inferences about the coefficients of the estimated VAR models are quite difficult and confusing to interpret (Tracey, 2007). For this reason, the interpretation of the VAR framework is explained through the so-called Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD). Albeit, there exists a very thin line between the information captured by the IRF and those reported by the FEVD. Specifically, the IRF trace the responsiveness of a one-time shock to one of innovations in the VAR system on current as well as the future values of the endogenous variables contained in the VAR system; while the FEVD provides the proportion of the movements in the regressand variables that are due to their 'own' shocks, versus shocks to the other variables in the system (Brooks, 2019). In particular to this study, the IRF measures the responses of NPL to a shock in each of the six macro indicators, whereas the FEVD provides the proportion of the movements in NPL that are due to their 'own' shocks, versus shocks to the other six macro indicators featured in the system.

5.2.2 Data and description of variables

The secondary time-series dataset used to carry out the sensitivity analysis as well as forecast the asset quality of Namibia's banking sector are the same as those stipulated and discussed under Chapter IV. In this current chapter, the quarterly series of the indices developed through the PCA methodology are herein utilised to answer the last two objectives of this thesis. With the exception for when the quality of the loan portfolio is forecasted[96], the series time frame employed in this

[96] *Time-series data from 1996Q1 to 2023Q4 is employed to forecast NPL.*

Chapter runs from the periods 1996Q1 – 2021Q4.

This being the case, the summary statistics of the six composite measures (MACRO, BANK, INTER, FINA, INTER, and INST) as well as the dependent variable (NPL) is maintained as computed and discussed in Chapter IV. Same goes for the unit root properties of the data, the *a priori* expectations, the lag selection criteria, and the findings for cointegration.

5.2.3 Estimation procedures

To attain the specific objectives set out in this chapter, the econometric procedures go as follows: firstly, the standard VAR model is estimated. Secondly, the model's robustness check, specifically the VAR stability condition is tested. Thirdly, the standard/structured VAR is estimated, before finally computing the IRF and FEVD. Lastly, a forecast of the riskiness of the quality of loan portfolio is evaluated using the ARIMA model. The procedures for each of the aforementioned tests are outlined in the following sections.

5.2.3.1 VAR estimation model

Prior to estimating the VAR model, the maximum lag lengths required to generate the white-noise of error terms which must be incorporated in all the subsequent estimations has to be determined. As stated in Chapter IV, the Schwarz information criterion (SC) is used in determining the optimal lag length. To establish the appropriateness of the selected lag length and ensure that the model (especially Equation 5.1) does not exhibit explosive behavioural patterns, the VAR stability condition, which is based on the roots of the characteristic polynomial is assessed. The null hypothesis for instability is rejected if the eigenvalues of a modulus is equal to or less than unity. For the IRF and FEVD results obtained through the VAR model to be reliable, meaningful, and credible, it is indispensable to ensure stability.

5.2.3.2 Robustness Check

This section outlines the robustness checks which ensure the validity of the estimations. The error term is subjected to a series of diagnostic checks undertaken in chapter IV, but here VAR stability condition which is centred on the AR Roots is presented. The VAR model satisfies the stability condition if all AR roots are less than unity and no root fell outside the circle.

5.2.3.3 VECM model estimation

Since cointegration has already been established in Chapter IV, Equation 5.0 is herein slightly transformed in order to capture the aspect of cointegration. In this regard, the VECM in its compact form is specified as:

$$\Delta Y_t = \lambda_0 + \sum_{i=1}^{p-1} \lambda_i \Delta Y_{t-i} + \varphi ECT_{t-1} + v_t \tag{5.8}$$

Where the φ is the coefficient of the Error Correction Term (ECT) which measures the speed of adjustment to equilibrium when deviations from the cointegration relationships occur in the system, Δ is the first difference operator and the rest of the denotations remain as previously defined.

5.2.3.4 Impulse Response Functions (IRF)

As previously stated, the dynamic effects of the model's responsiveness to certain shocks in the VAR/VECM framework of seven endogenous variables as well as the effects amongst the seven variables are assessed via the IRF. With regards to the IRF, the Generalised Impulse Response Function (GIRF) which disregards the order in which the variables enter the system of equations is employed. In fact, the GIRF is unbiased with regards to any particular school of thought as it does not favour any school of thought in relation to how variables are ordered and it does not require orthogonalization in the errors (Amuakwa-Mensah et al., 2017; Konstantakis et al., 2016; Sheefeni, 2015a). A major drawback of the GIRF lies in its inability to obtain the variance decomposition for any single equation of the VAR/VECM framework. As a result, it becomes impossible to differentiate between the impacts of policy intervention on any particular variables of the system versus impacts that are due to shocks in other variables within the system (Sheefeni, 2013). The IRF of NPL are graphically presented.

5.2.3.5 Forecast Error Variance Decomposition (FEVD)

As for the dynamic effects of the model's responsiveness to a random shock in any of the seven endogenous variables of the VAR/VECM framework is assessed using the FEVD. The variance decomposition determines the sources of a change in a series and it splits the variation of an endogenous variable into components of shocks to the system (Brooks, 2019). This being the case, the variance decomposition conveys information of relative importance about each random innovation that influences the system variables. In this regard, the results of stress-testing relay the response of a one standard deviation shock to variables in the system within the two standard deviation bands of confidence. The FEVD of the NPL model is reported in a tabular form.

5.2.3.6 Forecasting the quality of the loan portfolio of the Namibian banking sector

In economics, the need for accurate and reliable time-series forecasting is indispensable for informed decision making. In a world full of uncertainty, the demand for accurate future predictions of some economic data, such as the future trend of NPL, is incessant due to the need of finding reliable and efficient forecasting methods. Amongst the existing forecasting methods[97], is a widely used technique for univariate time-series forecasting called the Autoregressive Integrated Moving Average (ARIMA). The ARIMA is also popularly known as the Box-Jenkins (1976) methodology and has over the years gained preeminence as a forecasting tool in financial econometrics. Its usage in economics as well as other data-driven fields is based on its straightforwardness and ability to accurately predict the future values of a series whilst using the past information of the series itself. For this reason, the ARIMA model, just as in the case of a VAR model discussed in the earlier part of this study, are sometimes referred to as *atheoretic* model. This is due to the fact they are not based on any particular economic theory.

Against this background and in conformity with the studies of Rakotonirainy et al. (2020) and Amediku (2006), the ARIMA model has been employed to forecast the quality of the Namibian

[97] *Other alternative forecasting methods include the machine learning models, exponential smoothing methods, ARIMA-X or hybrid models, to mention but a few. It is worth stressing that the choice of a forecasting method is largely determined by the characteristics of the data and the purpose for which the study is being conducted.*

banking sector loan portfolio for 8 quarters, from 2023Q4 to 2025Q4, using NPL past sample data of NPL for the period 1996Q1 - 2023Q4. An ARIMA(ρ, d, q) model is a combination of an autoregressive (ρ) and a moving average (q) processes. The d aspect represents the order of integration in which the series is stationary. The general ARIMA model is expressed as,

$$NPL_t = a + \sum_{i=1}^{\rho} bNPL_{t-i} + \sum_{j=1}^{q} c\xi_{t-j} + \xi_t \tag{5.9}$$

Where NPL in time t is explained by its immediate past values $(t - i)$ and a white-noise term, ξ. α is the constant, ρ is the order of the autoregressive component, b is the coefficient of the autoregressive model, q is the order of the moving average component, and c is the coefficient of the moving average model. NB: Stationarity is assumed with $|b| < 1$. The optimal lag length is determined by the various information criteria. The ARIMA model is hinged on two underlying assumptions namely, the series being forecasted must be stationary and invertible (Brooks, 2019). Therefore, the underlying time-series properties are determined by specifying an ARIMA(ρ, d, q) model. In the event that one or more of the terms are zero, the zero terms can be dropped out of the model. Put simply, an ARIMA$(1, 0, 0)$, ARIMA$(0, 0, 1)$and ARIMA$(0, 1, 0)$ becomes AR(1), MA(1) and I(1), respectively.

To select the appropriate model and forecast a series, a three stage process as outlined by the Box-Jenkins (1976) methodology is undertaken. These include:

a) Identification. The identification process is segmented into two parts namely, the establishment of the unit root process of the data (Autocorrelation and partial autocorrelation functions) and the determination of the order of the autoregressive and moving average. Simply put, under this stage the "ρ", "d", and "q" is determined.
b) Estimation. Once the possible ARIMA models have been identified, the most appropriate model is selected by considering the model with the most significant coefficient and smallest values of information criterions (i.e., Schwartz, Akaike and Hannan-Quinn).

c) Diagnostic and Forecasting. Under the diagnostic check, the Ljung-Box statistics is used to evaluate white-noise property of the residual. The model is ready for forecasting the moment the residuals are confirmed to be white-noise, else a new model selection is required. The accuracy of prediction is determined by the results of the root mean square, mean absolute error, mean absolute percentage error, et cetera.

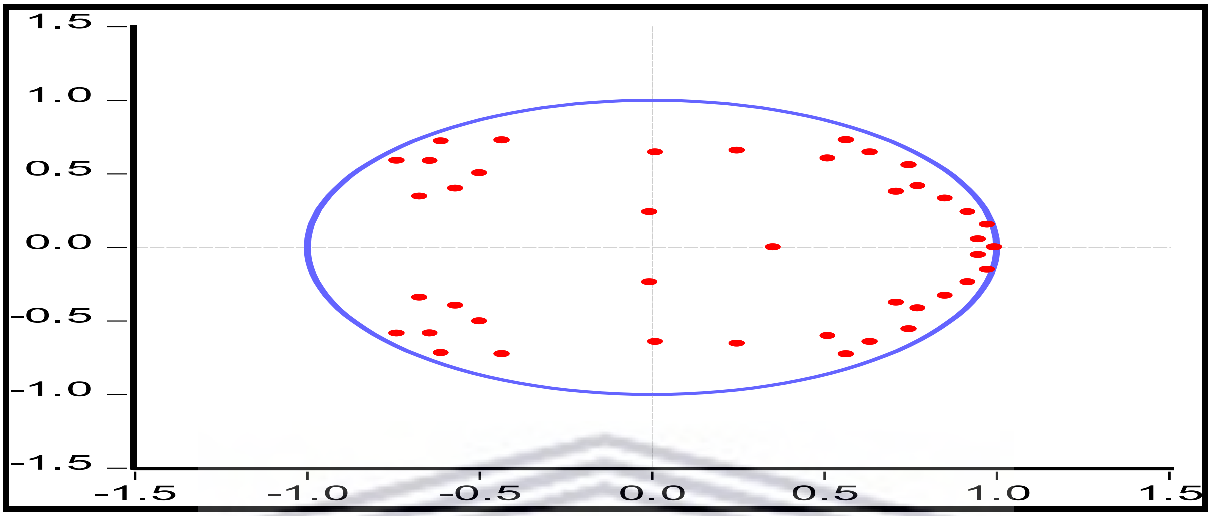
There are two approaches used in EViews for forecasting namely, the static and dynamic methods. The static approach uses a one-step-ahead forecast, whilst a dynamic method computes a short term $t + h$ forecast. Where t denotes the time period and h is a number of step-ahead to be forecasted. Unlike the static forecasting process, the forecasts of the dynamic approach rapidly converge upon the long-term unconditional mean value as the time horizon increases (Brooks, 2019).

5.3 Empirical results and discussion

5.3.1 Robustness Check: VAR stability condition

In Chapter IV it has already been established that the optimum lag length to be used base on the SC criterion is 1. Moreover, the unit root test results revealed that, except for NPL, MACRO and BANK indices that have been found to be stationary in level, the rest of the composite scores become stationary after first difference. The results of the VAR stability conditions are provided in Figure 5.2.

Figure 5.2: Inverse roots of AR characteristics polynomials



Source: Own compilation

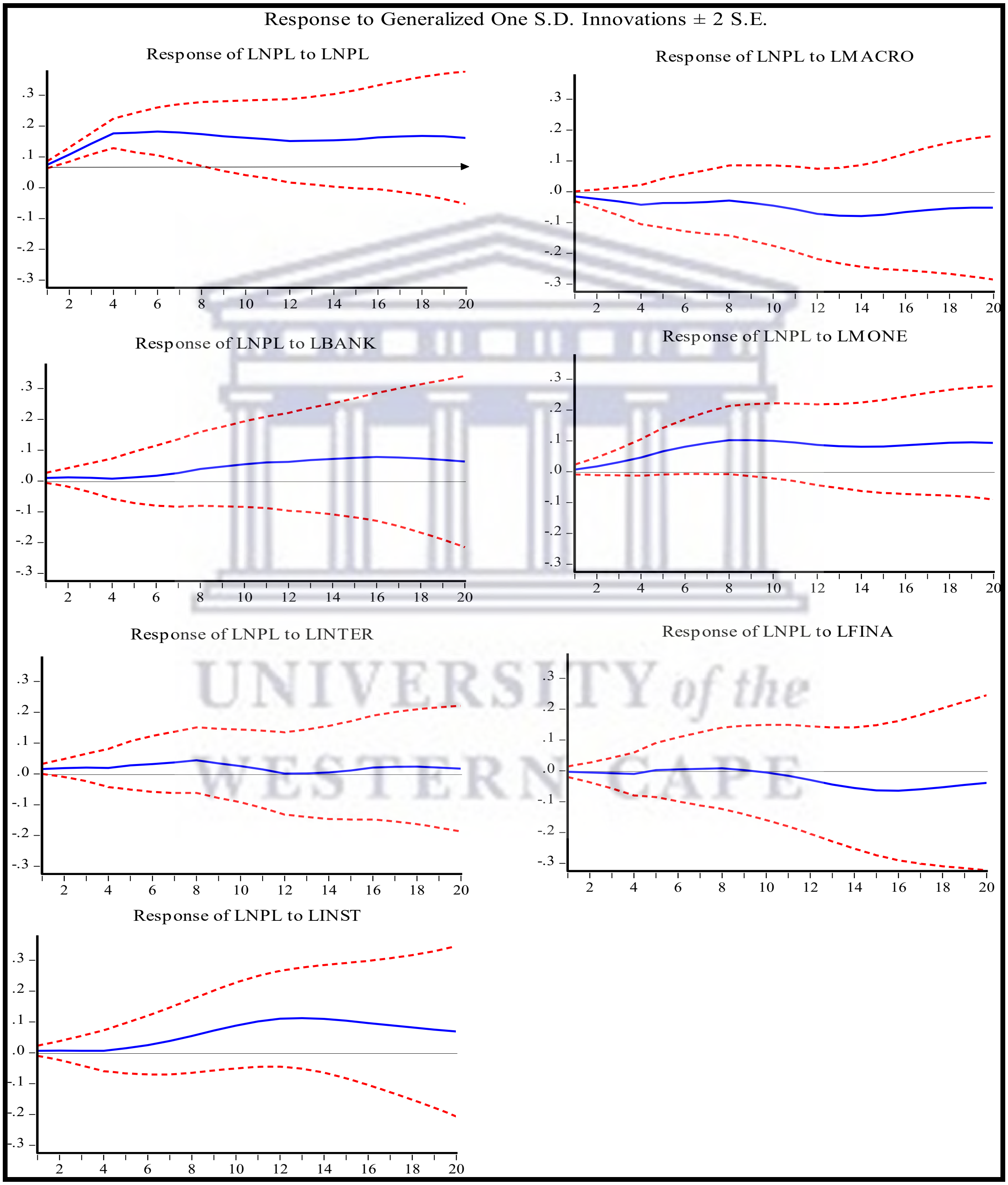
Note: All roots lie within the cycle. This implies that the estimated model is stable.

Figure 5.2 shows that all the eigenvalues lie inside the unit circle. Thus, it is safe to conclude that the VAR model is stable and satisfies stability conditions. A similar conclusion is reached on Table H.3 found in Appendix H as the result shows that all the inverse roots of the characteristic AR polynomial have a modulus of less than one and lie inside the unit circle. Technically, this implies that despite the unprecedented rise in the ratio of NPL experienced over the past eight years, the ratio has altogether been stable in the sample period, 1996Q1 -2021Q4.

5.3.2 Impulse Response Functions (IRF)

Now that the diagnostics test for the VECM model have been established, further analysis of the generalised IRF based on the VAR and VECM frameworks are hereby evaluated for a forecast horizon of 20-quarters. The IRF is used to determine both the direction as well as volume of the response of a series featured in the VAR model to unexpected innovations in the disturbance terms. Put differently, the IRF is useful in determining how the other series in a system react to a shock in one of the system's series. Both the VAR and VECM models are used to generate the stress-testing scenarios for credit risk in Namibia, which is one of the main objectives of this chapter, which serve as the basis for probabilistic interpretations. The stress-testing results pertaining to a one standard deviation shock in all variables in the system, together with a two standard deviation band is presented on Figure 5.3. The result of the IRF of the NPL model obtained via the VECM is provided in Figure 0.13 of Appendix H.

Figure 5.3: Impulse Response Functions on NPL



Source: Own compilation

As reported in Figure 5.3 (as well as in Figure 0.13 presented under Appendix H) the structural shocks of both the VAR and VECM framework have been identified through the use of the Generalises Impulse Response Functions (GIRF) which is insensitive to the ordering of the variables in the system. The results of the GIRF show how an isolated shock to one system variable affects non-performing loans (NPL). In this regard, Figure 5.3 shows the response of NPL to innovations/ shocks NPL, MACRO, BANK, MONE, INTER, FINA, and INST. It is worth noting that the IRF obtained through the VECM, which are presented in Figure 0.13 of Appendix H, are herein employed to simply provide insights into the direction (positive or negative) of the relationship.

More specifically, the results reveal that NPL increases sharply until the 4th quarter following a one-time unexpected positive shock to itself. It continues in a prolonged steady state positive region. By magnitude, a one standard deviation shock in NPL will lead to about 0.18%-point rise in NPL after four quarters. These dynamics are in alignment with those observed by other researchers (Gaur et al., 2022; Koju et al., 2018b; Radivojevic & Jovovic, 2017) where they concluded that increases in NPL in previous periods are positively related with the NPL in the current period. All in all, the response of NPL to a positive shock in itself is quite large, but not permanent, indicated by the substantiated IRF result obtained via the VECM framework on the same variable.

With regards to the response of NPL to a positive shock in the MACRO index, the result shows that the ratios of NPL declines, as expected, until the 5th quarter before it slightly rises until the 8th quarter. The lowest decline is recorded in the 14th quarter, before it slightly rises, but still in the negative region. Clearly, a positive shock in the MACRO index bears an asymmetric impact on NPL in both the short- and long run. By magnitude, a one standard deviation shock in MACRO leads to a decline of about 0.04%-points in NPL during the first four quarters, with the lowest decline of about 0.08%-points recorded in the 14th quarter. The result simply means that, once there is an unexpected positive shock in MACRO, NPL is bound to decline.

The impulse response function of NPL to an unexpected positive shock in the BANK index is observed to initially not have any impact on NPL in quarters 1 to 6. As can be seen in Figure 5.3, NPL starts rising beginning from the 6th quarter up until the 17th quarter where it reaches its highest of a 0.08%-points. The finding, although not compatible with the a priori expectation, is not surprising considering that for years the assets composition of Namibia's banking sector has been tied up in loans, with over 50% of its assets being mortgages. One would normally expect that as the BANK index, which typifies the financial and performance metrics of banks, rises, NPL is supposed to decline. On the contrary, this result suggests that as the banking sector becomes more and more profitable, banks management tend to engage in riskier investment activities with the aim of increasing profits. However, due to the problems of adverse selection and moral hazard, it ends up alluring unworthy borrowers who end up defaulting on their loan repayment obligations, leading to a rise in NPL ratios (Novellyni & Ulpah, 2017).

The response of a one standard deviation shock in the MONE index, an indicator measuring the monetary and liquidity condition of an economy, is found to be positively related with NPL. The period of response in NPL is immediate and it rises up until quarter 8. Beyond the 8th quarter, it somewhat stabilises and it remains in a steady state throughout the forecasted time horizon. More specifically, a one standard deviation shock in the MONE index causes the ratios of NPL to rise by a 0.10%-point after 9 quarter or three years. In others words, the result suggests that NPL rises as the monetary index rises. The rise in NPL is possibly caused by the failures of some banks to adequately set high standards for responsible lending.

The response of a one standard deviation shock in the INTER index, representing the prevailing interest rate environment, is also found to be positively related with NPL. In particular, the result shows that NPL increases steadily up until the 8th quarter by 0.04%. Thereafter, it gradually decreases until it hits its steady state level in the 12th month, and it continues in that state up until the 14th month, before it rises again. On the other hand, a one standard deviation shock in the FINA index, a proxy for the soundness of both the banking and financial sector, is for the first 5 quarters reported to negatively influence NPL. After that, it enters a steady state, which is short lived as it is immediately accompanied by positive response until the end of the 8th quarter. By the beginning of the 9th quarter it drastically declined into the negative zone for the rest of the forecasted period.

In as much as to say that, shocks in the FINA index have little impact on NPL in the first 10 quarters before it plummets in the negative zone. The FINA index has an asymmetric impact on NPL in the short- and long run.

The response of a one standard deviation shock in the INST index, a gauge of the extent to which the broader regulatory and governance environment within which banks operate affect NPL, is found to be positively related with NPL. More precisely, the result shows that innovations in the INST index initially have no impact on NPL during the first four quarters. Nonetheless, from the 4th quarter NPL is found to rise reaching a peak of 0.11% in the 12th quarter and it remains at that level until the 14th quarter, before it gradually declines for the remainder of the forecast period. All in all, the INST index is positively related with NPL.

To sum up, the results of the IRF, presented in Figure 5.3, summarise the response of NPL to a shock in one of the variables in the system while holding other innovations constant. The results reveal that a rise in NPL itself, BANK index, MONE index, INTER index, and INST index, respectively, increases NPL; meanwhile, a rise in MACRO index and FINA index, respectively, decreases NPL.

5.3.3 Forecast Error Variance Decomposition (FEVD)

Furthermore, analysis of the FEVD based on the VECM framework has been forecasted over the horizon of 20-quarters. The variance decomposition determines the sources of a change in a series. The stress-testing results pertaining to a one standard deviation shock in all variables in the system, together with a two standard deviation band is presented on Tables 5.9. The result of the FEVD of the other system equations are provided in Table H.4 of Appendix H.

Table 5.9: Forecast Error Variance Decomposition of NPL

Forecast	Forecast	Variance Decomposition (Percentage Points)						
Horizon	Standard Error	LNPL	LMACRO	LBANK	LMONE	LINTER	LFINA	LINST
Q1	0.066	100	0	0	0	0	0	0
Q5	0.233	80.70	0.72	2.45	2.69	7.74	0.90	4.80
Q10	0.386	58.98	1.16	5.25	4.75	4.69	10.32	14.85
Q15	0.581	40.19	6.84	4.26	2.82	9.62	14.83	21.45

Q20	0.755	33.55	10.02	3.05	1.75	14.57	14.35	22.71

Source: Own computation

The variance decomposition results presented in Table 5.9 were derived using a Monte Carlo simulation[98] of 1000 iteration, due to the fact that the JB test for normality found the residuals not being normally distributed.

In the short run, represented by quarter 1 to 5, more than 80% of the forecast error variance in NPL is explained by the variable itself. In other words, in the short run, NPL is strongly endogenous; whereas, the influence of the MACRO, BANK, MONE, INTER, FINA and INST index is strongly exogenous.

In the long run, represented by quarters 15 to 20, the influence of the MACRO, INTER, FINA and INST index rises gradually over the horizon while the influence of NPL on itself dwindles. On the other hand, influences from both the BANK and MONE index are strongly exogenous throughout the time horizon. In other words, their influence on NPL is very weak and possibly insignificant.

5.3.4 A Forecast of the Quality of the Namibian Banking Sector Loan Portfolio

Before forecasting, it is worth noting that the unit root property of the NPL variable has been formally tested and confirmed by both the DF-GLS as well as the CMR unit root test to be stationary in levels (See Table 5.4) which implies dealing an ARIMA(ρ, d, q) model[99]. Following is the identification of the values of parameter ρ and q which is obtained by evaluating the autocorrelation function (ACF) and partial autocorrelation function (PACF), respectively. The ACF and PACF results suggest the possible ARIMA models that can be considered. Figure 5.4 illustrates the ACF and PACF results based on NPL data forecasting.

[98] *The Monte Carlo simulation technique is often employed by various practitioners especially if the properties of a particular estimation method are not known and aspects of asymptotic apply. For more details on the Monte Carlo simulations, see Brooks (2019).*

[99] *An ARIMA(1,0,1) is equal to an ARMA(1,1).*

Figure 5.4: Correlogram of the Residual of the ARIMA (ρ, d, q) model

Autocorrelation | Partial Correlation

	AC	PAC	Q-Stat	Prob
1	0.960	0.960	102.41	0.000
2	0.875	-0.614	188.15	0.000
3	0.757	-0.186	253.00	0.000
4	0.624	0.002	297.42	0.000
5	0.495	0.178	325.63	0.000
6	0.377	-0.023	342.19	0.000
7	0.281	0.063	351.46	0.000
8	0.211	0.091	356.76	0.000
9	0.164	-0.047	360.01	0.000
10	0.134	-0.085	362.19	0.000
11	0.116	0.002	363.83	0.000
12	0.103	0.029	365.15	0.000
13	0.098	0.086	366.35	0.000
14	0.094	-0.060	367.46	0.000
15	0.088	-0.041	368.44	0.000
16	0.077	-0.054	369.20	0.000
17	0.062	0.041	369.71	0.000
18	0.044	-0.040	369.97	0.000
19	0.023	-0.031	370.04	0.000
20	-0.002	-0.023	370.04	0.000
21	-0.034	-0.098	370.19	0.000
22	-0.066	0.037	370.79	0.000
23	-0.095	0.017	372.06	0.000
24	-0.120	0.022	374.10	0.000
25	-0.136	0.034	376.73	0.000
26	-0.144	-0.069	379.75	0.000
27	-0.147	-0.037	382.94	0.000
28	-0.145	-0.029	386.08	0.000
29	-0.142	-0.001	389.12	0.000
30	-0.138	0.024	392.00	0.000
31	-0.133	0.008	394.74	0.000
32	-0.130	-0.006	397.37	0.000
33	-0.126	-0.025	399.89	0.000
34	-0.123	-0.010	402.30	0.000
35	-0.120	-0.008	404.63	0.000
36	-0.117	-0.002	406.88	0.000

Source: Own computation

Looking at the correlogram presented in Figure 5.4, the results reveal that the ACF exponentially decays with lags 1 to 8 being statistically significant. As for the PACF, lags 1 and 2 are found to be statistically significant. Based on this outcome, it is evident that the models to be estimated are not strictly autoregressive, AR(ρ), nor moving average, MA(q), but a combination of both AR(ρ)

and MA(q). Thus, the parsimonious model is obtained after comparing and selecting the iteration of the ARIMA (ρ, d, q) structure, where d is zero (0), with the least values in the model criterions and with most significant terms amongst the possible models. The results of the tentative models evaluated before the best required model is selected for further analysis and the findings are presented in Table 5.10.

Table 5.10: ARIMA model selection criteria

Criteria	Possible ARIMA Models			
	A) ARIMA (1,0,1)	B) ARIMA (1,0,2)	C) ARIMA (2,0,1)	D) ARIMA (2,0,3)
AR p-value	0.0000	0.0000	0.0000	0.0000
MA p-value	0.0000	0.9966	0.9982	0.0000
$Sigma^2$	0.5364[b]	0.2504	0.3821	1.0211[b]
Adjusted R^2	0.9474	0.9527	0.9279	0.8073
AIC	1.6644	1.6294	1.9837	2.9571
SC	1.7638	1.7287	2.0830	3.0564

Source: Own computation

Note: The asterisks ([b]) on Sigma^2 signify that the coefficient of the volatility of the ARIMA model is significant at 5% level.

The results presented on Table 5.10 indicate that, out of the four possible ARIMA models (A, B, C, and D), the ARMA components of both A and D models are highly significant as opposed to those of models B and C. Over all, when comparing the model A and D, it becomes indisputably clear that the ARIMA (1,0,1) structure (model A) is the most appropriate model to considered for further analysis due to its low volatility ($\sigma^2 = 0.5364$), highest Adjusted R^2 (0.9474) and the least AIC (1.6644) and SC (1.7638) when comparing to ARIMA (2,0,3) structure (model D).

Having identified ARIMA (1,0,1) as being the most appropriate model, next is to perform some diagnostics on its residuals. To ascertain that there is no information left uncaptured by the chosen ARIMA (1,0,1) model, the correlogram of the residuals of the said model are plotted. Based on the correlogram plot presented in Figure 0.14 of Appendix H, the result shows that the correlogram for the residuals are not altogether flat since not all lag structures are falling within the 95% confidence interval. This implies that the ARIMA (1,0,1) model needs to be re-adjusted to include any of the omitted lags (i.e., AR (2), AR (4), MA (2), MA (6) and MA (8)), thereby being able to capture important information omitted in the ARIMA (1,0,1) model. Table 5.11 contains the results of the adjusted ARIMA model.

Table 5.11: Adjusted ARIMA Model Selection Criteria

Criteria	Possible ARIMA Models	
	E) AR (1) AR (1) AR (4)	F) AR (1) AR (1) MA (6)
Significant ARIMA terms	3	3
$Sigma^2$	0.2199	0.2545
Adjusted R^2	0.9581	0.9515
AIC	1.4515	1.6098
SC	1.5757	1.7340

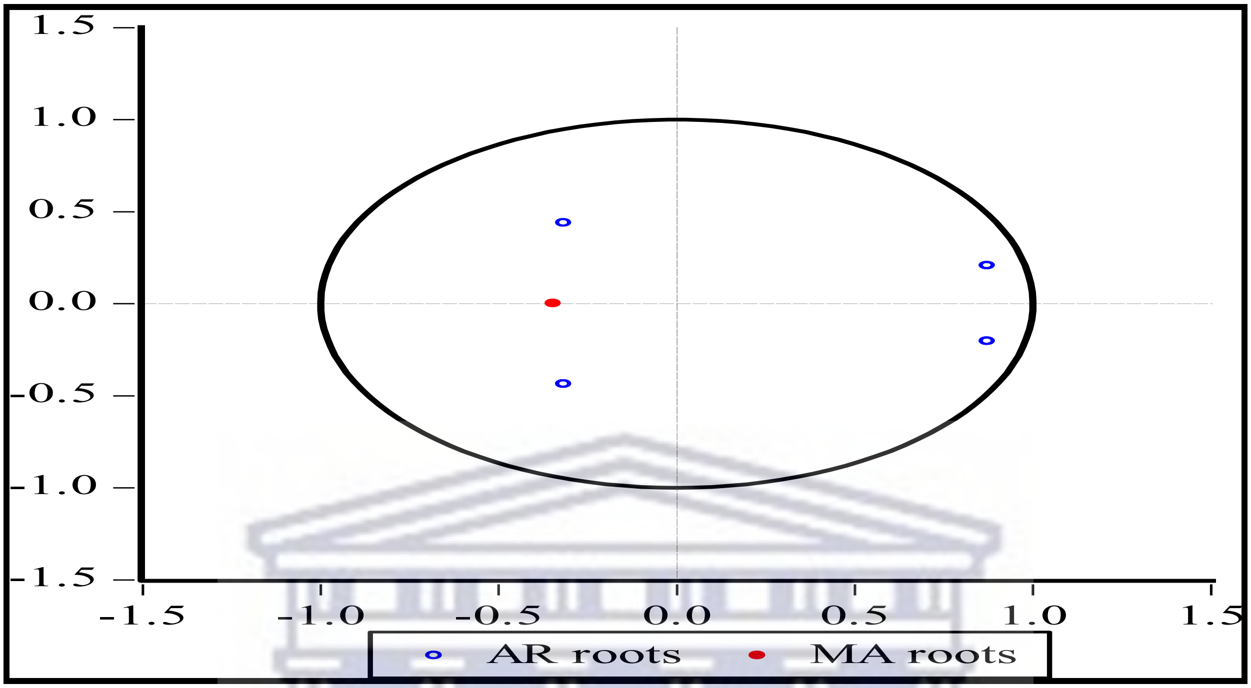
Source: Own computation

Note: The asterisks (b) on $Sigma^2$signify that the coefficient of the volatility of the ARIMA model is significant at 5% level.

The results contained in Table 5.11 show that of the two possible adjusted ARIMA models (model (E) and (F)), model (E) stands out as the most appropriate model for further analysis due to its significant ARIMA terms, lower volatility ($\sigma^2 = 0.2199$), highest Adjusted R^2 (0.9581), as well as its least AIC (1. 4515) and SC (1.5757) values when compared to model (F). Upon this establishment the appropriateness of the adjusted ARIMA model, the diagnostics on the residuals of the adjusted model (E) is performed. The result of the correlogram test of the residuals is presented in Figure 0.15 of Appendix H and shows that the correlogram for the residuals are now flat since all lag structures fall within the standard error bounds. This implies that all information previously not captured by the initial tentative ARIMA (1,0,1) model is now captured in the adjusted ARIMA model (E).

Next, the Ljung Box Q statistics test for autocorrelation is conducted to test for the null hypothesis of no autocorrelation in the residuals of the adjusted ARIMA model (E). The results presented in Figure 0.15 of Appendix H show that the residuals are white-noise. Finally, before the adjusted ARIMA model (E) is forecasted, its stability condition is evaluated in order to ascertain that the underlying conditions of stationarity and invertibility of the model is satisfied before the future values of the NPL series can be forecasted. The finding is present in Figure 5.5 which contains the inverse root of the AR/MA polynomial.

Figure 5.5: Inverse root of the AR/MA polynomial



Source: Own compilation

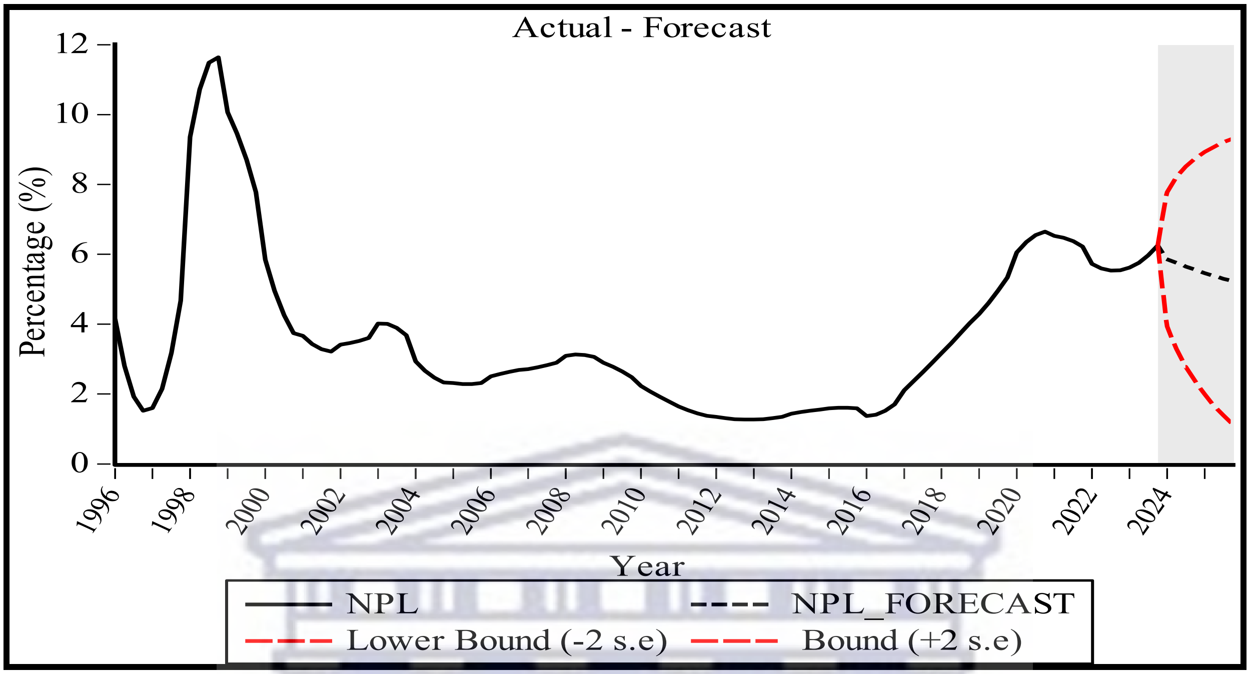
Note: All roots lie within the circle. The model is stable.

According to Figure 5.5, the stability condition of the adjusted ARIMA model (E) is satisfied since all the inverse roots are lying within the unit circle. On this basis, the last step of predicting the future values of the Namibian banking sector loan portfolio is carried out.

Figure 5.6 presents the plot for the actual series for the period 1996Q1 to 2023Q4 as well as the out of sample short-term dynamic forecast of NPL for the period 2023Q4 to 2025Q4.[100]

[100] *The results of the adjusted ARIMA forecast (which includes the root mean square, mean absolute error, mean absolute percentage error, et cetera) for the Namibian banking sector can be found in Figure 0-17 of Appendix H.*

Figure 5.6: Forecast of the Quality of the Namibian Banking Sector Loan Portfolio



Source: Own computation

Figure 5.6, which is generated by the adjusted ARIMA model (E), indicates that the outcome of the model fits the series very well as the forecast values fall within the ±2 standard error bands. Furthermore, the model's accuracy is ascertained by the evaluated results of the four error measurement test statistics (the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Theil Inequality Coefficient (TIC)). The tests measure the distance between the actual series from forecasted values. The results of these tests, provided in Figure 0.17 of Appendix H, show that the adjusted ARIMA model (E) is highly accurate in predicting the future values of the loan portfolio of Namibia's banking sector. This is because the values of the test statistics are relatively smaller which is indicative of the fact that the model used to forecast NPL is efficient.

With regards to the trajectory of the forecasted loan portfolio, Figure 5.6 shows that as the country's banking sector continues to recover from the adverse effects of the aftermath of the COVID-19 pandemic, the level of NPL is bound to decline from 5.9% in 2024Q1 to 5.2% in 2025Q. Put differently, the ratios of NPL is projected to contract by 1.1%. The construction is insufficient to bring down the prevailing ratio of NPL below the 4.0%-point benchmark set by the

Bank of Namibia. All in all, the forecast results indicate that the quality of the loan portfolio for the Namibian banking sector is still in danger as the signs of improvements over the forecast horizon is insufficient to revert it below the established benchmark. This conclusion differs from Kamati et al (2022)'s and Amediku (2006)'s findings which used data from the Namibian and Ghanaian banking sectors, respectively, to forecasted the quality of their loan portfolio.

5.4 Summary

In this chapter, a factor base stress-test model, particular to Namibia, was developed to examine the resilience of its banking sector by identifying the indicators for early warning of worsening loan quality and forecast the quality of loan portfolio. To achieve these inquisitions, the paper uses secondary time-series data from 1996Q1 to 2021Q4 and from 1996Q1 to 2023Q4, respectively. The techniques used for stress-testing the Namibian banking sector and detecting the indicators for early warning of deteriorating loan portfolio included the Impulse Response Functions (IRF) and Forecast Error Variance Decomposition (FEVD) obtained through the VAR/VECM model. Meanwhile, the second objective of forecasting the quality of the loan portfolio was conducted using the out of sample dynamic forecasting technique of the Autoregressive Integrated Moving Average (ARIMA) model. As for the forecasting of NPL, the result shows that the credit risk dilemma continues, as it is yet to be put under control. This is because the trend of NPL forecast is still quite higher, ranging over the stipulated benchmark region of 4.0%-point set by the Bank of Namibia. The contribution of this chapter to the ever-growing body of literature, especially in Namibia, lies in not just the inclusion of a vast array of composite factors, but in its data usage which encompasses the period before, during and after one of the worst crises experienced in recent memories.

CHAPTER VI: CONCLUSION AND POLICY RECOMMENDATIONS

6.1 Introduction

This chapter provides a synopsis of the six interdependent chapters of this thesis. Section 6.2 summarises the key findings of the thesis. Section 6.3 highlights the policy implications arising from the thesis. Section 6.4 outlines the limitations of the thesis. Finally, Section 6.5 delineates some potential areas for future research.

6.2 Summary of Key Findings

This thesis sought to examine issues relating to the indicators culpable of influencing credit risk in Namibia. Broadly put, a total of thirty-two secondary time-series variables, covering the periods 1996 to 2021,[101] were both individually and jointly assessed. Jointly, the thirty-two variables were compacted into six composite indices using the PCA methodology. The composite indices include the macroeconomic, bank specific, monetary, interest rate, financial and institutional indicators. The specific objectives investigated include a) assessing the evolution of Namibia's financial system post-independence in 1990; b) determining the indicators responsible for influencing the quality of the loan portfolio; c) testing the causal relationship between the indicators and NPL; d) stress-testing the vulnerability of Namibia's banking sector to credit risk shocks, thereby identifying the indicators for early warning of worsening loan portfolio and e) forecasting the quality of Namibia's loan portfolio.

Before delving into the intricate analytical nuances of this thesis, Chapter II was conducted to provide an overview of the Namibian banking and financial system. This exploratory review was necessary in order to explore the evolutions of financial system, in the face of credit risk. The review demonstrated that over the years, the influence of non-bank financial intermediaries significantly increased, whilst the dominance of the banking and financial system shrunk. Statistical data from BoN revealed that, despite the sector's contribution to economic development,

[101] *Note: The periods used to forecast the quality of Namibia's loan portfolio covered the periods, 1996Q1- 2022Q4.*

it has still come under immense credit risk pressures. Over the past couple of years, the levels of NPL have continued to hover above the critical limits of 4.0%-points. The sector's contribution to employment creation has been very minimal, and it is expected continue so with advancements happening in the Artificial Intelligence world.

Chapter III reviews the literature surrounding this thesis. It provides a systematic empirical review of each class of indicator used to evaluate the credit risk conundrum. The literature review, which is subdivided into theoretical and empirical, not only served to uncover the existing empirical gaps in the area, it also served the basis for recommending future research direction. Coincidentally, the theoretical literature also consisted of six sets of relevant theories relating to this current study. Furthermore, the various modelling techniques were scrutinised under the empirical literature section before finally deciding on the most appropriate technique to address the specific objectives of this study. It also served as a basis for comparing the findings relayed in this study. The divergent views were useful in drawing few lessons for the current study.

Chapter IV examines the second set of specific objectives outlined in Chapter I. Specifically, the chapter analysed the indicators responsible for influencing and Granger causing the quality of the loan portfolio of the Namibian banking sector. Both the ARDL and the VAR pairwise Granger causality modelling approaches are employed to evaluate the two corresponding sets of hypotheses relating to the mentioned objectives. The findings, based on the model consisting of the composite measures show that over the long run, ceteris paribus, the macroeconomic and the interest rate indices were both found to influence NPL. As for the short run, ceteris paribus, the results reveal that previous accumulations of NPL amplify the rise in NPL in the current quarter. The macroeconomic indicator was still found to strongly stabilise the rise in the ratios of NPL in the current quarter. Conversely, a tighter interest rate environment is estimated to exacerbate the quality of the loan portfolio, as it is found to be positively related to NPL. On the other hand, a positive relationship is found between governance (institutional) indicator and NPL in current quarters. In terms of causality, the results indicate that both the macroeconomic as well as the interest rate indicators have a long run causal effect on NPL. In the short run, however, the results show that there is a strong short run causal effect running from the past quarter values of NPL to NPL as well as from the macroeconomic indicator to NPL.

Chapter V involves a sensitivity stress-test analysis for the credit risk stability of the Namibian banking sector. Furthermore, it forecasts the assets quality of the loan portfolio using not only the impulse response functions and variance decomposition simulations, but also the out of sample dynamic forecasting technique of the ARIMA model to predict the behavioural patterns of NPL. The empirical outcomes reveal that the financial indicator has an asymmetric effect on NPL, with its negative effect being more persistent in the long run. The macroeconomic indicator is found to negatively influence NPL. These results imply that stability of both the macroeconomic and financial environment is pivotal to countering rising credit risk in Namibia's banking sector. In the event that the banking system is exposed to varying degrees of stress, the indicators for early warnings of worsening loan portfolios are recorded to firstly rise from a positive shock in the NPL itself, followed by the monetary indicator, institutional indicators, bank specific indicator, and the interest rate indicator. The projection for the quality of the loan portfolio is forecasted to continue following a downward trend up to the end of the year 2025. The dynamic forecast of the ARIMA model is robust and unbiased as the predicted values of NPL fall well within the 95% confidence levels (or the ±2 standard error bands). Notwithstanding, the result shows that the credit risk dilemma continues as it is yet to be put under control as NPL is forecasted to still range above the stipulated benchmark region of 4.0%-point set by the Bank of Namibia.

The noteworthy contribution of this thesis to the body of knowledge on the issue of non-performing loans revolved around the spectrum of factors and/or indicators evaluated in the various stages of the empirical analysis. The combinations of methodological approaches used to investigate/complement the sets of objectives underlying this thesis, the majority of which have never before been used in the context of Namibia and the topic at hand. The results from this study can be generalised to other developing countries with similar characteristics or features as Namibia. For such countries, lower levels of credit risk are probably also required to guarantee the stability of their banking and financial systems, which will reflect well on their economic development as the quality of the loan portfolio is upheld.

6.3 Policy implications

The empirical findings emanating from this thesis have serious policy interventions that should be considered so as to minimise and contain the phenomenon of non-performing loans in Namibia' banking sector.

Firstly then, as identified in chapter (II), Namibia's banking sector is majorly dominated by foreign owned banks, whose parent companies are mostly headquartered in South Africa. Albeit, the state-owned institutions play a vital supervisory and legislative role that is crucial in stabilising the banking and financial system. The government continues to have a leverage effect of influencing the day-to-day operations of banks, by for instance protecting its citizens from being exploited by banks that are mainly profit driven. Therefore, instead of allowing these banks, which are oligopolistic in nature, to unfairly fix higher interest rates and charge hefty bank charges, the government should use its discretionary power and intervene by placing a ceiling on the margins of interest that banks can reasonably charge the citizens while still being able to make profit.

Secondly, the fact that the institutional indicator is found to positively relate to NPL, indicates that there are some levels of regulatory inefficiencies that could be dampening the asset quality of the Namibian banking sector loan portfolio. This might be due to the fact that some policies governing the operations of the banking sector, might be irrelevant for the successful operation of the banking industry. Hence, from time to time, policy makers, regulators and banking authorities should endeavour to re-evaluate the existing policies, so that policies that might be adversely affecting the quality of the loan portfolio are ridded-off, thereby eliminating the level of inefficiencies in the banking industry. The outcome between the institutional indicator and NPL are not solely limited to regulatory inefficiencies but also deterioration in good governance, corruption, weakening governance systems, et cetera. In fact, a report from the Mo Ibrahim Foundation (2023) highlighted that, despite Namibia featuring on the list of the top 10 countries with a high overall governance index, the country reported to have regressed backward between the years, 2017-2021.

Against this background, the law enforcement agencies of Namibia (the Namibian police (NAMPOL), Financial intelligent centre (FIC), and the Anti-corruption commission (ACC)), mandated to combat financial crime, money laundering and corruption need to ensure that such crimes are meticulously investigated until the perpetrators are brought to book. The efficient execution of this nobler cause will shift the perception that enforcement institutions are inefficient and raise their reputation higher. Thus, a speedy execution of cases that are currently before the courts is required in order to give closure to cases that are long overdue and avoid treating them as if they are inconclusive. In the same vein, ill-gotten money must be recovered and a portion of it be used to strengthen the existing law enforcement institutions, thereby strengthening the resilience of the banking industry.

The finding that the macroeconomic indicators is negatively related to NPL and that it has both a short- and long run causal effect on NPL, demonstrates how important a sound macroeconomic environment is in ameliorating the asset quality of Namibia's banking sector loan portfolio. The same can be said for the macroeconomic and financial index findings under the sensitivity stress-test analysis. Thus, policy makers, regulators and bank managers should continuously adhere to policies that have so long fostered a sound macroeconomic and financial environment. These could include, the usual inflation targeting policy undertaken by the BoN in order to ensure price stability, the monitoring and evaluation of banks in order for them to adhere to the best risk management practices, as well as the minimum capital adequacy ratios required of banks to adhere to prudential standards. These efforts, amongst others, will continue to ensure a conducive macroeconomic environment that would serve as a bedrock for maintaining the stability of the banking and financial system.

The finding that the interest rate index was obtained to positively influence NPL, signifies that as the cost of borrowing (interest rate) rises, the ratios of NPL tends to increase due to the fact that it becomes burdensome for borrowers to service their debts. Considering that the monetary authority in Namibia does not fully enjoy an independent monetary stance, policies that support borrowers during the periods of heightened interest rates, must be adopted. For instance, the government could provide subsidies on interest payments in order to alleviate the debt serving burden on borrowers' shoulders during the period of rising interest rates. Banks could also assist their clients who are financially stressed, with some temporal debt relief, by, for example, being in a position to renegotiate favourable loan repayment terms. Additionally, grants, or any other forms of financial support could be extended to the affected businesses, industries, or sectors to assist them in coping with the hostile interest environment, thereby capacitating them to honour their contractual debt obligations with banks which ultimately leads to a reduction in the ratio of NPL.

Moreover, since a positive shock in NPL itself is identified as the foremost early warning indicator for the banking sector, bank authorities should consider strengthening the mechanisms for monitoring NPL. For instance, banks could adopt proactive surveillance systems for identifying and mitigating the challenges of NPL in a timely manner. The monetary indicator was the second early warning indicator for deteriorations in the asset quality of the loan portfolio. This should cause the already constrained monetary authority, to explore alternative tools such as the capital restrictions and prudential requirements that would ensure appreciations in the asset quality of the loan portfolio. The institutional indicator which was also identified as a third early warning signal for worsening loan portfolio, requires that banking sector authorities re-evaluate the set of policies and potentially reform the institutional frameworks governing the Namibian banking and financial system, thereby making it more resilient. Bayar (2019) encourages policy makers to avoid embracing institutional and economic policies which endanger banks.

Finally, a positive shock in both the bank specific and interest rate measures are also identified to respectively be the fourth and fifth early warnings signals of worsening loan portfolio. As such, banks should consider implementing targeted measures aimed at enhancing the stability and resilience of the individual banks, thereby impacting the overall stability of the banking sector. Accounting for the factor loadings results (See, Table C1.2 in Appendix C) of the variables underlying the bank specific index, it is incumbent for individual banks to strengthen their risk management practices as well as the performance of the following underlying variables: the returns on assets, returns on equity, capital adequacy, and the net interest margin.

6.4 Limitations of the study

As with most studies, the current study is not without limitations. Firstly, it is worth highlighting that the NPL variable, used to proxy credit risk and evaluate the fragility of the banking sector, is not the only measure for banking sector credit risk. As acknowledged in chapter one, there exists a number of alternative indicators used to proxy credit risk. It is thus not farfetched that the outcomes could turn out different in the event that an alternative measure is used. Notwithstanding, the usage of NPL as a proxy for credit risk is considered to be one of the most commonly used measure for such.

Secondly, despite attempts to exhaustively scout out all the key indicators most likely to influence NPL, it was quite impossible to explore and employ all of them due to their data unavailability. An example of such was when several attempts were made to obtain the set of disaggregated bank specific data from the banking industry. This proved difficult to obtain as most of the approached institutions deemed such information to be highly confidential. Thus, it was not possible to conduct the bank by bank analysis of NPL. Nevertheless, in the absence of disaggregated bank specific data, the aggregate bank specific series data proved to be very useful in affording an insight of the dynamics of such factor on NPL. Therefore, this study was unable to ascertain the various transmission channels through which NPL is affected. Instead, it was able to provide clarity on how the macroeconomic, bank specific, interest rate, monetary, financial, and institutional indicators are related to NPL.

Thirdly, although the ARDL, VAR and ARIMA modelling techniques have some drawbacks, they are herein used to complement each other. For instance, both the VAR and ARIMA models are a theoretical in nature and because of this they are often criticised for it, especially considering the endogenous nature in which the variables are featured into the system. Thus, to deviate from making such a generalisation assumption and avoid reporting inaccurate results, the results obtained through the VAR are compared to those obtained through the ARIMA model. Moreover, the results are complemented by those obtained through the alternative use of the ARDL modelling approach, which relaxes the a theoretical assumption of the VAR and ARIMA models. In addition, the three modelling approaches assume linearity amongst the variables. This may not necessarily be the case for all variables featured in the estimation model, as some of them might be non-linear in nature. Nonetheless, the empirical results considered in this study were mainly those that emanated from models whose correct functional form was ascertained, thereby avoiding misguided inferences and conclusions.

All in all, despite the highlighted drawbacks and the adopted counter measures taken to mitigate and possibly eliminate the error in the estimation processes, the outcomes of this study have been tested to be robust. The modelling techniques employed in chapters four and five in this dissertation continue to be indispensable macro-econometrics tools for examining the effect, causality, and the sensitivity analysis stress-test for credit risk of banking and financial systems, among others.

6.5 Possible areas for future research

While the limitations outlined in this chapter are not meant to undermine the conclusions and policy implications of this study, addressing the issues can only augment the robustness of this study. The constraints outlined in this study underscore the necessity for additional research on the factors underlying the phenomenon of NPL in Namibia.

Having mentioned this, future studies could consider looking at other dimensions relating to credit risk in Namibia, which may include exploring the role of financial inclusion, credit rating, regime change, compliance to the Basel III regulations and a change in the leadership of the central bank in influencing NPL. Moreover, since the modelling techniques employed in this study are linear in nature, future researchers could explore the possibilities of directly estimating the models that are non-linear. In particular, the nonlinear ARDL (NARDL) approach to cointegration, which has nonlinearity properties and is considered to be highly superior to standard cointegration model, could be utilised to determine the dynamic interactions between NPL and the indicators.

Alternative proxies for credit risk measures should also be considered and the results compared to this present study. Furthermore, the use of disaggregated industry (panel) data could be obtained in order to gain insight into the bank specific factors responsible for influencing NPL in Namibia's commercial banks. Analyses based on such data are arguably more informative in catering for heterogeneous characteristics of individual banks, thereby would support and refine the results obtained in this investigation.

APPENDICES

Appendix A: The Methodology for the Principle Component Analysis (PCA) Estimation

As indicated in Chapter IV, the PCA offers the privilege of representing a vast dataset into new and fewer variables, such as the six categories of the Macroeconomic (MACRO), Bank specific (BANK), Monetary (MONE), Interest rate (INTER), Financial (FINA) and Institutional (INST) indicators. This study adopts Yildirm (2021)'s general formulation of the principal components used in the construction of the six indicators (indices) used as determinants of credit risk in Namibia's banking sector. Firstly then, before obtaining the solution for the PCA, an eigenvalue decomposition of the correlation matrix is performed by obtaining the principal axes of the shape formed by the scatter plot of the data. This decomposition produces a set of eigenvalues, λ, which measure the variance associated with the principal components, V, alongside their corresponding eigenvectors, X. The eigenvectors capture the direction of one of the principal axes. From the following mathematical Equation: $(C - \lambda X)V = 0$, where C is the sample correlation matrix of the original data, the eigenvalue, λ, is calculated using the following expression:

$$\lambda = \frac{C}{X} \tag{1A}$$

The proportions of the variance in each original variable, X, accounted for by the first contributing factors is given by sum of squared factor loadings, $\sum f_{ik}^2$. The Equation capturing the factor loadings, which are the correlations between X and Y, is specified as follows:

$$F = corr(X, Y) = V\sqrt{D} \tag{2A}$$

Where $D = diag(\lambda)$ is the diagonal covariance matrix of the components, X, Y and V are as previously defined.

Finally, per the PCA approach, the p^{th} factor indices are computed using basic principal components, $Y = [Y_1, Y_2, \dots, Y_p]$, that are a linear combination, $V = [V_1, V_2, \dots, V_p]'$, of the original data, $X = [X_1, X_2, \dots, X_p]$ containing a p number of variables used to maximise variance for each of the contributing factor index is specified as follows:

$$Y_p = \sum_{n=1}^{p} V_{np} X_p \tag{4A}$$

Where the vector Y represents the aforementioned transformed indicators (indices); p numbers of variables used to construct a particular index; n is the size of the sample; V is the weight of the parameters of the principal components (PCs) also referred to as factor scores or eigenvector; X is vectors of matrices of the original dataset related to the components. It is worth stating here that the variance of the PCA is only maximized provided $X'X = 1$.

Therefore, from the generic equation, Equation 4A, the specific mathematical equations used to construct the individual factor index for the $MACRO, BANK, MONE, INTER, FINA$ and $INST$ indicators are hereby specified in the order mentioned:

$$MACRO_p = V_{n1}OPEN_1 + V_{n2}DEBT_2 + V_{n3}GAP_3 + V_{n4}HP_4 + V_{n5}UN_5 + V_{n6}INF_6 \tag{5A}$$

$$BANK_p = V_{n1}ROA_1 + V_{n2}ROE_2 + V_{n3}ROE_3 + V_{n4}CAR_4 + V_{n5}LB_5 + V_{n6}LDR_6 + V_{n7}LG_1 \tag{6A}$$

$$MONE_p = V_{n1}M_1 + V_{n2}M_2 + V_{n3}NFA_3 \tag{7A}$$

$$INTER_p = V_{n1}REPO_1 + V_{n2}LEND_2 + V_{n3}DEPO_3 + V_{n4}IS_4 + V_{n5}TBILL_5 \tag{8A}$$

$$FINA_p = V_{n1}RER_1 + V_{n2}PSCE_2 + V_{n3}OIL_3 + V_{n4}MCAP_4 + V_{n5}COVID19_5 \tag{9A}$$

$$INST_p = V_{n1}VA_1 + V_{n2}PS_2 + V_{n3}CC_3 + V_{n4}RQ_4 + V_{n5}GE_5 + V_{n6}RL_6 + V_{n7}ACC_1 \tag{10A}$$

The definition of all the independent variables embedded in each of the equations represented in Equation 5A to 10A are as previously defined in Chapter 4.

Appendix B: Construction of the macroeconomics (MACRO) Index

Table B1.1: Eigenvalues of the principle components for the MACRO index

Number	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	1.861448	0.573418	0.3102	1.861448	0.3102
2	1.28803	0.143014	0.2147	3.149478	0.5249
3	1.145016	0.187287	0.1908	4.294495	0.7157
4	0.957729	0.437269	0.1596	5.252224	0.8754
5	0.520461	0.293146	0.0867	5.772685	0.9621
6	0.227315	---	0.0379	6	1

Source: Own computation

Note: Based on Kaiser (1960)'s criterion, only components with Eigenvalues greater than one must be retained.

According to Table B4.1, a total of 3 out of the 6 eigenvalues have been suggested to be used for further analysis. Thus, only three principal components (PCs), representing about 72% of the total variations in the data, must be retained. This means that for the compact $MACRO$ index, the desired threshold can be attained by the weighting of the cumulative explained variance. The three components account for an approximate proportion of variations of 31.0%, 21.5%, and 19.1% of the total variations in the data, respectively. The eigenvectors (loadings) illustrating the percentage of variation in the three PCs (factors or component) are presented in Table B1.2.

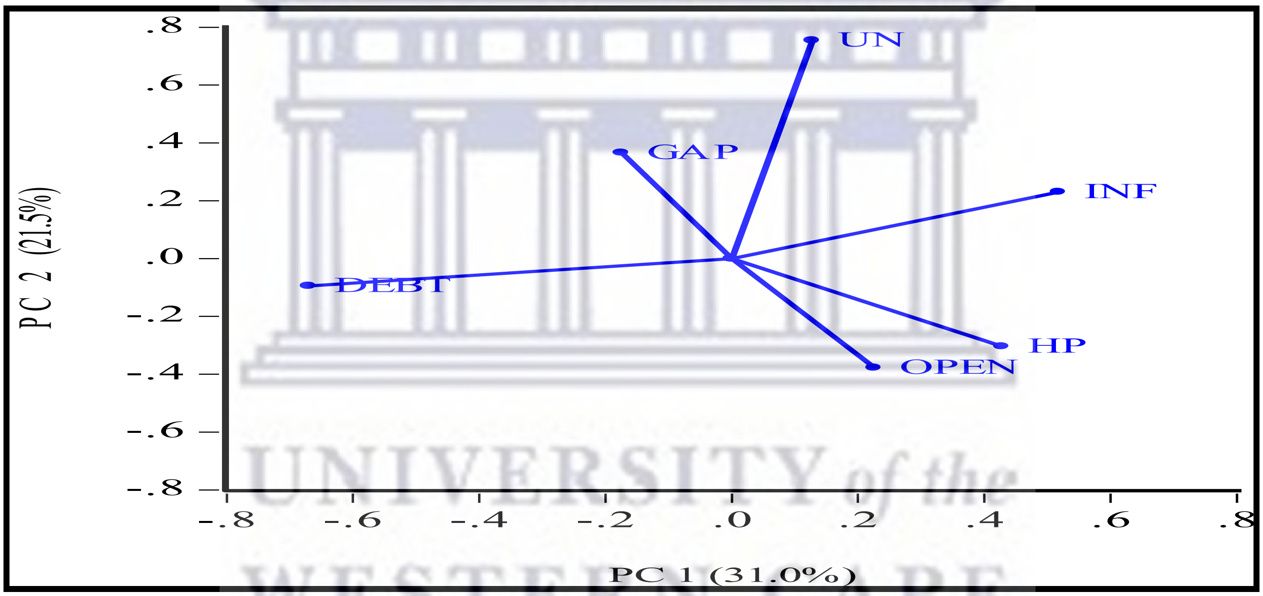
Table B1.2: Loadings of the 3 principal component weighting factors for the MACRO index

Variable	PC 1	PC 2	PC 3
OPEN	0.22645	-0.37775	0.69426
DEBT	-0.66981	-0.09490	0.03569
GAP	-0.17439	0.36592	0.57018
UN	0.12820	0.75426	-0.13497
HP	0.42911	-0.30397	-0.33600
INF	0.51875	0.23041	0.24599

Source: Own computation

Table B1.2 presents a linear combination of the six original variables used to construct the $MACRO$ indicator. In general, a dominant variable will tend to contribute a higher loading to a particular principal component (PC). Thus, the influence of an original variable is considered to be of importance if the value of its loading is positively or negatively larger than 0.5. Based on the first principal component (PC1), which accounts for 31.0%, INF (0.52) has the largest positive loading whilst DEBT (-0.67) has the largest negative loading. The second principal component (PC2), which accounts for 21.5%, found the variable UN (0.75.) to contribute with the largest positive loading. With regards to the third principal component (PC3), which accounts for 19.1%, OPEN (0.69) was found to have the largest positive loading, followed by GAP (0.57). The visual presentation of the basic directions between the variables is plotted in the orthonormal loading chart provided in Figure 0.1A.

Figure 0.1: Orthonormal loadings for the MACRO index



Source: Own computation

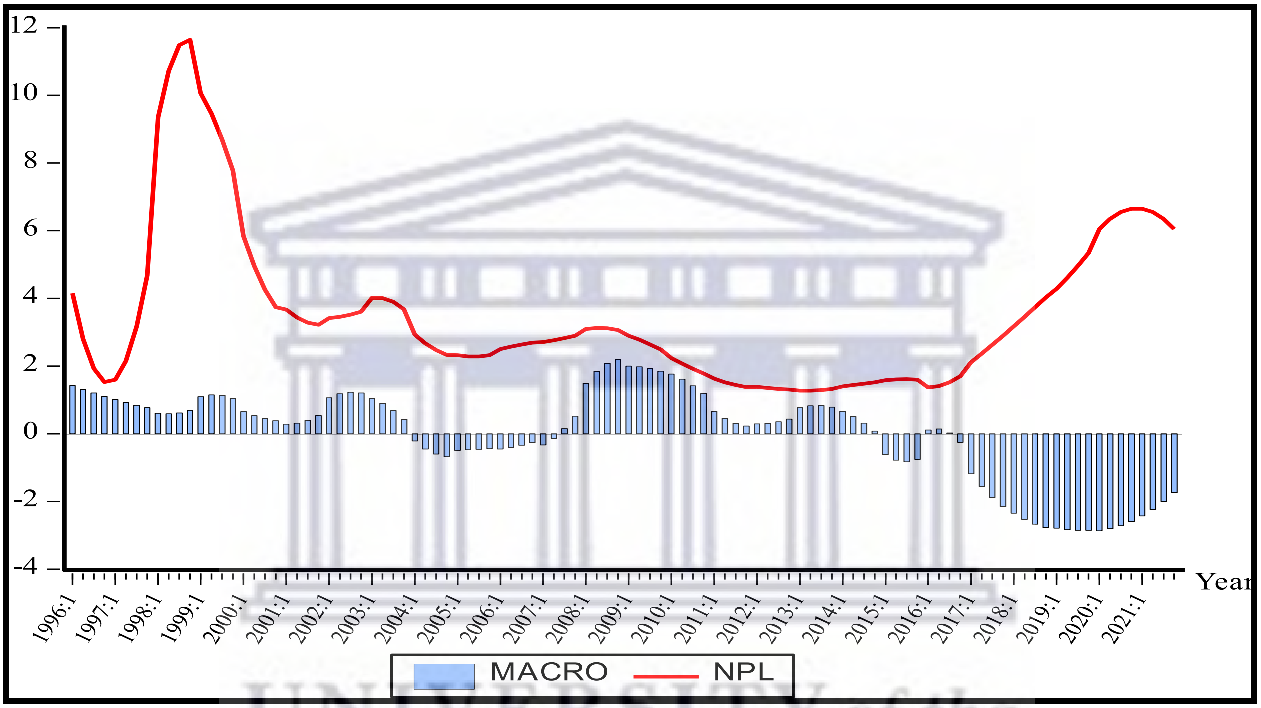
Although the information conveyed on Figure 0.1 is the same as those provided by Table B1.2, the chart provides a clear visual aid of how close the variables in the first two components are related.

The final process, before plotting the time graph of the generated MACRO index, is to compute the matrix weights of the MACRO indicator as follows:

$$MACRO = \frac{31.02}{71.57}PC1 + \frac{21.47}{71.57}PC2 + \frac{19.08}{71.57}PC3$$

The time graph of the $MACRO$ index obtained by the PCA is presented alongside NPL in Figure 02 as follows:

Figure 0.2: Time graph of Namibia's Macroeconomic indicator, 1996Q1-2021Q4



Source: Own computation

Figure 0.2 illustrates that despite the global recession of 2008-2009 that resulted from the collapse of the US housing market, the $MACRO$ index, which is used as a proxy for Namibia's economic environment, reached its peak performance in 2008Q4. This outcome is attributed to a series of factors that preceded the crisis period, especially the prudent macroeconomic policies (i.e., the expansionary fiscal policies) and improvements in the commodity prices of some mineral products (AfDB, 2012). These factors enabled the country to accumulate sufficient cash balances which helped it to withstand the negative shocks that emanated from the global economic meltdown at the time. As a matter of fact, the country's strengthened fiscal space enabled it to register a series of budget surplus for three consecutive years beginning from 2006 (MoF, 2015). Unsurprisingly, the time graph shows that following the peak, the index took a nosedive followed by three troughs, with the lowest trough being in 2020Q1. Undoubtedly, the sustained expansionary fiscal policy, driven by unstained debt accumulation, are likely to have been at the root of the negative ramifications for the economy. The global COVID-19 pandemic merely amplified the hardships of the economic conditions that the country had been undergoing at the time prior to the advent of the pandemic. The variables used to construct the MACRO index are: Trade openness ($OPEN$), Debt stock (*DEBT)*, Output gap (*GAP*), Unemployment (*UN*), House price index (*HP*) and inflation (*INF*).

Appendix C: Construction of the bank specific (BANK) index

Table C1.1: Eigenvalues of the principle components for the BANK index

Number	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.34316	1.78372	0.4776	3.34316	0.4776
2	1.55944	0.74294	0.2228	4.902596	0.7004
3	0.8165	0.01785	0.1166	5.71909	0.817
4	0.79864	0.42896	0.1141	6.517734	0.9311
5	0.36969	0.27835	0.0528	6.88742	0.9839
6	0.09133	0.07009	0.013	6.978753	0.997
7	0.02125	---	0.003	7	1

Source: Own computation

Note: Based on Kaiser (1960)'s criterion, only components with Eigenvalues greater than one must be retained.

According to Table C1.1, a total of 2 out of the 7 eigenvalues have been suggested to be used for further analysis. Thus, only two principal components (PCs), representing about 70% of the total variations in the data, must be retained. This means that for the compact $BANK$ index, the desired threshold can be attained by the weighting of the cumulative explained variance. The two components account for an approximate proportion of variations of 47.8% and 22.3% of the total variations in the data, respectively. The eigenvectors (loadings) illustrating the percentage of variation in the three PCs (factors or component) are presented in Table C1.2.

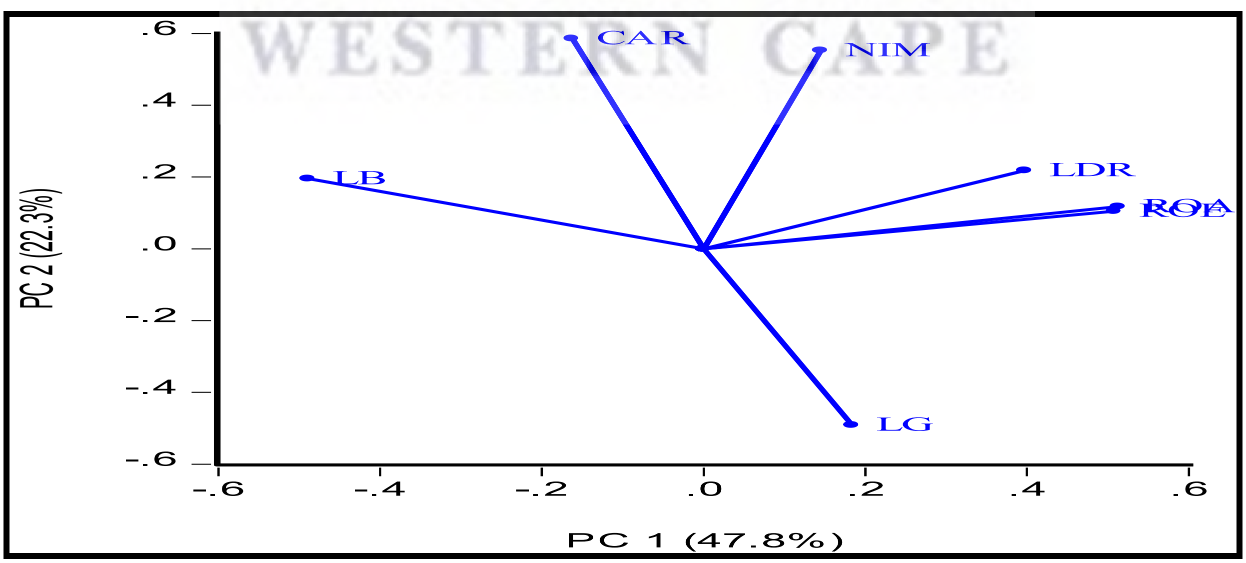
Table C1.2: Details of the 2 principal component weighting factors for the BANK index

Variable	PC 1	PC 2
ROA	0.51338	0.11748
ROE	0.50834	0.10498
CAR	-0.1619	0.58553
LB	-0.4888	0.1954
NIM	0.14499	0.55256
LG	0.18368	-0.4912
LDR	0.39768	0.21814

Source: Own computation

Table C1.2 presents a linear combination of the seven original variables used to construct the $BANK$ indicator. Generally, a dominant variable is one that contributes a higher loading to a particular principal component (PC). Thus, the influence of an original variable is considered to be of importance if the value of its loading is positively or negatively larger than 0.5. Based on the first principal component (PC1), which accounts for 47.8%, Both ROA and ROE have the largest positive loadings of about 0.51. The second principal component (PC2), which accounts for 22.2%, found the variable CAR (0.58) to exert the largest positive loading, followed by NIM (0.55). The visual presentation of the basic directions between the variables as plotted in the Orthonormal loading chart provided in Figure 0.3.

Figure 0.3: Orthonormal Loadings for the BANK index



Source: Own computation

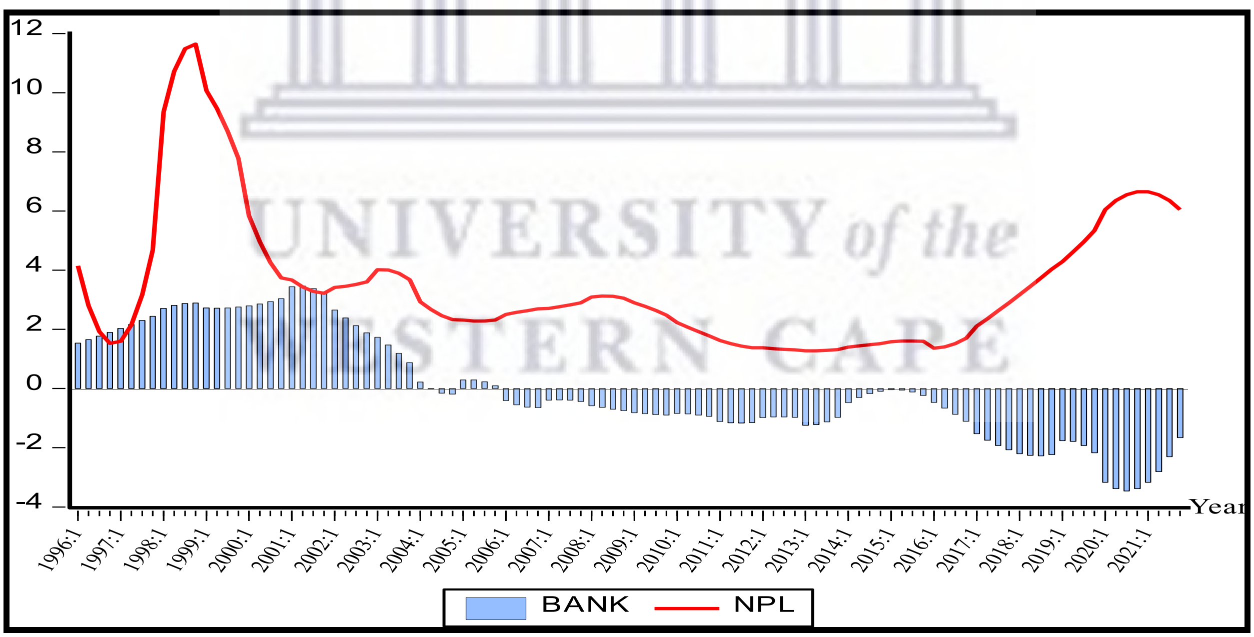
Although the information conveyed on Figure 0.3 is the same as those provided by Table C1.2, the chart provides a clear visual aid of how close the variables in the first two components are related. Particularly, the chart shows that ROA, ROE and LDR have a large positive loading on component 1, while NIM and CAR have the largest loadings on component 2.

The final stage, before plotting the time graph of the generated $BANK$ index, is to compute the matrix weights of the $BANK$ indicator as follows:

$$BANK = \frac{47.8}{70.04}PC1 + \frac{22.2}{70.04}PC2$$

The time graph of the $BANK$ index obtained by the PCA is presented alongside NPL in Figure 04 as follows:

Figure 0.4: Time graph of Namibia's Bank specific indicator and NPL, 1996Q1-2021Q4



Source: Own computation

As illustrated in Figure 0.4, the BANK index, used to proxy the performance or risk exposure of the banking system, showed a healthy and sound banking sector for the periods 1996Q1 – 2004Q2. It is a vital index for assessing the combined impact of bank specific indicators on the resilience of the banking sector. Normally, the higher the BANK index, the healthier and more stable the banking sector is. Based on Figure 0-4, the highest value of the BANK index was recorded in the second quarter of 2001. According to Bank of Namibia (2001)'s annual report, the banking sector was said to have been healthy and sound as the total asset base of commercial banks' assets grew by 11.8%.

Moreover, the same report indicated that the banking sector was said to be adequately capitalised as its capital adequacy ratio stood at 15.5% as opposed to 14.8% in the previous year. There was also a sharp decline in NPL during that year. Overall, the figure depicts that the BANK index has been trending downwards, with the lowest trough due to COVID-19 recorded in the third quarter of 2020. Clearly, the banking sector has been under immense pressures since 2015 as the countries continued to record poor economic growth due to drastic economic declines and rising NPL. The variables utilised in developing the BANK index are: Return on assets (ROA), Return on Equity (ROE), Capital adequacy ratio (CAR), Lending behaviour (LB), Net interest margin (NIM), Loan to deposit ratio (LDR) and Loan growth (LG).

Appendix D: Construction of the monetary (MONE) index

Table D1.1: Eigenvalues of the principle components for the MONE index

Number	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	2.95586	2.91711	0.9853	2.955857	0.9853
2	0.03875	0.03335	0.0129	2.994604	0.9982
3	0.0054	---	0.0018	3	1

Source: Own computation

Note: Based on Kaiser (1960)'s criterion, only components with Eigenvalues greater than one must be retained.

According to Table D1.1, a total of 1 out of the 3 eigenvalues have been suggested to be used for further analysis. Therefore, only one principal component (PC1), representing about 98.5% of the total variations in the data, must be retained. This means that for the compact $MONE$ index, the desired threshold can be attained by the weighting of the cumulative explained variance. The first component accounts for an approximate proportion of variations of 98.5% of the total variations in the original dataset. The eigenvectors (loadings) illustrating the percentage of variation in the first component are presented in Table D1.2.

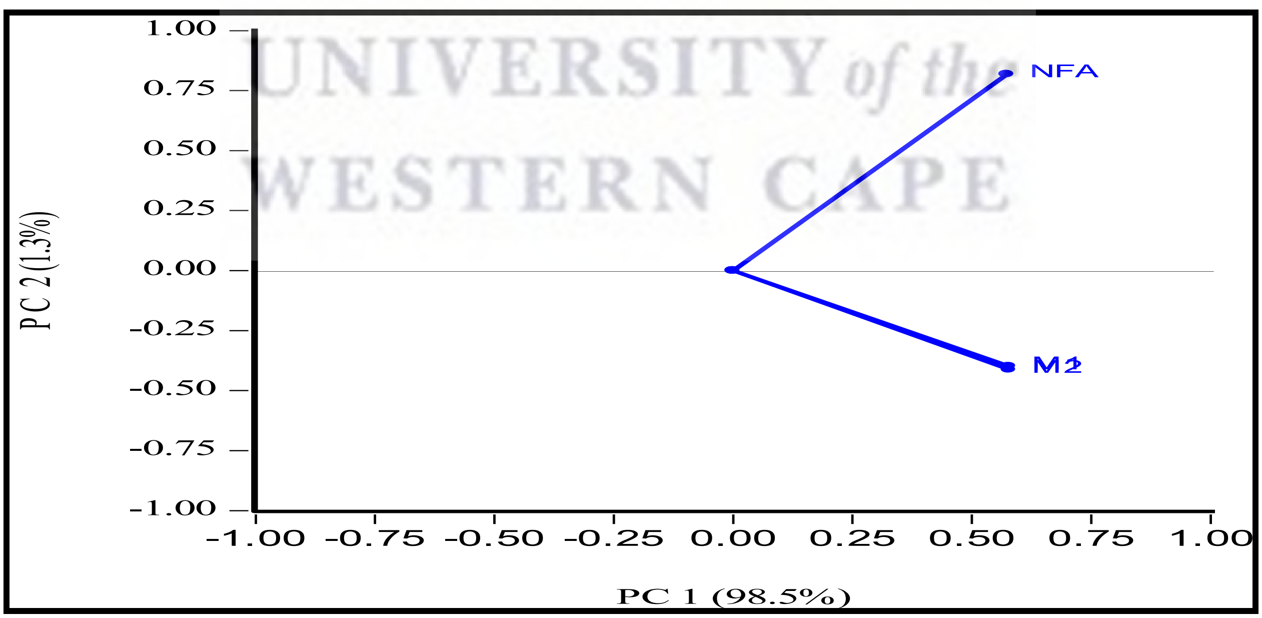
Table D1.2: Details of the single principal component weighting factor for the MONE index

Variable	PC 1
M1	0.57906
M2	0.57894
NFA	0.57404

Source: Own computation

Table D1.2 presents a linear combination of the three original variables used to construct the $BANK$ indicator. In general, a variable is considered to be dominant if it exerts a higher loading on a particular principal component, i.e., PC1. The importance of a variable is determined if its loading value is positively or negatively larger than 0.5. Based PC1, which accounts for 98.5% of the total variations, M1, M2 and NFA have a positive loading of about 0.57 each. The visual presentation of the basic directions between the variables as plotted in the Orthonormal loading chart is provided in Figure 0.5.

Figure 0.5: Orthonormal loadings for the MONE index



Source: Own computation

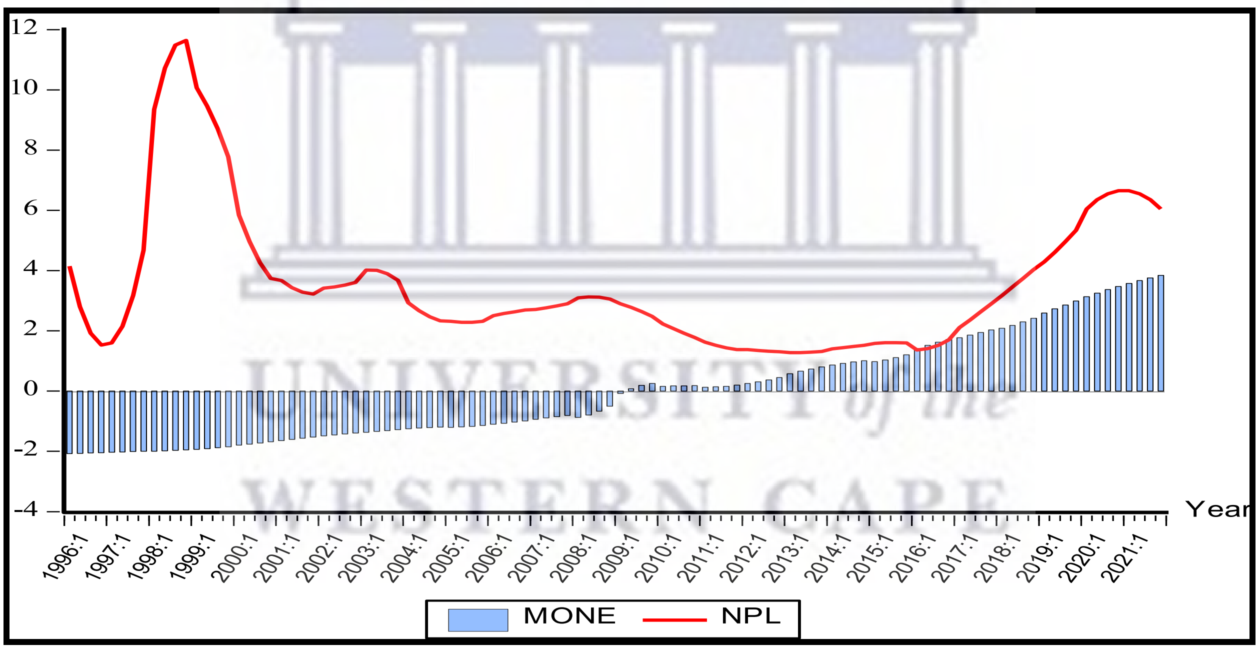
Although the information conveyed in Figure 0.5 is the same as those provided by Table D1.2, the chart provides a clear visual aid of how close the variables in the first two components are related.

The final process, before plotting the time graph of the generated $MONE$ index, is to compute the matrix weights of the $MONE$ indicator as follows:

$$MONE = \frac{98.53}{98.53} PC1$$

The time graph of the $MONE$ index obtained by the PCA is presented alongside NPL in Figure 06 as follows:

Figure 0.6: Time graph of Namibia's Macroeconomic indicator and NPL, 1996Q1-2021Q4



Source: Own computation

Based on Figure 0.6, depicting the time graph of the monetary (MONE) index, which is used to predict the evolution of money stock in Namibia, it is safe to argue that Namibia has experienced an expansion of the monetary policy as for the most part the MONE index exhibits an upward trend. This indicator is of interest to this study, considering that it is one of the only limited tools at the hand of the monetary authority in Namibia. The tool is useful in predicting the influence of an expansionary monetary policy on NPL in Namibia. Normally, an expansionary monetary policy is likely to be associated with a rise in NPL. For this reason, it is necessary to carefully scrutinise such an indicator. The variables used to compile the MONE index are: Narrow money (M1), Broad money (M2) and Net Foreign Assets (NFA).

Appendix E: Construction of the interest rate (INTER) index

Table E4.1: Eigenvalues of the principle components for the INTER index

Number	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.688815	3.424917	0.9222	3.688815	0.9222
2	0.263897	0.227854	0.0660	3.952712	0.9882
3	0.036043	0.024798	0.0090	3.988755	0.9972
4	0.011245	---	0.0028	4.000000	1.0000

Source: Own computation

Note: Based on Kaiser (1960)'s criterion, only components with Eigenvalues greater than one must be retained

In relation to Table E1.1, a total of 1 out of the 4 eigenvalues have been suggested to be used for further analysis. Thus, only one principal component (PC1), representing about 92.22% of the total variations in the data, must be retained. This means that for the compact $INTER$ index, the desired threshold can be attained by the weighting of the cumulative explained variance. The first component accounts for an approximate proportion of variations of 92.22% of the total variations in the original dataset. The eigenvectors (loadings) illustrating the percentage of variation in the first component are presented in Table E1.2.

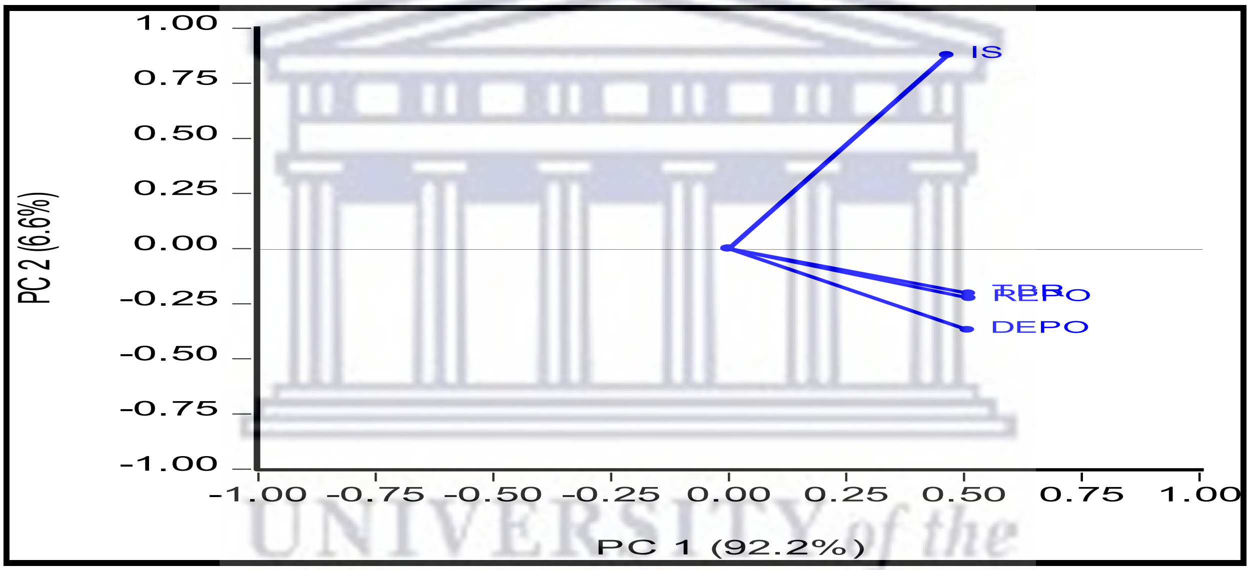
Table E1.2: Details of the single principal component weighting factor for the INTER index

Variable	PC 1
REPO	0.513017
DEPO	0.511574
IS	0.509151
TBR	0.464619

Source: Own computation

Table E1.2 presents a linear combination of the five original variables used to construct the $INTER$ indicator. The guideline for determining how dominant a variable is in contributing to a particular principal component (PC) states that the influence of an original variable is considered to be of importance if its loading value is positively or negatively larger than 0.5. Based on the result the first principal component (PC1), which accounts for 92.22%, the variables found to exert the largest loading are REPO (0.51), DEPO (0.51) and IS (0.50). The visual presentation of the basic directions between the variables as plotted in the Orthonormal loading chart provided in Figure 0.7.

Figure 0.7: Orthonormal loadings for the INTER index



Source: Own computation

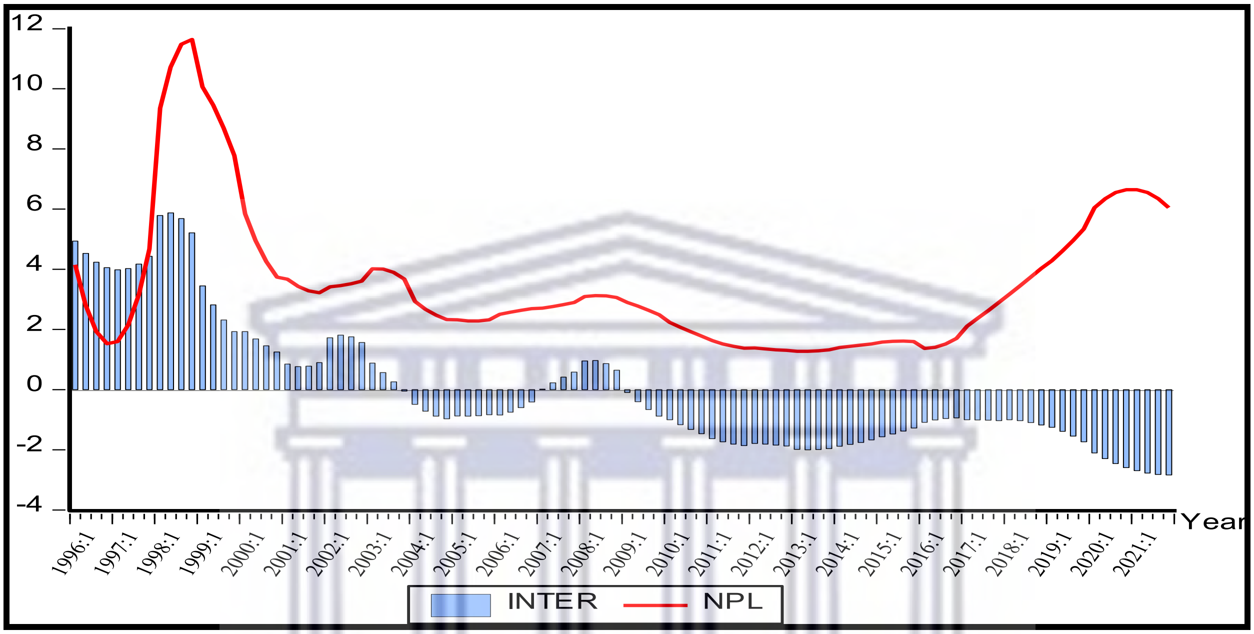
Although the information conveyed on Figure 0.7 is the same as those provided by Table E1.2, the chart provides a clear visual aid of how close the variables in the first two components (PC 1 and 2) are related. Based on the chart, the same conclusions can be reached that the variables REPO, DEPO and IS influence PC1 positively.

Next, before plotting the time graph of the generated INTER index, is to compute the matrix weights of the INTER indicator as follows:

$$INTER = \frac{92.22}{92.22} PC1$$

The time graph of the $INTER$ index obtained by the PCA is presented alongside NPL in Figure 0.8 as follows:

Figure 0.8: Time graph of Namibia's interest rate indicator and NPL, 1996Q1-2021Q4



Source: Own computation

Figure 0.8 demonstrates that, even though the behaviour of the interest rate (INTER) indicator has occasionally experienced some sudden jumps, its patterns have in general been downward trending. The first trough was registered in 1997Q1, before the indicator hit its highest peak in 1998Q2 against the backdrop of the turbulences experienced in emerging markets at the start of the year 1997. According to Bank of Namibia (2008)'s financial stability report, in 1998 Namibia experienced higher inflationary pressures which caused the monetary authority to hike the interest rate. The period 1997-1998 were also characterised by heightened political instabilities in Russia coupled with fears of devaluation in a number of Latin American countries (Bank of Namibia, 1999). These events are likely to have negatively influenced the factors used to construct the INTER index. From 1998Q2 the index declined sharply, hitting a second lingering trough in 2001Q1 before rising again in 2002Q1.

The INTER index is quite related to NPL as it measures the cost of borrowing which in turn affects NPL. A rise in the INTER index rises is normally expected to be associated with a rise in NPL, as it causes the cost of borrowing to rise, making it harder for borrowers to repay their debts. Based on the observed patterns of both the INTER index and NPL rates, the aforementioned postulation seems to be consistent in some periods, and inconsistent in other periods. For instance, upon closely observing Figure 08, it can be observed that the rise in the INTER index during the period 1997 – 1998 corresponds with a decline in the observed NPL date from Namibia's banking sector, from 2.9% to 10.8%, respectively. Likewise, the sharp decline in the INTER index from 1998Q2 appears to correspond with a sharp fall in NPL from 10.8% in 1998 to 3.4% in 2001, before correspondingly rising up again to 3.5% in 2002. Similarly, the sharp decline in the INTER index, from the periods 1998Q2 to the first trough in 2001Q2, reveals the same conclusion.

Interestingly, the patterns exhibited between the periods 2014 – 2021, offer some fascinating insights that are worth exploring in this study. What is more striking, is the nature in which both the INTER index and NPL diverge from each other during the periods of the global downturn that began unfolding in 2014 and persisted during the era of the COVID-19 pandemic. The ratio of NPL was registered to have risen to unprecedented levels, despite the interventions undertaken by the monetary authorities of the Central Bank of Namibia. The successive declines in the repo rates, which were aimed at easing the economic pressure on citizens and stimulate the economy, did little to deter the unprecedented rise in the ratio of NPL beyond the benchmark of 4.0 % basis as well as beyond the supervisory intervention trigger point of 6.0% set by the Bank of Namibia. The variables used to construct the INTER index involve: Repo rate (REPO), Deposit rate (DEPO), Interest spread (IS) and Treasury bills rates (TBR).

Appendix F: Construction of the financial (FINA) index

Table F1.1: Eigenvalues of the principle components for the FINA index

Number	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.310687	2.220588	0.6621	3.310687	0.6621
2	1.090099	0.608035	0.2180	4.400786	0.8802
3	0.482064	0.391668	0.0964	4.882850	0.9766
4	0.090396	0.063642	0.0181	4.973246	0.9946
5	0.026754	---	0.0054	5.000000	1.0000

Source: Own computation

Note: Based on Kaiser (1960)'s criterion, only components with Eigenvalues greater than one must be retained.

With respect to Table F1.1, a total of 2 out of the 5 eigenvalues have been suggested to be used for further analysis. This means that only two principal components (PCs), representing about 88% of the total variations in the data, must be retained. The desired threshold for compact $FINA$ index can be attained by the weighting of the cumulative explained variance. The two components account for an approximate proportion of variations of 66.2% and 21.8% of the total variations in the data, respectively. The eigenvectors (loadings) illustrating the percentage of variation in the two PCs (factors or component) are presented in Table F1.2.

Table F1.2: Details of the 2 principal component weighting factors for the FINA index

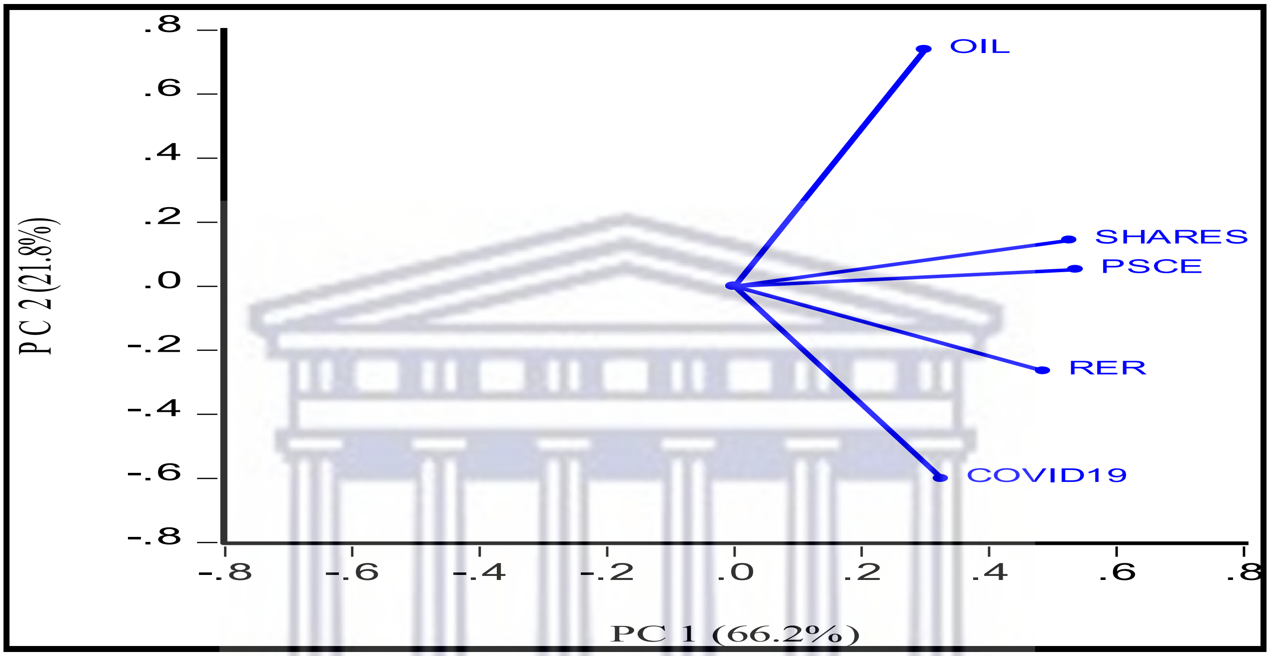
Variable	PC 1	PC 2
RER	0.486759	-0.264902
PSCE	0.537387	0.051732
OIL	0.299413	0.738786
COVID-19	0.326055	-0.600599
SHARES	0.527561	0.143623

Source: Own computation

Table F1.2 presents a linear combination of the original variables used to construct the $FINA$ indicator. In general, a variable is said to be dominant to a particular principal component (PC) if its contributing loading is higher than 0.5. Based on the first principal component (PC1), which accounts for 66.2%, the PSCE (0.54) has the largest positive loadings, followed by SHARES (0.53). The second principal component (PC2), which accounts for 21.8%, found the variable OIL

(0.74) to exert the largest positive loading, followed by a negative loading from the variable COVID-19 (-0.60). The visual presentation of the basic directions between the variables as plotted in the Orthonormal loading chart provided in Figure 0.9.

Figure 0.9: Orthonormal loadings for the FINA index



Source: Own computation

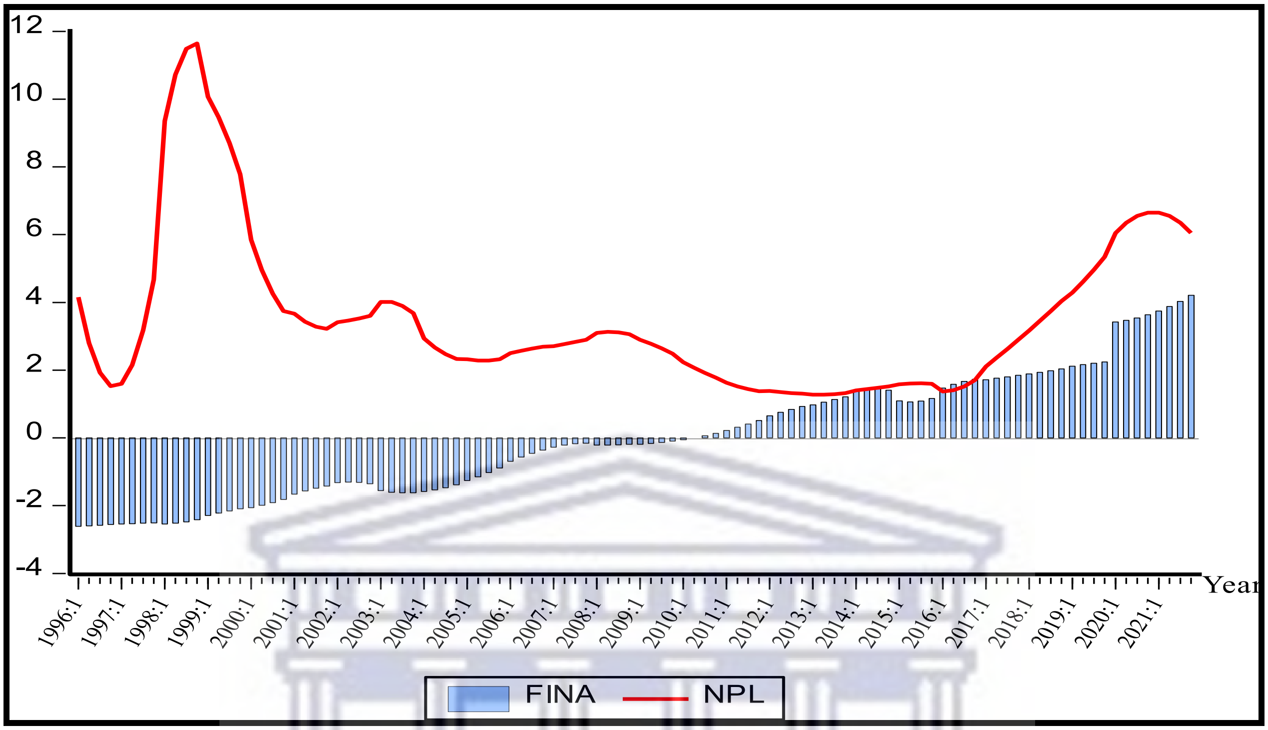
Even though the information contained in Figure 0.9 conveys the same kind of information as provided in Table F1.2, the chart simply avails a much clear visualisation of how close the variables in the first two components are related.

The final process, before plotting the time graph of the generated FINA index, is to compute the matrix weights of the FINA indicator as follows:

$$FINA = \frac{66.21}{88.02} PC1 + \frac{21.80}{88.02} PC2$$

The time graph of the $FINA$ index obtained by the PCA is presented alongside NPL in Figure 0.10 as follows:

Figure 0.10: Time graph of Namibia's financial indicator and NPL, 1996Q1-2021Q4



Source: Own computation

Figure 0.10 illustrates the dynamic of the FINA index in relation to NPL. The index, which represents the financial condition of both the banking sector and the financial system, is crucial in assessing the soundness and stability of the banking sector in Namibia. Based on Figure 0.10, the FINA index has over the years been trending upwardly. This suggests that, as Namibia's banking and financial system evolved over the years coupled with recent mineral discoveries, investors have developed a positive market sentiment and optimism in the economy. Another factor leading to investors' confidence in Namibia lies in the fact that Namibia ranks amongst the top 10 rule-based African countries that are well governed with a sound political stability.[102] Since financial systems are influenced by a wide range of endogenous and/or exogenous factors, this study accounted for all essential aspects when developing the FINA index. The variables underlying the FINA index are: the real exchange rate (RER), the private sector credit extension (PSCE), the oil prices (OIL), the share prices (SHARE), and a dummy variable (COVID-19). Normally, a rise in the FINA index is supposed to correlate with declines in NPL; however, due to other factors that

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[102] *In 2021 Namibia was ranked 8th in Africa (out of 54 countries) in terms of overall governance as per the Ibrahim Index of African Governance (Mo Ibrahim Foundation, 2023).*

might be at play, it is not so easy to establish their influences by simply observing from the patterns depicted in Figure 0.10 as to how such variables are related to each other. For this reason, a formal econometric analysis is carried out to ascertain the dynamic relationship between the FINA index and NPL.

Appendix G: Construction of the institutional (INST) index

Table G1.1: Principal component for the index of the INST indicator

Number	Eigenvalue	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.16097	1.45466	0.4516	3.160971	0.4516
2	1.70632	0.78641	0.2438	4.867286	0.6953
3	0.9199	0.43176	0.1314	5.787186	0.8267
4	0.48814	0.0745	0.0697	6.275326	0.8965
5	0.41364	0.17226	0.0591	6.688967	0.9556
6	0.24138	0.17173	0.0345	6.93035	0.9901
7	0.06965	---	0.0099	7	1

Source: Own computation

Note: Based on Kaiser (1960)'s criterion, only components with Eigenvalues greater than one must be retained.

The results displayed in Table G1.1, suggest that a total of 2 out of the 7 eigenvalues are to be used for further analysis. Thus, only two principal components (PCs), representing about 70% of the total variations in the data, must be retained. This means that for the compact $INST$ index, the desired threshold can be attained by the weighting of the cumulative explained variance. The two components account for an approximate proportion of variations of 45.2% and 24.4% of the total variations in the data, respectively. The eigenvectors (loadings) illustrating the percentage of variation in the two PCs (factors or component) are presented in Table G1.2.

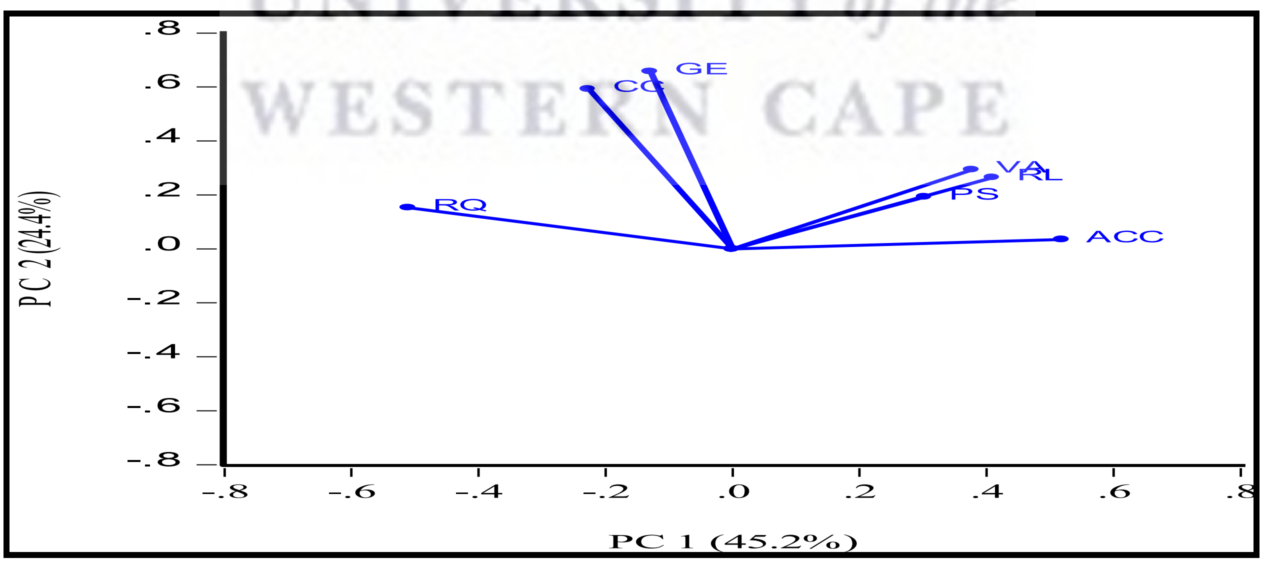
Table G1.2: Details of the 2 principal component weighting factors for the INST index

Variable	PC 1	PC 2
VA	0.37746	0.29337
PS	0.30348	0.19305
CC	-0.2259	0.59206
RQ	-0.5096	0.15199
GE	-0.1287	0.65714
RL	0.41015	0.26461
ACC	0.51951	0.0345

Source: Own computation

Table G1.2 presents a linear combination of the original variables used to construct the $INST$ index. In general, a variable is considered to be dominant to a particular principal component (PC) if its loading contribution is higher than 0.5. Based on the first principal component (PC1), which accounts for 45.2%, the ACC (0.52) has the largest positive loadings, followed by RQ (-0.51). The second principal component (PC2), which accounts for 24.4%, found the variable GE (0.66) to exert the largest positive loading, followed by CC (0.59). The visual presentation of the basic directions between the variables is plotted in the orthonormal loading chart provided in Figure 0.11.

Figure 0.11: Orthonormal loadings for the INST index



Source: Own computation

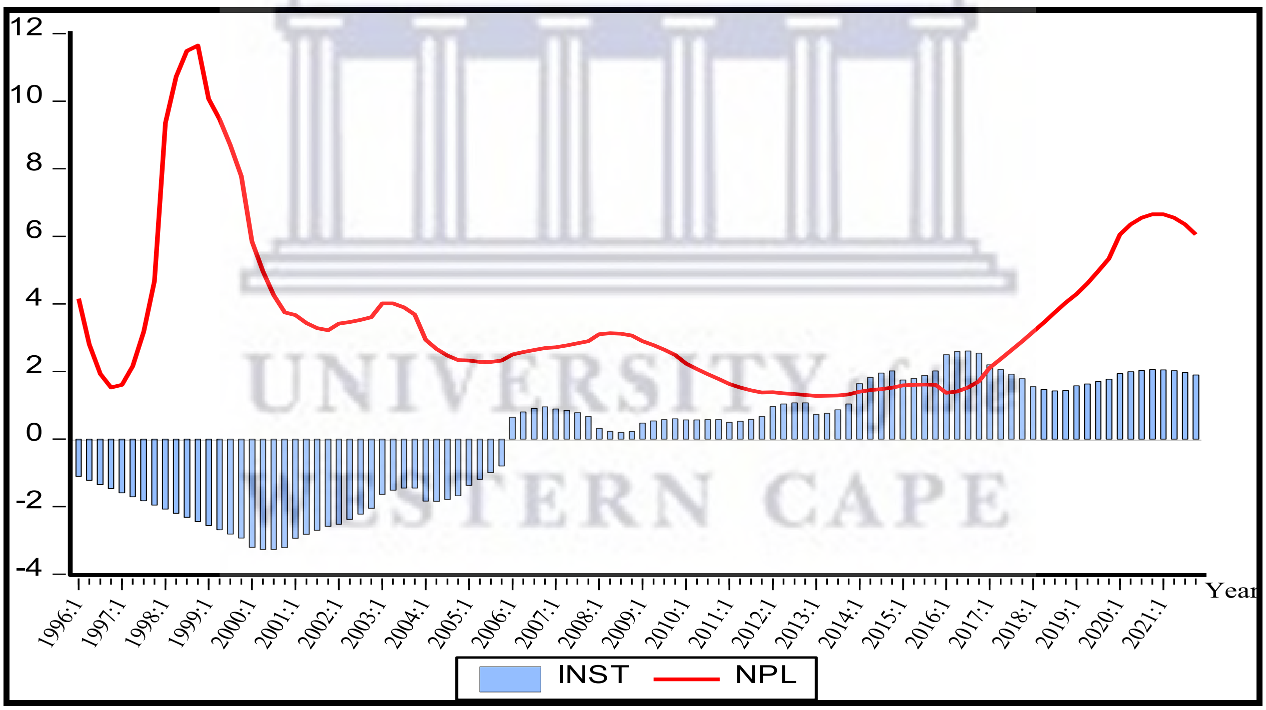
Despite the fact that the information presented on Figure 0.11 is similar to those provided in Table G4.2, the chart on Figure 0.11 provides a clear visual aid of how close the variables in the first two components are related.

The final process, before plotting the time graph of the generated INST index, is to compute the matrix weights of the INST indicator as follows:

$$INST = \frac{45.16}{69.53} PC1 + \frac{24.38}{69.53} PC2$$

The time graph of the $INST$ index obtained by the PCA is presented in Figure 0.12 as follows:

Figure 0.12: Time graph of Namibia's institutional indicator and NPL, 1996Q1-2021Q4



Source: Own computation

Figure 0.12 illustrates the dynamics of both the INST index together with NPL during the period of study. The INST index is used to evaluate the extent to which broader regulatory and governance environment within which banks operate provide insights into the systemic factors that are likely to influence the level of NPL and financial stability. Although Figure 0.12 does not show a clear definite pattern in relations with NPL, it is evident that Namibia has had a positive INST index from the period 2006Q1. The year 2006 is a very significant year in Namibia's financial history, because in it the country achieved its first ever budget surplus (MoF, 2015). Usually, a positive institutional index suggests that the governance structures and institutions within a country are very effective and efficient.

In terms of credit risk management, this implies that the legal framework which facilitates the process of loan recovery and minimise NPL are robust. Also, a positive INST index, suggests that there is a stable political environment which could imply a better economic prospect and a stable financial sector. The inclusion of institutional indicators is based on the fact that inefficiencies resulting from any factors are likely to influence market competitiveness, thereby deteriorating the condition of the debtors and lenders (Tanasković & Jandrić, 2015). The variables used to construct the INST index are: Voice and accountability (VA), Political stability and absence of violence/terrorism (PS), Control of corruption (CC), Regulatory quality (RQ), Government effectiveness (GE), Rule of law (RL), and Anti-corruption commission (ACC).

Appendix H: Vector Error Correction Model (VECM) test estimation results

Table H1: VECM results

Cointegrating Eq:	CointEq1	
LNPL(-1)	1.0000	
LMACRO(-1)	0.3168	**5.5910**
LBANK(-1)	0.1552	**1.4177**
LMONE(-1)	0.0947	**0.3859**
LINTER(-1)	-0.8130	**-8.7355**
LFINA(-1)	-0.3981	**-1.3703**
LINST(-1)	-0.1124	**-0.8335**
C	-1.2688	

Error Correction:	D(LNPL)	D(LMACRO)	D(LBANK)	D(LMONE)	D(LINTER)	D(LFINA)	D(LINST)
CointEq1	-0.1799	0.1165	0.0182	-0.0365	-0.0009	0.0158	0.2821
	-4.1616	**1.0996**	**0.2954**	**-1.5920**	**-0.0131**	**0.3651**	**2.4693**
D(LNPL(-1))	0.5325	0.0477	0.0842	-0.0857	-0.0866	-0.0283	-0.0281
	4.8807	**0.1784**	**0.5423**	**-1.4811**	**-0.4920**	**-0.2578**	**-0.0975**
D(LNPL(-2))	0.2141	-0.0666	0.0644	-0.0235	0.1845	-0.0070	0.0242
	1.9582	**-0.2484**	**0.4140**	**-0.4057**	**1.0465**	**-0.0633**	**0.0837**
D(LNPL(-3))	0.2149	-0.0784	0.0547	0.0000	0.2079	-0.0121	-0.1149
	1.9405	**-0.2887**	**0.3476**	**-0.0007**	**1.1642**	**-0.1091**	**-0.3927**
D(LNPL(-4))	-0.2477	0.2290	-0.3609	0.1274	-0.4379	-0.0079	-0.2561
	-2.1912	**0.8264**	**-2.2444**	**2.1252**	**-2.4015**	**-0.0670**	**-0.8572**
D(LNPL(-5))	-0.0244	-0.2371	0.2952	-0.0769	0.0226	0.0093	-0.1156
	-0.2430	**-0.9622**	**2.0649**	**-1.4425**	**0.1391**	**0.0925**	**-0.4350**
D(LMACRO(-1))	0.2089	0.5696	0.0305	-0.0051	-0.0346	-0.0124	-0.3159
	2.9578	**3.2906**	**0.3039**	**-0.1358**	**-0.3034**	**-0.1748**	**-1.6921**
D(LMACRO(-2))	0.0199	0.0402	-0.0196	0.0052	0.0200	0.0013	-0.0598
	0.3987	**0.3281**	**-0.2757**	**0.1966**	**0.2482**	**0.0259**	**-0.4524**
D(LMACRO(-3))	0.0263	-0.0146	-0.0054	0.0039	0.0125	0.0001	-0.0636
	0.5239	**-0.1183**	**-0.0760**	**0.1477**	**0.1539**	**0.0010**	**-0.4787**
D(LMACRO(-4))	-0.0214	-0.6070	-0.1708	0.1212	-0.2890	-0.0355	0.0562
	-0.4275	**-4.9373**	**-2.3945**	**4.5563**	**-3.5724**	**-0.7056**	**0.4235**

Table H.1 Continues

D(LMACRO(-5))	0.0930	0.2630	0.1794	-0.0555	0.0313	-0.0287	-0.2537
	1.4345	**1.6551**	**1.9460**	**-1.6134**	**0.2994**	**-0.4400**	**-1.4805**
D(LBANK(-1))	0.0226	0.0638	0.7580	0.0267	0.0299	-0.0455	-0.2266
	0.3006	**0.3468**	**7.1009**	**0.6707**	**0.2471**	**-0.6037**	**-1.1423**
D(LBANK(-2))	0.0094	-0.0388	0.0774	0.0093	-0.0294	-0.0108	-0.0326
	0.1365	**-0.2307**	**0.7933**	**0.2556**	**-0.2661**	**-0.1567**	**-0.1797**

D(LBANK(-3))	0.0005	-0.0136	0.0228	0.0094	-0.0399	-0.0129	-0.1010
	0.0069	**-0.0805**	**0.2322**	**0.2559**	**-0.3589**	**-0.1865**	**-0.5542**
D(LBANK(-4))	0.0624	-0.0572	-0.7209	-0.1046	0.1670	0.0512	0.3473
	0.9055	**-0.3391**	**-7.3602**	**-2.8644**	**1.5040**	**0.7404**	**1.9083**
D(LBANK(-5))	-0.0424	0.1567	0.6114	0.0774	-0.0036	-0.0354	-0.2540
	-0.5675	**0.8549**	**5.7479**	**1.9507**	**-0.0299**	**-0.4712**	**-1.2847**
D(LMONE(-1))	-0.6501	0.1371	0.0555	0.5553	0.1869	0.1889	0.9546
	-2.4200	**0.2082**	**0.1453**	**3.8965**	**0.4313**	**0.7002**	**1.3444**
D(LMONE(-2))	-0.0323	0.3122	0.0041	0.0845	0.0875	-0.0015	0.2222
	-0.1463	**0.5777**	**0.0130**	**0.7228**	**0.2459**	**-0.0068**	**0.3813**
D(LMONE(-3))	-0.0426	0.1175	0.0035	0.0182	0.0384	-0.0324	0.1751
	-0.1921	**0.2160**	**0.0111**	**0.1546**	**0.1073**	**-0.1455**	**0.2986**
D(LMONE(-4))	0.3374	0.7413	0.6216	-0.5539	-0.2257	-0.1493	-0.2301
	1.5322	**1.3735**	**1.9849**	**-4.7426**	**-0.6355**	**-0.6753**	**-0.3954**
D(LMONE(-5))	-0.7194	-0.6832	-0.5295	0.2841	0.2028	0.1432	0.8305
	-2.9007	**-1.1240**	**-1.5012**	**2.1599**	**0.5071**	**0.5747**	**1.2671**
D(LINTER(-1))	-0.4147	-0.0669	-0.0465	0.0045	0.5257	0.0728	0.5024
	-3.4725	**-0.2286**	**-0.2740**	**0.0704**	**2.7296**	**0.6073**	**1.5917**
D(LINTER(-2))	-0.0637	0.2050	0.0042	-0.0136	0.1311	0.0111	0.1802
	-0.7333	**0.9622**	**0.0342**	**-0.2946**	**0.9353**	**0.1270**	**0.7844**
D(LINTER(-3))	-0.0983	0.1367	-0.0183	-0.0227	0.0539	0.0005	0.1741
	-1.1071	**0.6281**	**-0.1447**	**-0.4811**	**0.3768**	**0.0051**	**0.7420**
D(LINTER(-4))	0.1725	0.4927	0.2434	-0.0568	-0.3390	-0.0882	0.2455
	1.9123	**2.2285**	**1.8976**	**-1.1865**	**-2.3304**	**-0.9738**	**1.0300**
D(LINTER(-5))	-0.4135	-0.2552	-0.2715	0.0394	0.2484	0.0384	0.3322
	-3.7509	**-0.9443**	**-1.7316**	**0.6739**	**1.3970**	**0.3469**	**1.1401**
D(LFINA(-1))	-0.1681	0.0948	0.3160	-0.0114	0.2012	0.1817	0.2550
	-1.1379	**0.2618**	**1.5041**	**-0.1457**	**0.8447**	**1.2247**	**0.6532**

Table H1 continues

D(LFINA(-2))	0.0018	0.0888	0.1156	-0.0145	0.1008	0.1077	0.1358
	0.0130	**0.2547**	**0.5716**	**-0.1928**	**0.4396**	**0.7540**	**0.3613**
D(LFINA(-3))	0.0350	0.0652	0.1265	-0.0236	0.1261	0.0487	0.0072
	0.2456	**0.1866**	**0.6242**	**-0.3118**	**0.5488**	**0.3400**	**0.0191**
D(LFINA(-4))	0.2808	-0.1195	0.0436	-0.1898	0.4914	-0.0714	-0.0575
	1.9693	**-0.3419**	**0.2151**	**-2.5101**	**2.1372**	**-0.4989**	**-0.1526**
D(LFINA(-5))	-0.1186	0.3747	0.3065	0.1333	-0.0183	0.0793	-0.1433
	-0.7919	**1.0208**	**1.4392**	**1.6781**	**-0.0758**	**0.5273**	**-0.3620**
D(LINST(-1))	0.0529	-0.0828	-0.0995	0.0019	-0.0043	0.0315	0.1626
	1.0301	**-0.6575**	**-1.3614**	**0.0694**	**-0.0514**	**0.6096**	**1.1977**
D(LINST(-2))	0.0231	-0.0382	-0.0326	0.0074	-0.0141	0.0107	0.0258
	0.4600	**-0.3098**	**-0.4561**	**0.2760**	**-0.1739**	**0.2125**	**0.1942**
D(LINST(-3))	0.0092	-0.0326	-0.0510	0.0014	-0.0036	0.0006	-0.0334

	0.1848	**-0.2670**	**-0.7206**	**0.0530**	**-0.0444**	**0.0128**	**-0.2534**
D(LINST(-4))	0.0258	-0.2409	-0.0825	-0.0293	0.1967	-0.0183	-0.1182
	0.5220	**-1.9858**	**-1.1716**	**-1.1144**	**2.4648**	**-0.3674**	**-0.9038**
D(LINST(-5))	0.0902	0.2323	0.0163	0.0032	-0.0135	-0.0189	-0.1581
	1.5548	**1.6330**	**0.1971**	**0.1037**	**-0.1441**	**-0.3241**	**-1.0306**
C	0.0098	-0.0298	-0.0432	0.0276	-0.0671	0.0184	-0.0101
	0.5881	**-0.7284**	**-1.8179**	**3.1129**	**-2.4912**	**1.0942**	**-0.2287**
R-squared	0.8072	0.6194	0.7323	0.7064	0.7318	0.2474	0.2881
Adj. R-squared	0.6935	0.3948	0.5743	0.5331	0.5735	-0.1967	-0.1321
Sum sq. resids	0.2625	1.5772	0.5309	0.0739	0.6827	0.2648	1.8338
S.E. equation	0.0656	0.1608	0.0933	0.0348	0.1058	0.0659	0.1734
F-statistic	7.0962	2.7578	4.6353	4.0768	4.6228	0.5571	0.6857
Log likelihood	151.1479	63.2820	116.6289	213.2825	104.3077	150.7162	55.8956
Akaike AIC	-2.3296	-0.5364	-1.6251	-3.5976	-1.3736	-2.3207	-0.3856
Schwarz SC	-1.3536	0.4396	-0.6491	-2.6216	-0.3977	-1.3448	0.5903
Mean dependent	0.0106	-0.0219	-0.0285	0.0358	-0.0395	0.0388	0.0276
S.D. dependent	0.1185	0.2067	0.1430	0.0509	0.1620	0.0602	0.1630
Determinant resid covariance (dof adj.)							2.260E-16
Determinant resid covariance							8.170E-18
Log likelihood							9.546E+02
Akaike information criterion							-1.405E+01
Schwarz criterion							-7.036E+00
Number of coefficients							2.660E+02

Source: Own computation

Note: The standard errors have been deliberately omitted due to space. The values in bold are the t-statistics.

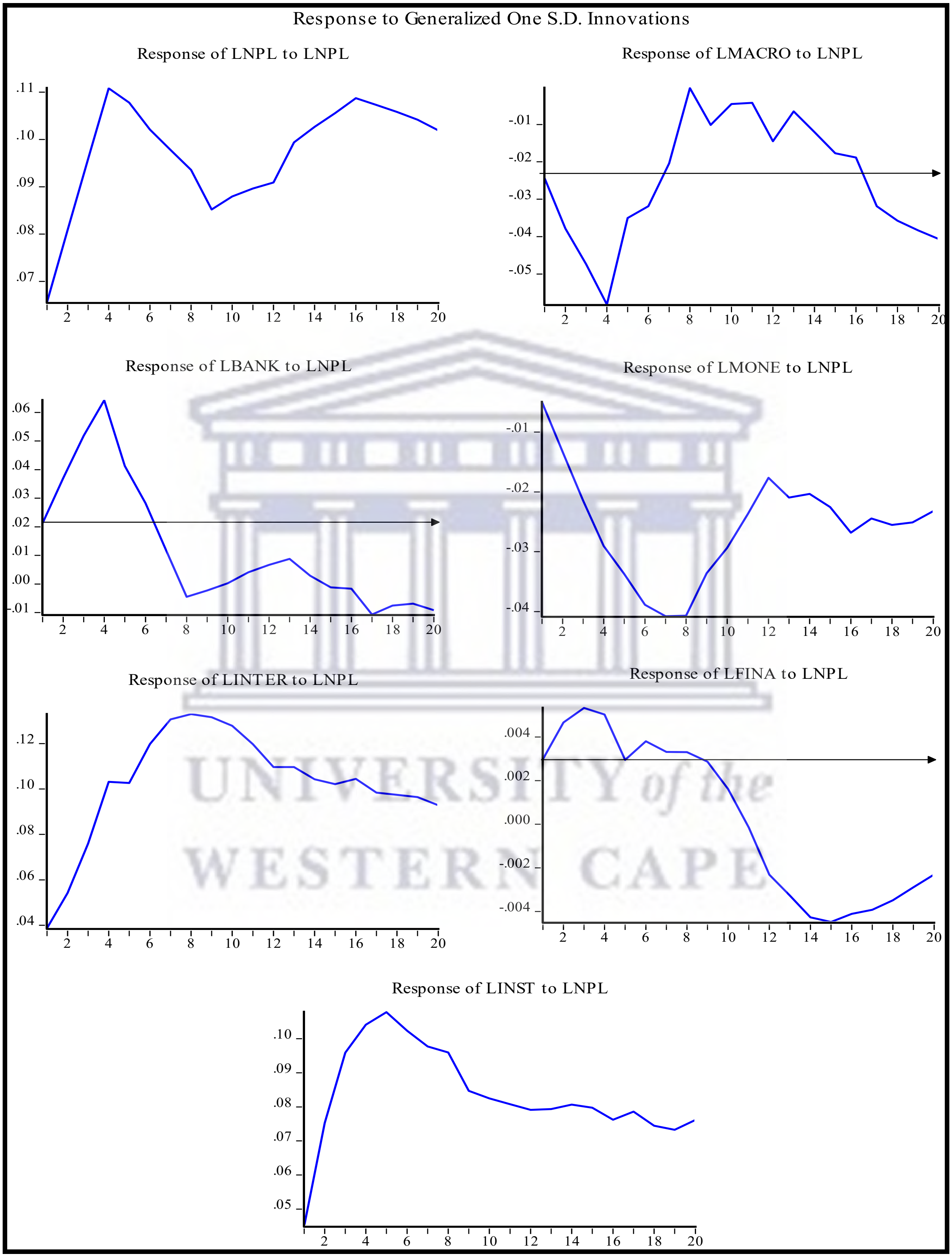
Table H.2: Roots of characteristic polynomial of the composite model

Root		Modulus
0.996311		0.996311
0.975506	- 0.153027i	0.987435
0.975506	+ 0.153027i	0.987435
0.949085	- 0.053782i	0.950608
0.949085	+ 0.053782i	0.950608
0.920252	- 0.237726i	0.950461
0.920252	+ 0.237726i	0.950461
-0.736519	+ 0.587832i	0.942341
-0.736519	- 0.587832i	0.942341
-0.607997	- 0.719682i	0.942127
-0.607997	+ 0.719682i	0.942127
0.748256	- 0.558031i	0.933427
0.748256	+ 0.558031i	0.933427
0.566563	+ 0.728141i	0.922596
0.566563	- 0.728141i	0.922596
0.854083	- 0.331066i	0.916004
0.854083	+ 0.331066i	0.916004
0.635890	- 0.643838i	0.904921
0.635890	+ 0.643838i	0.904921
0.775224	- 0.415366i	0.87949
0.775224	+ 0.415366i	0.87949
-0.640312	+ 0.585776i	0.867832
-0.640312	- 0.585776i	0.867832
-0.431110	+ 0.727021i	0.845231
-0.431110	- 0.727021i	0.845231
0.712255	+ 0.378202i	0.806439
0.712255	- 0.378202i	0.806439
0.513682	+ 0.602787i	0.791973
0.513682	- 0.602787i	0.791973
-0.670360	- 0.343680i	0.753324
-0.670360	+ 0.343680i	0.753324
-0.496621	+ 0.504248i	0.707741
-0.496621	- 0.504248i	0.707741
0.249327	+ 0.655960i	0.701746
0.249327	- 0.655960i	0.701746
-0.567002	- 0.398153i	0.692833
-0.567002	+ 0.398153i	0.692833
0.014643	- 0.643711i	0.643878
0.014643	+ 0.643711i	0.643878
0.355357		0.355357
-0.004198	+ 0.237760i	0.237797
-0.004198	- 0.237760i	0.237797

Source: Own compilation

Note: Since no root lies outside the unit circle, the VAR is said to satisfy the stability condition.

Figure 0.13: Impulse response functions (from the VECM, Model 1)



Source: Own compilation

Table H.4: Forecast error variance decomposition for all endogenous variables

Variance Decomposition of LNPL:

Period	S.E.	LNPL	LMACRO	LBANK	LMONE	LINTER	LFINA	LINST
1	0.066	100	0	0	0	0	0	0
5	0.233	80.700	0.717	2.448	2.693	7.740	0.900	4.803
10	0.386	58.981	1.157	5.252	4.754	4.689	10.321	14.845
15	0.581	40.188	6.837	4.257	2.815	9.623	14.831	21.448
20	0.755	33.554	10.023	3.052	1.748	14.569	14.348	22.706

Variance Decomposition of LMACRO:

Period	S.E.	LNPL	LMACRO	LBANK	LMONE	LINTER	LFINA	LINST
1	0.161	2.303	97.697	0	0	0	0	0
5	0.695	1.840	94.666	0.190	0.290	0.124	0.115	2.774
10	1.079	0.896	91.796	1.254	0.240	0.401	1.671	3.742
15	1.347	0.615	89.005	1.195	0.517	1.244	3.953	3.470
20	1.570	0.686	87.136	1.088	0.507	2.699	3.680	4.204

Variance Decomposition of LBANK:

Period	S.E.	LNPL	LMACRO	LBANK	LMONE	LINTER	LFINA	LINST
1	0.093	5.204	0.138	94.658	0	0	0	0
5	0.460	4.891	0.331	85.204	0.147	0.565	4.125	4.736
10	0.750	2.008	1.194	64.899	0.768	2.742	18.763	9.626
15	1.004	1.135	1.018	57.495	0.552	4.842	22.367	12.592
20	1.206	0.807	1.035	52.652	0.418	5.792	26.168	13.128

Variance Decomposition of LMONE:

Period	S.E.	LNPL	LMACRO	LBANK	LMONE	LINTER	LFINA	LINST
1	0.035	2.062	9.963	0.353	87.621	0	0	0
5	0.146	12.460	9.615	0.757	73.455	3.413	0.205	0.095
10	0.231	17.733	17.145	1.508	49.400	12.745	0.301	1.167
15	0.315	11.790	15.145	4.125	44.706	19.163	4.308	0.763
20	0.393	9.604	11.604	4.548	43.450	22.170	8.102	0.521

Variance Decomposition of LINTER:

Period	S.E.	LNPL	LMACRO	LBANK	LMONE	LINTER	LFINA	LINST
1	0.106	13.372	29.075	6.468	21.649	29.436	0	0
5	0.431	16.907	32.959	5.040	11.104	26.888	6.561	0.540
10	0.769	19.292	13.668	3.730	3.727	22.469	30.831	6.283
15	0.986	17.893	8.405	3.575	2.675	24.065	36.313	7.075
20	1.104	18.215	6.847	4.053	2.453	25.511	36.334	6.588

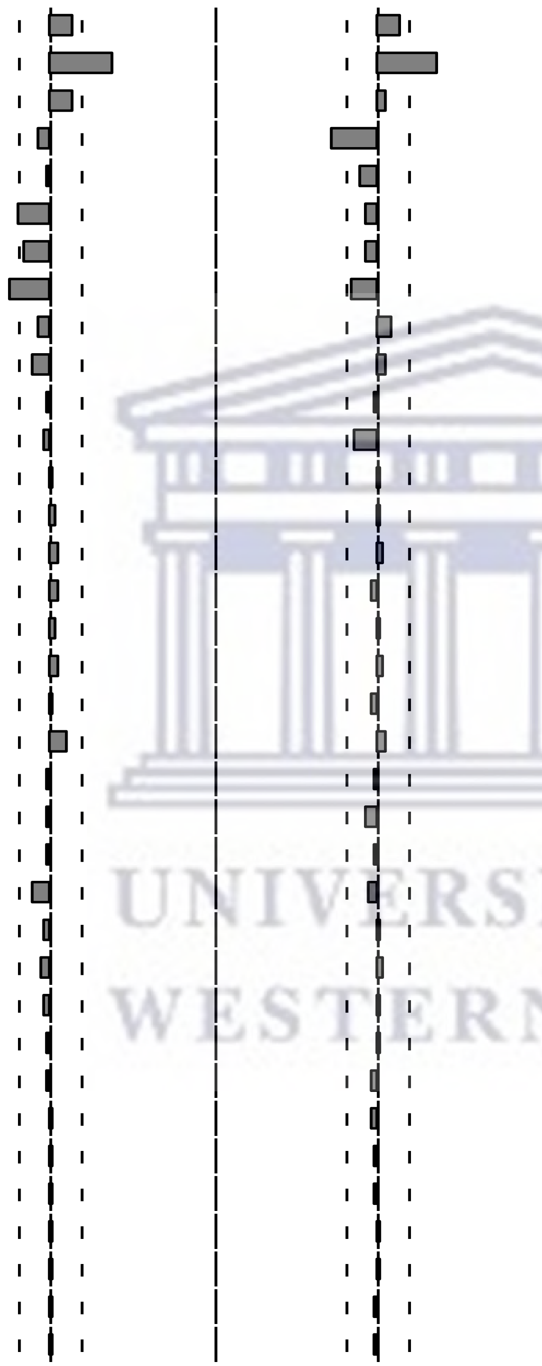
Table H4 Continues

Variance Decomposition of LFINA:								
Period	S.E.	LNPL	LMACRO	LBANK	LMONE	LINTER	LFINA	LINST
1	0.066	0.205	10.643	4.786	3.595	2.645	78.126	0
5	0.201	0.230	13.627	7.274	7.733	1.005	69.479	0.651
10	0.289	0.168	7.547	9.781	9.662	1.730	70.365	0.747
15	0.341	0.167	5.938	12.908	10.903	3.255	66.238	0.592
20	0.380	0.175	6.265	15.326	10.638	4.801	62.315	0.480

Variance Decomposition of LINST:								
Period	S.E.	LNPL	LMACRO	LBANK	LMONE	LINTER	LFINA	LINST
1	0.173	6.739	1.815	0.273	11.602	3.806	5.051	70.714
5	0.502	15.587	1.009	0.455	21.013	0.891	4.711	56.335
10	0.686	17.531	1.565	0.386	24.242	0.710	2.752	52.814
15	0.825	16.832	2.125	0.274	27.062	2.621	2.097	48.989
20	0.941	16.179	4.418	0.211	26.194	6.602	2.858	43.537

Source: Own compilation

Figure 0.14: Correlogram of the residual of the ARIMA (1,0,1) model



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.145	0.145	2.3219	
		2	0.393	0.380	19.663	
		3	0.143	0.063	21.990	0.000
		4	-0.072	-0.285	22.583	0.000
		5	-0.022	-0.100	22.641	0.000
		6	-0.202	-0.080	27.389	0.000
		7	-0.169	-0.074	30.738	0.000
		8	-0.255	-0.159	38.436	0.000
		9	-0.076	0.097	39.135	0.000
		10	-0.114	0.050	40.702	0.000
		11	-0.011	-0.020	40.717	0.000
		12	-0.047	-0.141	40.991	0.000
		13	0.016	-0.007	41.021	0.000
		14	0.025	0.024	41.103	0.000
		15	0.058	0.041	41.539	0.000
		16	0.045	-0.036	41.799	0.000
		17	0.033	0.002	41.942	0.000
		18	0.060	0.040	42.423	0.000
		19	-0.004	-0.030	42.426	0.001
		20	0.107	0.061	43.979	0.001
		21	-0.021	-0.012	44.042	0.001
		22	-0.010	-0.072	44.055	0.001
		23	-0.021	-0.018	44.115	0.002
		24	-0.108	-0.058	45.778	0.002
		25	-0.028	0.006	45.892	0.003
		26	-0.065	0.034	46.497	0.004
		27	-0.043	0.002	46.774	0.005
		28	-0.021	-0.007	46.839	0.007
		29	-0.018	-0.037	46.890	0.010
		30	-0.005	-0.039	46.894	0.014
		31	0.005	-0.018	46.898	0.019
		32	-0.005	-0.015	46.901	0.025
		33	-0.002	-0.002	46.902	0.033
		34	-0.004	-0.008	46.905	0.043
		35	-0.000	-0.009	46.905	0.055
		36	-0.005	-0.022	46.909	0.069

Source: Own compilation

Note: The correlogram of the residual is not flat, indicating that not all information is captured, which means this model does not qualify to be used for forecasting.

Figure 0.15: Correlogram of the residual for the adjusted ARIMA model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.043	0.043	0.2050	
		2	0.178	0.176	3.7445	
		3	0.004	-0.010	3.7462	
		4	-0.093	-0.128	4.7317	0.030
		5	0.088	0.102	5.6218	0.060
		6	-0.027	0.007	5.7044	0.127
		7	-0.028	-0.068	5.7957	0.215
		8	-0.127	-0.138	7.7254	0.172
		9	0.098	0.162	8.8680	0.181
		10	0.070	0.110	9.4671	0.221
		11	0.124	0.056	11.365	0.182
		12	0.023	-0.051	11.428	0.247
		13	0.037	0.067	11.603	0.313
		14	0.036	0.040	11.763	0.382
		15	0.064	0.036	12.287	0.423
		16	0.031	-0.025	12.409	0.494
		17	-0.011	0.025	12.425	0.572
		18	0.010	0.035	12.438	0.646
		19	-0.024	-0.016	12.517	0.708
		20	0.119	0.082	14.443	0.636
		21	-0.007	-0.009	14.449	0.699
		22	-0.007	-0.052	14.455	0.757
		23	-0.024	-0.025	14.539	0.802
		24	-0.110	-0.098	16.263	0.755
		25	-0.009	-0.032	16.274	0.802
		26	-0.031	-0.007	16.415	0.837
		27	-0.021	-0.015	16.479	0.870
		28	-0.008	0.002	16.490	0.899
		29	-0.014	-0.026	16.518	0.923
		30	-0.006	-0.032	16.523	0.942
		31	0.001	-0.025	16.523	0.957
		32	-0.016	-0.028	16.565	0.969
		33	-0.022	-0.007	16.640	0.977
		34	-0.026	-0.005	16.753	0.983
		35	-0.024	-0.005	16.850	0.987
		36	-0.033	-0.020	17.024	0.990

Source: Own compilation

Note: The correlogram of the residual is flat, indicating that all information has been captured and the model can be used for forecasting.

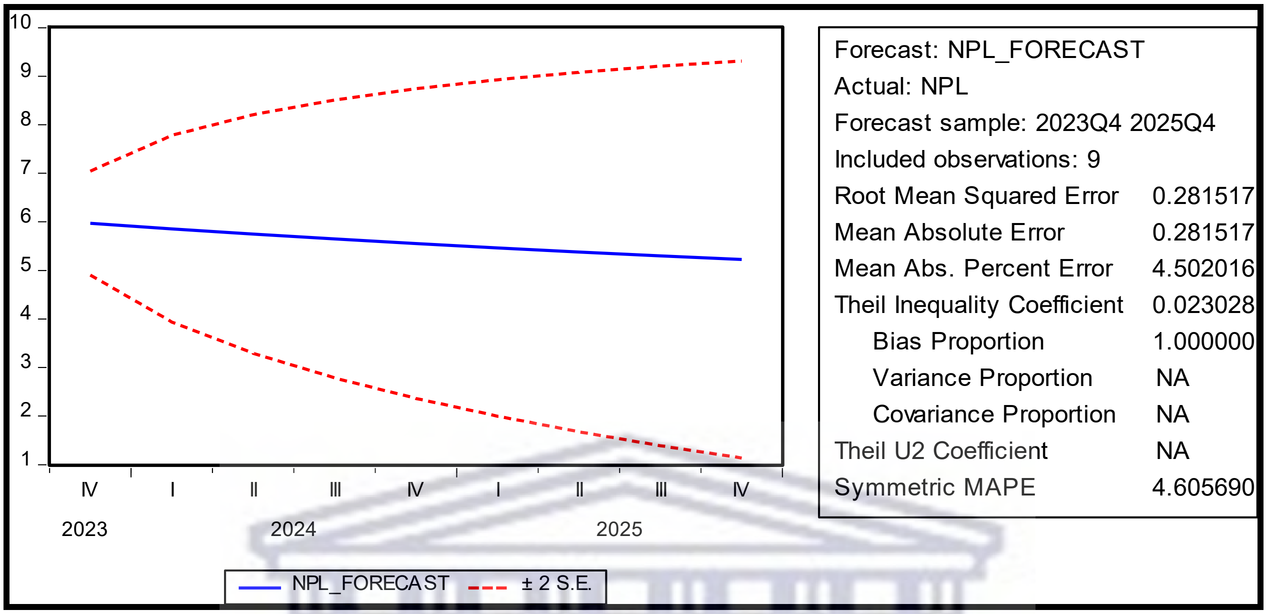
Figure 0.16: Correlogram of the residual squared for the adjusted ARIMA model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.101	0.101	1.1363	0.286
		2	0.013	0.003	1.1545	0.561
		3	0.029	0.028	1.2496	0.741
		4	0.072	0.067	1.8482	0.764
		5	0.012	-0.002	1.8653	0.867
		6	-0.015	-0.018	1.8916	0.929
		7	0.059	0.059	2.2943	0.942
		8	0.062	0.046	2.7477	0.949
		9	0.017	0.006	2.7814	0.972
		10	-0.002	-0.004	2.7817	0.986
		11	0.007	-0.003	2.7872	0.993
		12	0.003	-0.006	2.7884	0.997
		13	-0.005	-0.005	2.7920	0.999
		14	-0.006	-0.006	2.7966	0.999
		15	-0.000	-0.005	2.7966	1.000
		16	0.002	-0.002	2.7969	1.000
		17	-0.005	-0.005	2.8002	1.000
		18	-0.005	-0.004	2.8038	1.000
		19	-0.004	-0.003	2.8064	1.000
		20	0.005	0.006	2.8095	1.000
		21	-0.002	-0.001	2.8099	1.000
		22	-0.005	-0.003	2.8137	1.000
		23	-0.001	0.000	2.8139	1.000
		24	0.018	0.018	2.8590	1.000
		25	-0.005	-0.008	2.8630	1.000
		26	-0.007	-0.004	2.8694	1.000
		27	-0.007	-0.007	2.8762	1.000
		28	-0.007	-0.009	2.8840	1.000
		29	-0.007	-0.004	2.8919	1.000
		30	-0.007	-0.004	2.9003	1.000
		31	-0.006	-0.006	2.9062	1.000
		32	-0.008	-0.007	2.9164	1.000
		33	-0.007	-0.004	2.9240	1.000
		34	-0.008	-0.005	2.9341	1.000
		35	-0.008	-0.004	2.9439	1.000
		36	-0.008	-0.004	2.9543	1.000

Source: Own compilation

Note: The correlogram of the residual is flat. Therefore, the residuals are white-noise since the null hypothesis of no autocorrelation is rejected for all the 36 lags.

Figure 0.17: ARIMA forecast for the Namibian banking sector loan portfolio, 2023-2025



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