Evaluating the Impact of Bank Specific Determinants of Non-performing Loans in Namibia

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Abstract
This paper aimed at assessing the bank-specific determinants for non-performing loans in commercial banks in Namibia. The study employed time-series econometric techniques of unit root, co-integration, impulse response functions and forecast error variance decomposition on the quarterly data covering the period 2001 to 2014. Two models were estimated in which return on assets and return on equity were alternating as profitability measures, among other variables that explain non-performing loans. The results reveal that return on assets, return on equity, loan to total asset ratio, log of total assets are the main determinants of non-performing loans. In specific terms, a negative relationship between non-performing loans and return on assets as well as return on equity was found. Furthermore, a positive relationship between non-performing loans and loan to total asset ratio was found. Lastly, the results revealed a positive relationship between non-performing loans and log of total assets.

Keywords: bank-specific, commercial banks, non-performing loans, Namibia, unit root, co-integration, impulse response function
1. Introduction

The role of commercial banks goes beyond the intermediation function, in that it also rewards the shareholders for their investment as a result of good financial performance. This in turn encourages additional investment and brings about economic growth while, poor banking performance can lead to banking failure and crisis which have negative repercussions on economic growth. Therefore, of greater importance is their role of financing economic activity in most economies (Ongore and Kusa, 2013 and Soyemi, Akinpelu and Agunleye, 2013).

It is also generally known that financial institutions play a crucial role of financial intermediaries between lenders and borrowers. The role of intermediaries eases the flow of credit in the economy and additionally boosts the productivity by revitalising the investment (Farhan, Sattar, Chaudhry and Khalil, 2012). The increase in production implies economic growth and economic growth will not take place in the absence of a sound financial sector. Therefore, good performance exhibited by the financial institutions symbolises good prospects of economic growth (Khan and Senhadji, 2001).

The financial institutions are largely dominated by banks. Hence, the link between financial institutions and economic growth is interlinked with the banking sector. Commercial banks are the most important financial intermediaries because of their ability to provide a range of bundle of different services. In particular, commercial banks provide various services to both lenders (depositors) and borrowers. In terms of depositors, banks provide liquidity and safekeeping for savings, which allows depositors to smoothen consumption over time. Furthermore, commercial banks conduct credit analysis, disburse loans and monitor outstanding credits for borrowers who require more financing than they can raise (Berger, Hancock and Humphrey, 1993).

In the Namibian case, the banking industry is characterized by an oligopolistic market structure in which a few institutions dominate the industry (Andongo and Stork, 2005). As of December 2013, the structure of banking sector still continues to be dominated by the four major commercial banking institutions with a Herfindahl- Hirschman Index (HHI) of 2729 (Financial Stability Report 2014) in December 2013, compared to 2734 points June 2013. Therefore, any changes in the banking sector being it positive or negative will affect the economy in the direction of the effect. Chijoriga (1997) and Farhan et al (2012) specifically pointed out that banking failures have adverse effect on economic growth such that (i) bank failures is said to cause banking crisis and (ii) bank failure also reduces the flow of credit in the economy which in turn affects the efficiency and productivity of the business sector. Furthermore, according to Brownbridge (1998), most empirical researches supports confirms that most banking failure or banking crisis has been caused by non-performing loans.
According to the Financial Stability Report (2014), the banking sector continues to operate in accordance with the regulatory requirements and that the financial soundness indicators for the banking sector remain at comfortable levels by international standards. The only concern is the assets of banking institutions, which are highly concentrated in mortgage loans, and thus, requires continuous monitoring. In view of banking failure resulting from non-performing loans, any failure in the sector has enormous potential effect on the economy. Hence, a study of this nature will be of great importance for a country where the financial sector is dominated by commercial banks as it the case for Namibia.

Numerous studies have been conducted on this subject elsewhere in the world and little is known about Namibia. Therefore, the objective of this study is to investigate the bank-specific determinants of non-performing loans in Namibia’s banking sector. The paper is organized as follows: the next section presents a literature review. Section 3 discusses the methodology. The empirical analysis and results are presented in section 4. Section 5 concludes the study.

2. Literature Review

2.1 Theoretical Literature

The theoretical framework on the non-performing loans acknowledges and concluded that bank specific determinants do influence the non-performing loans. Geletta (2012) identified the following bank specific determinants namely, rapid loan growth, high interest rate, lenient credit terms, credit orientation, bank size, cost efficiency, ownership structure, poor loan follow-up (monitoring), poor risk assessment and lack of strict admittance exit policies. Furthermore, Geletta identified the following bank specific factors like, bank size, credit terms, interest margin, rapid loan growth, credit orientation, operating efficiency, policies on borrower admittance, risk assessment and monitoring as the most significant in explaining NPL.

It is generally accepted and acknowledged that commercial banks accept customer’s deposits and use those funds to provide loans to other customers or invest in other assets with anticipation of yielding higher returns. That is why Gezu (2014) argues that customer’s deposits are the main source of bank loans and this explain the existing positive relationship between customer’s deposits and commercial bank’s lending. Hence, in this regard, it is argued that commercial banks’ actions are two folded. Firstly, making profit and secondly, providing credit. In offering credit, a loan portfolio is created which is simply a debt. Like any other debt instruments a loan involves a redistribution of financial assets over a period of time.

The danger is that loans are the largest major source of income for commercial banks and that makes it risky because of the highest degree of default. This due to the fact that the
borrower does not repay the loan (and the interest on loan) at once immediately, but rather arrange to repay at a later date (Gezu, 2014). The moment the loan offered does no longer generate interest for a prolonged period automatically becomes default or NPL. This situation may come about as a result of the problem of asymmetric information.

The theory of asymmetric information state that it may be difficult to differentiate between good and bad borrowers. The problem of asymmetric information arise a result of incomplete information possessed by the lender and to a certain extend complete information being possessed by the borrower about the transaction (Richard, 2011). Accordingly, the lender might make a right or wrong decision about the transaction. This may result into adverse selection and moral hazards problems as it is well known in microeconomic theory. Adverse selection and moral hazards have led to significant accumulation of non-performing loans in banks (Bester, 1994).

The “moral hazard” hypothesis was first discussed by Keeton and Morris (1987), who argued that banks with relatively low capital respond to moral hazard incentives by increasing the riskiness of their loan portfolio, which in turn results in higher non-performing loans on average in the future. Louzis, Vouldis and Metaxas (2011) also state that the moral hazard of too-big-to-fail banks represents another channel relating bank-specific features with non-performing loans. Furthermore, a policy concern is that too-big-to-fail banks may opt for undertaking even excessive risk since market discipline is not imposed by its creditors who expect government protection in case of a bank’s failure. Consequently, large banks may compromise and increase their leverage unnecessarily and in turn offer loans to lower quality borrowers.

Another theoretical viewpoint that could not be ignored is that of ownership of a firm. Louzis et al. (2011) argue that dispersed ownership of corporate equity may result in poorer performance of the firm. This could arise as a result of a decline (weaken) in the supervision of managements by the shareholders.

2.2 Empirical Literature

Numerous studies have empirically looked at the various bank-specific determinants of non-performing loans. A few selected empirical studies are listed below.

Keeton (1999) examined the relationship between bank-specific determinants. This study used data from commercial banks in the United States for 1982 to 1996. A vector auto regression model was used in this study and revealed an association between loan and rapid credit growth, supporting the hypothesis that loan delinquencies are associated with rapid credit growth.

Salas and Saurina (2002) analysed the determinants of problems of loans of commercial and saving banks in Spain. The study employed a dynamic model and a panel dataset
covering the period 1985-1997. The results from this study show that rapid credit expansion, 
bank size, capital ratio and market power are the bank-specific determinants that explain 
variation in NPLs.

In Taiwan, Hu, Yang and Yung-Ho (2006) investigated the relationship between NPLs and 
ownership structure of commercial banks in Taiwan. A panel modelling technique was 
applied to a panel dataset covering the period 1996-1999. The findings show that banks with 
higher government ownership recorded lower non-performing loans.

Dimitrios, Angelos and Vasilios (2011) analysed the determinants of non-performing loans 
in Greek. The study contains panel data of nine largest Greek banks and a generalized method 
of moment on the data covering the period of 2003 to 2009. Different loan categories 
(consumer loans, business loans and mortgages were separately analysed. The study showed 
that bank specific variable i.e. performance and quality of management with risk management 
practices or system are also responsible for variation in NPLs.

Klein (2013) investigated the non-performing loans (NPLs) in Central, Eastern and South-
Eastern Europe (CESEE) during the period 1998–2011. The panel modelling technique was 
applied to the annual data and the results reveals that the level of NPLs can be attributed to 
both macroeconomic conditions and banks’ specific factors, though the latter set of factors 
was found to have a relatively low explanatory power.

Messai and Jouini (2013) evaluated the determinants of non-performing loans for a sample 
of 85 banks in three countries (Italy, Greece and Spain) for the period of 2004-2008. A 
method of panel data was employed on the following bank-specific variables, return on assets, 
the change in loans and the loan loss reserves to total loans. The results show that non-
performing loans vary negatively with the profitability of banks’ assets and positively with 
the loan loss reserves to total loans.

Warue (2013) investigated the relationship between NPLs and bank-specific and 
macroeconomic factors, and establish the extent to which these factors affect the occurrence 
of non-performing loans in commercial banks in Kenya. The macroeconomic factors 
included; real GDP, GDP per capita, lending interest rates, inflation, government expenditure, 
export and imports, exchange rate between the Kenya shilling and US dollar and asset value 
as measured by the Nairobi Securities Exchange (NSE) 20 share Index. Bank specific factors 
included; credit risk management techniques, bank structures, and quality management 
factors. The study covers the period 1995 to 2009 utilising both secondary and primary data. 
Particularly, a census of 44 commercial banks in Kenya was taken. A causal- comparative 
research design based on bank structures was adopted. The study used panel econometrics 
approach employing both pooled (unbalanced) panel and fixed effect panel models. The study 
found evidence that return on assets (ROA) was negative and significantly related to NPLs.
levels in large banks and small banks but insignificant in medium banks. In addition the study found that return on asset (ROA) was negative and significant in local banks and government banks but not in foreign banks. However the study found no evidence that banks asset size was related to NPLs levels across all bank categories in Kenya. In conclusion, the study found evidence that bank specific factors contribute to NPLs performance at higher magnitude.

Makri, Tsagkanos and Bellas (2014) study examined the factors affecting the non-performing loans rate (NPL) of Eurozone’s banking systems for the period 2000-2008. A dynamic panel regression method for our analysis specifically, a Generalized Method of the Moments (GMM difference) technique was applied. The variables used include both macro-variables (e.g. annual percentage growth rate of gross domestic product, public debt as percent of gross domestic product, unemployment) and micro-variables (e.g. loans to deposits ratio, return on assets and return on equity). The findings reveal strong correlations between NPL and bank-specific (capital adequacy ratio, rate of non-performing loans of the previous year and return on equity) factors.

Hassana, Ilyas and Rehman (2015) analysed the bank-specific and social factors that influences non-performing loans in Pakistan. A survey questionnaire methodology was used in this study. The results show that various bank-specific factors like credit assessment, credit monitoring and rapid credit growth have significant effect on Non-Performing Loans, whereas interest has a weak significance on NPLs.

Hue (2015) examined the main factor influencing the non-performing loans in the Vietnam’s banking system for the period 2009 to 2012. An ordinary least square method for panel data was applied to analyse the relationship between the NPLs and some bank-specific factors such as the lag of NPLs in the last year, the loans-to-asset ratio, total assets and the Dummy, which clarify whether a bank is state or not. The results showed that the four factors actually helped the growth of NPLs in recent years.

On the basis of the reviewed literature on the bank-specific determinants for non-performing loans, one can conclude the following: There are mixed findings due to the variation of the environment and data included in various studies. There are also different methodological approaches whether it is cross-country or individual country’s studies with panel data being the most dominant especially in cases where bank data-level (disaggregated). However, there seem to be no study on Namibia that has specifically looked at this subject. It is against this background this study intends to fill the gap and add to empirical literature for Namibia.

3. Methodology

In analysing the relationship between bank specific determinants and non-performing loans, this study followed a similar approach to that of Keeton (1999). Time series
econometric methods unit root, co-integration, impulse response functions and forecast error variance decompositions have been used within the vector autoregression (VAR) framework. This is due to the fact that the data used in this study are of aggregate in nature. The process is outlined in the next subsection.

3.1 Econometric or Analytical Framework and Model Specification

VAR is a system of dynamic linear equations where all the variables in the system are treated as endogenous. To draw the VAR mainframe, assume that the relationship between bank specific determinants and profitability is described by a dynamic system whose structural form equation is given by:

\[ A\Delta_y_t = \Psi + \Omega_1\Delta y_{t-1} + \Omega_2\Delta y_{t-2} + \ldots + \Omega_p\Delta y_{t-p} + B\mu_t \]  

where \( A \) is an invertible \((n \times n)\) matrix describing contemporaneous relations among the variables; \( y_t \) is an \((n \times 1)\) vector of endogenous variables such that \( y_t = (y_{t1}, y_{t2}, \ldots, y_{tn}) \); \( \Psi \) is a vector of constants; \( \Omega_i \) is an \((n \times n)\) matrix of coefficients of lagged endogenous variables \( (\forall i = 1, 2, 3, \ldots, p) \); \( B \) is an \((n \times n)\) matrix whose non-zero off-diagonal elements allow for direct effects of some shocks on more than one endogenous variable in the system; and \( \mu_t \) are uncorrelated or orthogonal white-noise structural disturbances ie the covariance matrix of \( \mu_t \) is an identity matrix \( E(\mu_t, \mu_t^\prime) = 1 \).

Equation (1) can be rewritten in compact form as:

\[ A\Delta_y_t = \Psi + \Omega(L)\Delta y_{t-i} + B\mu_t \]  

where \( \Omega(L) \) is a \((n \times n)\) finite order matrix polynomial in the lag operator \( L \).

The VAR presented in the primitive system of equations (1) and (2) cannot be estimated directly (Enders, 2004). However, the information in the system can be recovered by estimating a reduced form of VAR implicit in (1) and (2). Pre-multiplying equation (1) by \( A^{-1} \) yields a reduced form VAR of order \( p \), which in standard matrix form is written as:

\[ y_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i y_{t-i} + \epsilon_t \]  

Where:

\[ y_t = f(NPL_t, ROA_t, LTA_t, LNT_t) \]  

\( \Phi \) = matrix of coefficients of autonomous varibles

\( A_i \) = Matrix of coefficients of all variables in the model

\( y_{t-1} \) = is the vector of the lagged values of \( NPL, ROA, ROE, LTA \) and \( LNT \).
Two different models were used to separately cater for the effects of the two profitability measures that have been alternatively used as bank specific determinants. Given the estimates of the reduced form VAR in equation (3), the structural economic shocks are separated from the estimated reduced form residuals by imposing restrictions on the parameters of matrices $A$ and $B$ in equation (4):

$$A\varepsilon_t = B\mu,$$  \hspace{1cm} ...4

The model consists of four endogenous variables, hence the VAR model in matrix notation can be expressed in the following manner:

$$NPL_t = \alpha_1 + b_{11}NPL_{t-1} + b_{12}ROA_{t-1} + b_{13}LTA_{t-1} + b_{14}LNT_{t-1} + \varepsilon_t^{NPL}$$

$$ROA_t = \alpha_1 + b_{21}NPL_{t-1} + b_{22}ROA_{t-1} + b_{23}LTA_{t-1} + b_{24}LNT_{t-1} + \varepsilon_t^{ROA}$$

$$LTA_t = \alpha_1 + b_{31}NPL_{t-1} + b_{32}ROA_{t-1} + b_{33}LTA_{t-1} + b_{34}LNT_{t-1} + \varepsilon_t^{LTA}$$

$$LNT_t = \alpha_1 + b_{41}NPL_{t-1} + b_{42}ROA_{t-1} + b_{43}LTA_{t-1} + b_{44}LNT_{t-1} + \varepsilon_t^{LNT}$$

Where: $\varepsilon_t^{NPL}, \varepsilon_t^{ROA}, \varepsilon_t^{LTA}$ and $\varepsilon_t^{LNT}$ are the white noise error term and independent of the dependent variables. The matrix of coefficients is:

$$\gamma_t' = [\Delta NPL_t \hspace{0.5cm} \Delta ROA_t \hspace{0.5cm} \Delta LTA_t \hspace{0.5cm} \Delta LNT_t]$$

\[
\begin{pmatrix}
1 & 0 & 0 & 0
\end{pmatrix}
\begin{pmatrix}
\varepsilon_t^{NPL}
\varepsilon_t^{ROA}
\varepsilon_t^{LTA}
\varepsilon_t^{LNT}
\end{pmatrix} =
\begin{pmatrix}
b_{11} & b_{12} & b_{13} & b_{14}
\end{pmatrix}
\begin{pmatrix}
\varepsilon_t^{NPL}
\varepsilon_t^{ROA}
\varepsilon_t^{LTA}
\varepsilon_t^{LNT}
\end{pmatrix}
\]

$b_i$ is a (4x4) matrix of parameters that are non-zero.

$\varepsilon_t$ is a (4x1) column vector of the random disturbance term.

The second model also consists of four variables and the VAR model specified as follow:

$$NPL_t = \alpha_1 + b_{11}NPL_{t-1} + b_{12}ROE_{t-1} + b_{13}LTA_{t-1} + b_{14}LNT_{t-1} + \varepsilon_t^{NPL}$$

$$ROE_t = \alpha_1 + b_{21}NPL_{t-1} + b_{22}ROE_{t-1} + b_{23}LTA_{t-1} + b_{24}LNT_{t-1} + \varepsilon_t^{ROE}$$

$$LTA_t = \alpha_1 + b_{31}NPL_{t-1} + b_{32}ROE_{t-1} + b_{33}LTA_{t-1} + b_{34}LNT_{t-1} + \varepsilon_t^{LTA}$$

$$LNT_t = \alpha_1 + b_{41}NPL_{t-1} + b_{42}ROE_{t-1} + b_{43}LTA_{t-1} + b_{44}LNT_{t-1} + \varepsilon_t^{LNT}$$
Where: $\varepsilon_{t}^{NPL}$, $\varepsilon_{t}^{ROE}$, $\varepsilon_{t}^{LTA}$ and $\varepsilon_{t}^{LNT}$ are the white noise error term and independent of the dependent variables. The matrix of coefficient is:

$$y_{t}' = [\Delta NPL_{t} \quad \Delta ROE_{t} \quad \Delta LTA_{t} \quad \Delta LNT_{t}]$$

$$\begin{pmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{pmatrix} \begin{pmatrix}
\varepsilon_{t}^{NPL} \\
\varepsilon_{t}^{ROE} \\
\varepsilon_{t}^{LTA} \\
\varepsilon_{t}^{LNT}
\end{pmatrix} = \begin{pmatrix}
b_{11} & b_{12} & b_{13} & b_{14} \\
b_{21} & b_{22} & b_{23} & b_{24} \\
b_{31} & b_{32} & b_{33} & b_{34} \\
b_{41} & b_{42} & b_{43} & b_{44}
\end{pmatrix} \begin{pmatrix}
\mu_{t}^{NPL} \\
\mu_{t}^{ROE} \\
\mu_{t}^{LTA} \\
\mu_{t}^{LNT}
\end{pmatrix}$$

$b_{t}$ is a (4x4) matrix of parameter that are non-zero.

$\varepsilon_{t}$ is a (4x1) Column vector of the random disturbance term.

The main uses of the VAR model are the impulse response analysis and forecast error variance decomposition. The analysis is carried out in the following order. Before VAR estimation, test for non-stationary (unit root) of time series is essential to determine the order of integration. The test is conducted by employing one or a combination of the Augmented Dickey Fuller (ADF) test, the Phillips-Perrons (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests (Pindyck & Rubinfeld, 1991; Gujarati, 1995; 2003). Thereafter, the optimal lag length is tested as it affects the VAR model. There are many criteria used to indicate the number of optimal lags namely, Hannan-Quinn (HQ), Schwarz information criterion (SC), Akaike Information Criterion (AIC), Final prediction error (FPE) and Likelihood Ratio (LR). After determining the number of lags it is essential to also check whether VAR satisfies the stability condition. The next step would be to conduct tests for co-integration, i.e. if two or more series have long-run equilibrium. The co-integration test can be applied in several ways, according to the nature of the equation that is tested it is single or multivariate system. If co-integration is found among the variables, the adjustment of the short-run to the long-run equilibrium is obtained through the vector error correction model (VECM). When co-integration is not found, then a VAR model specification is estimated. Thereafter, the impulse response function and forecast error variance decomposition would be derived from the estimated VAR/VECM. In order to avoid biasedness towards a particular school of thought as a result of the ordering of the variables, a generalized impulse response function (GIRF) is used in this regard. This is because it is insensitive to the ordering of variables and it does not require orthogonalisation of shocks (Koop, Pesaran and Potter, 1996; Pesaran & Shin, 1998).

### 3.2 Data, Data Sources and Data Measurements

The data used in this paper are of quarterly frequency for the period 2001:Q1 to 2014:Q2. Secondary data were obtained from the Bank of Namibia’s various statutory publications. The
following variables have been used, non-performing loans (NPL), return on assets (ROA), return on equity (ROE), ratio of total loans to total asset (LTA) and log of total asset (LNT).

4. Empirical Analysis and Results

4.1 Unit Root Test

Table 1, reports the results of both the ADF and PP unit root tests. The results show that all variables are stationary in levels (integrated of order zero) with the exception of log of total assets which became stationary after being differenced once (integrated of order one).

Table 1: Unit root tests: ADF and PP in levels and first difference

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model Specification</th>
<th>ADF</th>
<th>PP</th>
<th>ADF</th>
<th>PP</th>
<th>Order of Integration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Levels</td>
<td>Levels</td>
<td>First Difference</td>
<td>First Difference</td>
<td></td>
</tr>
<tr>
<td>ROA&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Intercept and trend</td>
<td>-3.87**</td>
<td>-4.82**</td>
<td>-9.42**</td>
<td>-15.75**</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>-3.63**</td>
<td>-4.40**</td>
<td>-9.44**</td>
<td>-14.33**</td>
<td>0</td>
</tr>
<tr>
<td>ROE&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Intercept and trend</td>
<td>-5.07**</td>
<td>-5.06**</td>
<td>-8.96**</td>
<td>-19.90**</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>-5.52**</td>
<td>-5.49**</td>
<td>-8.87**</td>
<td>-22.12**</td>
<td>0</td>
</tr>
<tr>
<td>LTA&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Intercept and trend</td>
<td>-5.24**</td>
<td>-6.73**</td>
<td>-7.94**</td>
<td>-48.67**</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>-3.67**</td>
<td>-5.88**</td>
<td>-8.88**</td>
<td>-47.06**</td>
<td>0</td>
</tr>
<tr>
<td>LNT&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Intercept and trend</td>
<td>-3.46**</td>
<td>-3.69**</td>
<td>-7.15**</td>
<td>-9.29**</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>-2.99</td>
<td>-3.14</td>
<td>-8.33**</td>
<td>-12.92**</td>
<td>1</td>
</tr>
<tr>
<td>NPL&lt;sub&gt;it&lt;/sub&gt;</td>
<td>Intercept and trend</td>
<td>-2.70*</td>
<td>-2.69*</td>
<td>-6.05**</td>
<td>-6.00**</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Intercept</td>
<td>-3.57**</td>
<td>-3.64**</td>
<td>-6.11**</td>
<td>-6.11**</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: author’s compilation and values obtained from Eviews
Notes: (a)** and * means the rejection of the null hypothesis at 5% and 10% respectively

4.2 Selection of Optimal Lag

It is important to find the maximum lag on the VAR stability that is based on the roots of the characteristic polynomial. In this study VAR satisfies the stability condition as the value of its AR roots is less than one and there is no root that lies outside the unit circle. If there is unstable VAR, the results of impulse response function and variance decomposition will be invalid. The optimal lag length of 4 was chosen based on the available criteria information as shown in tables 2 and 3 respectively.

Table 2: Optimal lag length (first model with ROA)

<table>
<thead>
<tr>
<th>Lag</th>
<th>LogL</th>
<th>LR</th>
<th>FPE</th>
<th>AIC</th>
<th>SC</th>
<th>HQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>75.01321</td>
<td>NA</td>
<td>6.86e-07</td>
<td>-2.840528</td>
<td>-2.687567</td>
<td>-2.782280</td>
</tr>
<tr>
<td>1</td>
<td>270.8798</td>
<td>352.5598</td>
<td>5.16e-10</td>
<td>-10.03519</td>
<td>-10.75545</td>
<td>-9.743947</td>
</tr>
<tr>
<td>2</td>
<td>291.8274</td>
<td>34.35403</td>
<td>4.29e-10</td>
<td>-10.23309</td>
<td>-8.856438</td>
<td>-9.708856</td>
</tr>
<tr>
<td>3</td>
<td>316.0412</td>
<td>35.83642</td>
<td>3.19e-10</td>
<td>-10.56165</td>
<td>-8.573142</td>
<td>-9.804413</td>
</tr>
<tr>
<td>4</td>
<td>350.6687</td>
<td>45.70842</td>
<td>1.62e-10*</td>
<td>-11.30675*</td>
<td>-8.706399</td>
<td>-10.31652*</td>
</tr>
</tbody>
</table>

* indicates lag order selected by the criterion
Table 3: Optimal lag length (second model with ROE)

<table>
<thead>
<tr>
<th>Lag</th>
<th>LogL</th>
<th>LR</th>
<th>FPE</th>
<th>AIC</th>
<th>SC</th>
<th>HQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-66.17892</td>
<td>NA</td>
<td>0.000195</td>
<td>2.807157</td>
<td>2.960119</td>
<td>2.865406</td>
</tr>
<tr>
<td>1</td>
<td>126.3189</td>
<td>346.4960</td>
<td>1.68e-07</td>
<td>-4.252755</td>
<td>-3.487946*</td>
<td>-3.961512</td>
</tr>
<tr>
<td>2</td>
<td>142.8247</td>
<td>27.06948</td>
<td>1.66e-07</td>
<td>-4.272986</td>
<td>-2.896330</td>
<td>-3.748748</td>
</tr>
<tr>
<td>3</td>
<td>167.7048</td>
<td>36.82255</td>
<td>1.21e-07</td>
<td>-4.628191</td>
<td>-2.639687</td>
<td>-3.870957</td>
</tr>
<tr>
<td>4</td>
<td>205.8729</td>
<td>50.38197*</td>
<td>5.30e-08*</td>
<td>-5.514917*</td>
<td>-2.914566</td>
<td>-4.524688*</td>
</tr>
</tbody>
</table>

* indicates lag order selected by the criterion

4.3 Testing for Co-integration

The Johansen co-integration test was used to test for the possible existence of any long run relationship. The results in tables 4 and 5 show a presence of co-integration in all cases as it was supported by both test statistics.

Table 4: The Johansen co-integration test based on trace and maximal Eigen value (first model)

<table>
<thead>
<tr>
<th>Maximum Eigen Test</th>
<th>Trace Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>( H_0: \text{rank} = r )</td>
<td>( H_0: \text{rank} = r )</td>
</tr>
<tr>
<td>Statistic</td>
<td>95% Critical Value</td>
</tr>
<tr>
<td>r = 0</td>
<td>r = 1</td>
</tr>
<tr>
<td>r &lt;=1</td>
<td>r = 2</td>
</tr>
<tr>
<td>r &lt;=2</td>
<td>r = 3</td>
</tr>
<tr>
<td>r &lt;=3</td>
<td>r = 4</td>
</tr>
</tbody>
</table>

Source: author’s compilation and values obtained from Eviews
Note: Both Max-Eigen value and Trace tests indicates 2 cointegrating equations at the 0.05 level (**)

Table 5: The Johansen co-integration test based on trace and maximal Eigen value (second model)

<table>
<thead>
<tr>
<th>Maximum Eigen Test</th>
<th>Trace Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>( H_0: \text{rank} = r )</td>
<td>( H_0: \text{rank} = r )</td>
</tr>
<tr>
<td>Statistic</td>
<td>95% Critical Value</td>
</tr>
<tr>
<td>r = 0</td>
<td>r = 1</td>
</tr>
<tr>
<td>r &lt;=1</td>
<td>r = 2</td>
</tr>
<tr>
<td>r &lt;=2</td>
<td>r = 3</td>
</tr>
<tr>
<td>r &lt;=3</td>
<td>r = 4</td>
</tr>
</tbody>
</table>

Source: author’s compilation and values obtained from Eviews
Note: Both Max-Eigen value and Trace tests indicates 2 cointegrating equations at the 0.05 level

4.4 Long Run Model

The existence of co-integration among the variables suggests that a VECM model can be estimated in order to make long run analysis. The results of the long run estimations are presented below.

\[
\text{NPL} = -32.799 - 3.036\text{ROA} + 135.707\text{LTA} + 2.248\text{LNT (first model with ROA)}
\]

\[(-4.486) \quad (3.390) \quad (5.037) \quad (t\text{-statistics})\]

In the first model ROA is used as a profitability measure for commercial banks. Similar to Messai and Jouini (2013) as well as Warue (2013), the results show a negative relationship.
between NPL and ROA, suggesting that banks with higher profitability are less enticed to generate income. Hence, they are less constrained to engage in risky activities of granting risky loans. Furthermore, there is a positive relationship between NPL and LTA, similar to Salas and Saurina (2002) study. It implies that the quality of assets plays a role in the case of Namibia, the lower the quality assets the banks possess, the higher the NPL (not able to generate income). Lastly, there is a positive relationship between NPL and LNT, similar to Hue (2015) study. This also suggests that the bank size plays a role in determining NPL. That is the higher (larger) the bank size the higher the probability of defaulting. Overall, all the variables are statistically significant.

\[ \text{NPL} = -30.012 - 0.146\text{ROE} + 38.391\text{LTA} + 1.886\text{LNT} \text{ (second model with ROE)} \]

\[ ( -4.479) \quad (1.647) \quad (5.814) \quad \text{(t-statistics)} \]

In the second model ROE is used as a profitability measure for commercial banks. Similar to Makri, Tsagkanos and Bellas (2014), the results show a negative relationship between NPL and ROE. This confirms the findings in the first model. The study also finds positive relationships between NPL and LTA as well as NPL and LNT as it is the case in the first model. Overall, all the variables are statistically significant with the exception of LTA.

4.5 Impulse Response Functions

The results for the impulse response functions (IRF) show how non-performing loans (NPL) respond to the shocks of the bank specific determinants. Figure 1 shows a positive response and permanent effect of NPL to shocks in return on assets (ROA). The permanent effect sets in the 5th period as NPL finds a new level of equilibrium. Furthermore, NPL also show a positive response and permanent effect to shocks in ratio of loans to total asset (LTA). Lastly, NPL show a positive response and permanent effect to shocks in total assets (LNT).
Figure 1: Impulse response functions for non-performing loans (first model)

Response to Generalized One S.D. Innovations

Response of NPL to ROA

Response of NPL to LTA

Response of NPL to LNT

Source: author’s compilation using Eviews

Figure 2 shows the response of non-performing loans to other bank specific determinants except that return on equity has been used in this case. The results are similar to those in the first model in that NPL also shows a positive response and permanent effect to shocks in return on equity (ROE) as well as a positive response and permanent effect to shocks in ratio of loans to total asset (LTA). On the contrary, NPL show a negative response and permanent effect to shocks in total assets (LNT).
To sum up, the response of NPL to shocks in either ROA or ROE does not conform to that depicted in the long run relationship. This suggests that there is a grey area in credit risk with respect to profitability measures as bank specific determinants. Nevertheless, there is consistency in that there is a positive relationship between NPL and LTA in both cases as supported by Salas and Saurina (2002) study. Lastly, there is a positive relationship between NPL and LNT, similar to Hue (2015) study. On the contrary, there is a negative relationship between NPL and LNT when ROE replaces ROA as a profitability measure of bank specific determinant.

4.6 Forecast error variance decomposition

Table 6 shows the results of the forecast error variance decomposition over the horizon of 24 quarters. The forecast error variance decomposition for NPL is mostly attributed to itself in the first quarter. However, after 6 quarters the variables ROA and LTA also significantly contributed to the fluctuations in NPL. Their contribution has been increasing as the horizon increase. Meanwhile, the fluctuations from LNT also contribute to the fluctuations in NPL, but relatively lower in comparison with ROA and LTA.
Table 6: Variance Decomposition (first model)

<table>
<thead>
<tr>
<th>Quarter</th>
<th>NPL</th>
<th>ROA</th>
<th>LTA</th>
<th>LNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>75.30</td>
<td>11.15</td>
<td>9.02</td>
<td>4.53</td>
</tr>
<tr>
<td>12</td>
<td>68.65</td>
<td>14.96</td>
<td>10.44</td>
<td>5.95</td>
</tr>
<tr>
<td>18</td>
<td>67.89</td>
<td>15.09</td>
<td>10.75</td>
<td>6.27</td>
</tr>
<tr>
<td>24</td>
<td>67.31</td>
<td>15.29</td>
<td>10.93</td>
<td>6.47</td>
</tr>
</tbody>
</table>

Source: author’s compilation and values obtained from Eviews

Table 7: Variance Decomposition (second model)

<table>
<thead>
<tr>
<th>Quarter</th>
<th>NPL</th>
<th>ROE</th>
<th>LTA</th>
<th>LNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>65.02</td>
<td>31.21</td>
<td>1.03</td>
<td>2.74</td>
</tr>
<tr>
<td>12</td>
<td>52.77</td>
<td>41.70</td>
<td>1.54</td>
<td>3.98</td>
</tr>
<tr>
<td>18</td>
<td>50.75</td>
<td>43.63</td>
<td>1.68</td>
<td>3.94</td>
</tr>
<tr>
<td>24</td>
<td>49.47</td>
<td>44.76</td>
<td>1.75</td>
<td>4.02</td>
</tr>
</tbody>
</table>

Source: author’s compilation and values obtained from Eviews

5. Conclusion

This study examined the bank-specific determinants for non-performing loans in commercial banks in Namibia. This was done with the purpose of establishing which of the determinant affects bank’s non-performing loans. The study was based on quarterly data covering the period 2001:Q1 to 2014:Q2, utilizing the technique of unit root, co-integration, impulse response functions and forecast error variance decomposition. The study estimated two models where return on assets and return on equity were alternating as profitability measures, among the variables that explain non-performing loans. The results reveal that return on assets, return on equity, loan to total asset ratio, log of total assets are the main determinants of non-performing loans. The negative relationship between non-performing loans and return on assets as well as return on equity suggest that banks with higher profitability are less enticed to generate income. Thus, they are less constrained to engage in risky activities of granting risky loans. Furthermore, a positive relationship between non-performing loans and loan to total asset ratio, implies that the quality of assets plays a role in the case of Namibia, the lower the quality assets the banks possess, the higher the NPL (not able to generate income). Lastly, a positive relationship between non-performing loans and log of total assets suggests that the bank size plays a role in determining non-performing loans.
in Namibia. That is the higher (larger) the bank size the higher the probability of defaulting. The study recommends that Namibia should continue closely monitoring the determinants to detect any early warning of potential credit risk in the future.

References


