The Impact of Macroeconomic Determinants on Non-performing Loans in Namibia

Johannes Peyavali Sheefeni Sheefeni
Department of Accounting, Economics and Finance,
Polytechnic of Namibia,
Windhoek, Namibia.
Email: peyavali@gmail.com

Abstract

This study examined the macroeconomic determinants of non-performing loans in Namibia. The study was based on quarterly data covering the period 2001:Q1 to 2014:Q2, utilizing the technique of unit root, co-integration, Granger causality, impulse response functions and forecast error variance decomposition. The results for co-integration found a long run relationship between non-performing loan and log of gross domestic product, interest rate and inflation rate. The results for Granger causality found unidirectional causality from interest rate to non-performing loan in the long run. Moreover, there is also unidirectional causality running from all the macroeconomic determinants to non-performing loans in the short run. The results of the impulse response functions revealed that all the macroeconomic determinants plays a role in determining non-performing loans, while in the short run only log of gross domestic product and exchange rate.

Keywords: *macroeconomic determinants, commercial banks, non-performing loans, Namibia, unit root, co-integration, Granger causality, impulse response functions*

1. Introduction

"Non-performing loans are those loans which are ninety days or more past due or no longer accruing interest" (Joseph, Edson, Manuere, Clifford and Michael, 2012). Badar and Javid (2013) state that a loan is considered as non-performing if default or closed to being in default. They further explained that if the loan's principal and payment of interest overdue by 90 days, it may be regarded as non-performing loan.

The event of the global financial crisis has proved and revealed that external funding sources can induce macroeconomic instability. Consequently, there is potential risk of financial system vulnerability in the economy (Ouhibi and Hammami, 2015). Usually, financial vulnerability is evaluated on the basis of the levels of non-performing loans (NPLs) in the banking sector.

The non-performing loans are used as an indicator for financial stability and particularly banking system stability (Prasanna, 2014). According to Ouhibi and Hammami (2015), this is so because NPLs serve as a guide on the quality of the assets, credit risk and efficiency in the allocation of resources to productive sectors. Therefore, the relationship between NPLs and the macro-economy can be explained on the basis that the quality of a loan portfolio (which is the ratio of non-performing loans to total gross loans) is influenced by the systemic risks resulting from exposures to macroeconomic risk factors across banks. A rise in the ratio of non-performing loans to total gross loans suggests a bad state in the banking sector results, signalling trouble for bank's management as well as the regulator. On the contrary, a fall in the ratio of non-performing loans signals low levels of NPLs, implying a sound financial system (Badar and Javid, 2013).

Economic theory tells us that commercial banks play the role of lending. Joseph et al (2012) support the argument by categorically stating that the traditional role of commercial banks is lending credit or loans. In this regard, loans make up the bulk of their assets on which interest is generated, which contributes largely to the interest income of commercial banks. The nature of the business of lending is risky as commercial banks exposes themselves to the risk of default by the borrowers. This is generally known as the credit risk as it is expressed as the ratio of non-performing loans to total gross loan.

Credit risk is vital in the Namibian context where banking sector is characterized by an oligopolistic market structure in which a few institutions dominate the industry (Andongo and Stork, 2005). On the one hand, a market structure in which few large firms have a large market share is believed to have a positive impact on corporate profit. On the other hand, any failure in the banking sector has negative impact on the economy. For example any bankruptcy in the sector has a potential contagion effect that can lead to bank runs, crises and bring overall financial crisis and economic tribulations.

According to the Financial Stability Report (2014), Credit risk, as expressed by the ratio of non-performing loans (NPLs) to total loans, started to decline between June 2013 and December 2013, from 1.46 percent to 1.29 percent respectively. This development is said to be in line with the general overall downward trend in NPLs observed since 2009. However, credit risk remained the major risk on the asset side of the banking balance sheet, with bank lending composing approximately 76 percent of banking assets as at December 2013. Moreover, an increase in the weight of instalment credit as a proportion of total NPLs (from 12.53 to 13.75), overdrafts as a proportion of total NPLs (from 13.79 to 14.90) and unsecured lending in the form of credit card loans as a proportion of NPLs (from 1.40 to 1.86) over the same period was observed. This study draws its primary interests from this in that its objective is to examine the macroeconomic determinants of non-performing loans in Namibia.

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

It is well documented in literature and confirmed that undeniably, macroeconomic conditions matter for credit risk. In this regard, numerous studies have investigated the relationship between macroeconomic factors like gross domestic product, inflation, interest rates, unemployment etc. and loan performance (Farhan, Sattar, Chaudhry & Khalil, 2012 and Adebola, Yusoff & Dahalan, 2011). Therefore, it is important to review the existing literature on the macroeconomic factors that have bearing effects on Non-performing loans (NPL).

The link between loan quality and macroeconomic variables has been widely debated within the framework of business cycles by linking the boom and depression of business cycles with financial vulnerability and stability of the banking sector. Ahmad and Bashir (2013) discussed the different outcomes observed during the different business cycles. In specific terms, during boom there tend to be rapid growth in bank loans while growth in bank loans tend to decline during recessionary (depression) cycles. In support of Ahmad and Bashir are Abid, Ouertani and Zouari-Ghorbel (2014), who also stated that during the expansion phase of the economy, there tend to be relatively low number of NPLs, as borrowers face a sufficient stream of income to service their debts. However, the implication is that as the booming period extends, in the process credit is given to lower-quality debtors and subsequently, when the recession phase sets in, NPLs increases.

Geletta (2012) explained the behavioural relationship between NPLs and macroeconomic variables from two perspectives, demand and supply sides. First, on the demand side, during boom the cycle investors are optimistic about future returns. This futuristic optimism results in a relatively greater demand for more credit to invest in new projects. On the contrary, during the recessionary (depression) cycle the futuristic pessimism results in a relatively low demand for credit. This is to say, investors are over conscious about investing in new projects and thus, holding back the lending decisions. Secondly, on the supply side, it is all good for business in that there is stable cash flow streams of the debtors and banks, timely repayments of loans, good credit scores of borrowers, increasing credit worthiness and willingness of banks for lending to borrowers. However, in times of economic depression, banks are over conscious and doubtful about the economic conditions, future outcomes of projects, hence reluctant to lend to the borrowers.

There are also other variables such as inflation rate which influences bank's judgements and decision when making loan appraisal. From the firm's perspective, high inflation increases the volatility of business profits because of its unpredictability nature. Consequently, this variability manifest in the rates of increase of price of the particular goods and services which make up the overall price index. Therefore, the probability for firms making losses also rises, so does the probability of making earn windfall profits. This decreases the ability of the firms to honour its debt obligations too. Thus, likely to increase the NPLs. Alternatively, high inflation can boost the capacity of the borrower by reducing the real value of the outstanding debt (Farhan, Sattar, Chaudhry and Khalil, 2012). Moreover, from the consumer's perspective, the viability of potential borrowers depends upon unpredictable development in the overall rate of inflation, its individual components, exchange rates and interest rates. The uncertainty in the behaviours of these variables puts enormous pressures on bank loans offer. Furthermore, asset prices are also likely to be highly volatile under such conditions. Hence, the future real value of loan security is also very uncertain (Brownbrigde, 1998).

Gelleta (2012) also discussed the likely impact of an increase in the unemployment rate as it has potential of negatively affecting the cash flow streams of households and increase the debt burden which in turn increasing the chances of defaulting on loans. From the firm's perspective, increases in unemployment may signal a decrease production as a consequence of a drop in effective demand, resulting in revenue loss and highly potentially fragile debt condition.

Gezu (2014) shed light on the effect of interest rate in servicing debt especially for floating rate loans. An increase in interest rate worsen debt burden as a result of increased interest payment, resulting in high number of NPLs. This suggests a positive relationship between interest rate and NPLs.

2.2 Empirical Literature

There are numerous studies that have empirically investigated the various macroeconomic determinants of non-performing loans. Below is a list of few selected empirical studies on the abovementioned subject.

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 real growth in GDP is among the macroeconomic factors that explain variation in NPLs.

Khemraj and Pasha (2009) evaluated the determinants of non-performing loans in the Guyanese banking sector using a panel dataset at firm-level. A fixed effect model was estimated on data covering the period 1994 to 2004. The findings from this study reveal that the real effective exchange rate has a significant positive impact on non-performing loans. The results further show that GDP growth is inversely related to non-performing loans. It was also shown that banks that charge relatively higher interest rates and lend excessively are likely to incur higher levels of non-performing loans.

In Malaysia, Adebola, Yusoff and Dahlan (2011) explored the determinants of non-performing loans covering the period 2007 to 2009. An ARDL approach was applied in this study on the following macroeconomic variables, industrial production index, interest rate, and producer price. The findings indicated that, interest rate has a significant positive long run impact on NPLs of Islamic banking.

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 macroeconomic variables real GDP growth rate, unemployment and lending rate possess the ability to affect the level of non-performing loans.

Bonilla (2012) looked at the macroeconomic determinants of non-performing loans in Spain and Italy for the period from January 2004 to March 2012. A simple linear regression was estimated by employing ordinary least squares. The macroeconomic variables that were included in the model are credit growth, wages, inflation, unemployment and GDP. The study shows that only unemployment, wages and GDP, are statistically significant, while credit growth and inflation are statistically insignificant.

Badar and Javid (2013) assessed the long and short run dynamics between non-performing loans and macroeconomic variables for the period January 2002 to December 2011 of commercial banks in Pakistan. The analysis was conducted by employing co-integration, Granger causality and vector error correction models. The variables included in the model were inflation, exchange rate, interest rate, gross domestic product and money supply. A long run relationship is found among variables by employing Johansen and Juselius multivariate co-integration. While pair wise bivariate co-integration reveals pair wise long run relationship between non-performing loans with money supply and interest rate. Granger causality test reveals inflation and exchange rate Granger caused non-performing loans. The short run dynamics of the vector error correction model shows a weak short run relationship exist between non-performing loans with inflation and exchange rate. Hence, macroeconomic indicators are the sizeable determinants of non-performing loans.

In Pakistan, Faward and Taqodus (2013) used time series data for nine macroeconomic variables (annual growth in GDP, unemployment rates, real interest rates, inflation, the CPI, the real effective exchange rates, exports, industrial production and FDI) over the 1990-2011. Utilising the ordinary least squares (OLS) technique, the results show that GDP growth, interest rates, inflation rates, the CPI, exports and industrial production are significant in explaining non-performing loans, while three variables (unemployment rate, the real effective exchange rate and FDI) are insignificant in explaining variations in non-performing loans.

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 macroeconomic variables the rate of growth of GDP, unemployment rate and real interest rate. The results show that non-performing loans vary negatively with the growth rate of GDP and positively with the unemployment rate as well as the real interest rate.

Akinlo and Emmanuel (2014) looked at the determinants of non-performing loans in Nigeria utilizing annual data over the period 1981-2011. Time series techniques of co-integration and error correction modelling were used. The study finds that in the long run, economic growth is negatively related to non-performing loan. On the other hand, unemployment, credit to the private sector and exchange rate exerts positive influence on non-performing loans in Nigeria. In the short run, credits to the private sector, exchange rate, lending rate and stock market index are the main determinants of non-performing loans.

Nursechafia and Abduh (2014) examined the long run vulnerabilities of Islamic financing sustainability in term of its response to changes in key macroeconomic variables by using time series econometric approaches of co-integration and vector autoregression (VAR). Monthly data for the period October 2005 to May 2012 were used for analysis. Based on the result of simulating variance decomposition (VD) and impulse response function (IRF), it is found that, sufficient evidence of long-run relationship between credit risk ratio in Islamic banking industry and the selected macroeconomic variables exist. The exchange rate, supply side-inflation, and growth have been indicated to negatively influence credit risk rate in

Islamic banking, while money supply and Islamic interbank money market rate positively affect the risk rate.

Prasanna (2014) investigated the determinants of non-performing loans (NPL) in the Indian banking system by applying panel data modelling approach. Panel dataset of 31 Indian banks with yearly data that spans the period of 2000 to 2012 totalling 372 firm years has been analysed. The study found that higher growth rate in savings and GDP is negatively associated with NPLs in Indian banks. On the other hand, higher interest and inflation rates contribute positively to rising non-performing loans.

Makri, Tsagkanos and Bellas (2014) study assessed 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 various macroeconomic (public debt, unemployment, annual percentage growth rate of gross domestic product).

Ouhibi and Hammami (2015) analysed the determinants of financial soundness indicators (non-performing loans) of the banking system in the Southern Mediterranean countries. In particular, a sample of six out of ten countries of the Southern Mediterranean (Tunisia, Morocco, Egypt, Lebanon, Jordan and Turkey) was analysed. An ordinary least square (OLS) technique was applied on a general panel regression on the annual frequency for the period 2000 to 2012. The result shows that the non-performing loans negatively depend on the nominal exchange rate, the consumer price index and the gross capital formation.

The literature reviewed above varies significantly in terms of findings though there is a consensus regarding the macroeconomic factors affecting non-performing loans as identified in several studies. Notably, there are also different methodological approaches used in the studies with panel data being predominant, particularly for studies with disaggregated data. However, there seem to be no study on macroeconomic determinants for non-performing loans in Namibia. Hence, this study intends to fill the gap and add to empirical literature for Namibia.

3. Methodology

In evaluating the relationship between non-performing loans and its macroeconomic determinants, this study adopt the approach as used by model used by Nursechafia & Abduh (2014) and Badar & Javid (2013). The two studies employed time series econometric techniques such as unit root, co-integration, Granger causality, impulse response function and forecast error variance decompositions within the vector autoregression (VAR) framework. 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. The reduced form of the system gives one equation for each variable, which specifies each variable as a function of the lagged values of their own and all other variables in the system. The vector autoregression process is described by a dynamic system whose structural form equation is given by:

$$Ay_t = \Psi + \Omega_1 y_{t-1} + \Omega_2 y_{t-2} + ... + \Omega_p y_{t-p} + B\mu_t \qquad (1)$$

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; $y_t = (y_{1t}, y_{2t}, ..., y_{nt})$; Ψ is a vector of constants; Ω_i is an $(n \times n)$ matrix of coefficients of lagged endogenous variables $(\forall i = 1,2,3,..., p)$; 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 μ_t are uncorrelated or orthogonal white-noise structural disturbances i.e. the covariance matrix of μ_t is an identity matrix $E(\mu_t, \mu'_t) = 1$. Equation (1) can be rewritten in compact form as:

$$Ay_t = \Psi + \Omega\ (L) y_{t-i} + B\mu_t \qquad (2)$$

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:

$$y_t = \Phi_0 + \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t \qquad ...3$$

Where: $y_t = f(NPL_t, LNGDP_t, RR_t, IR_t)$ …(VAR model for the first model)

$y_t = f(NPL_t, LNGDP_t, REX_t, IR_t)$ …(VAR model for the second model)

$\Phi =$ matrix of coefficients of autonomous varibales.

$A_i =$ Matrix of coefficients of all variables in the model.

$y_{t-1} =$ is the vector of the lagged values of $NPL, LNGDP, RR, REX$ *and* IR

$\varepsilon_t =$ the vector of the error term

Two different models were used to separately cater for the effects of the two macroeconomic measures that have been alternatively. 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):

$$A\varepsilon_t = B\mu_t \qquad \ldots 4$$

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

$$NPL_t = \alpha_1 + b_{11}NPL_{t-1} + b_{12}LNGDP_{t-1} + b_{13}RR_{t-1} + b_{14}IR_{t-1} + \varepsilon_t^{NPL}$$

$$LNGDP_t = \alpha_1 + b_{21}NPL_{t-1} + b_{22}LNGDP_{t-1} + b_{23}RR_{t-1} + b_{24}IR_{t-1} + \varepsilon_t^{LNGDP}$$

$$RR_t = \alpha_1 + b_{31}NPL_{t-1} + b_{32}LNGDP_{t-1} + b_{33}RR_{t-1} + b_{34}IR_{t-1} + \varepsilon_t^{RR}$$

$$IR_t = \alpha_1 + b_{41}NPL_{t-1} + b_{42}LNGDP_{t-1} + b_{43}RR_{t-1} + b_{44}IR_{t-1} + \varepsilon_t^{IR}$$

Where: $\varepsilon_t^{NPL}, \varepsilon_t^{LNGDP}, \varepsilon_t^{RR}$ *and* ε_t^{IR} are the white noise error term and independent of the dependent variables. The matrix of coefficient is:

$$y_t' = [\Delta NPL_t \quad \Delta LNGDP_t \quad \Delta RR_t \quad \Delta IR_t]$$

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{bmatrix} \varepsilon_t^{NPL} \\ \varepsilon_t^{LNGDP} \\ \varepsilon_t^{RR} \\ \varepsilon_t^{IR} \end{bmatrix} = \begin{pmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{pmatrix} \begin{bmatrix} \mu_t^{NPL} \\ \mu_t^{LNGDP} \\ \mu_t^{RR} \\ \mu_t^{IR} \end{bmatrix}$$

$b_i =$ is a $(4x4)$ matrix of parameter that are non − zero.
$\varepsilon_i =$ 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:

$$NPL_t = \alpha_1 + b_{11}NPL_{t-1} + b_{12}LNGDP_{t-1} + b_{13}REX_{t-1} + b_{14}IR_{t-1} + \varepsilon_t^{NPL}$$

$$LNGDP_t = \alpha_1 + b_{21}NPL_{t-1} + b_{22}LNGDP_{t-1} + b_{23}REX_{t-1} + b_{24}IR_{t-1} + \varepsilon_t^{LNGDP}$$

$$REX_t = \alpha_1 + b_{31}NPL_{t-1} + b_{32}LNGDP_{t-1} + b_{33}REX_{t-1} + b_{34}IR_{t-1} + \varepsilon_t^{REX}$$

$$IR_t = \alpha_1 + b_{41}NPL_{t-1} + b_{42}LNGDP_{t-1} + b_{43}REX_{t-1} + b_{44}IR_{t-1} + \varepsilon_t^{IR}$$

Where: $\varepsilon_t^{NPL}, \varepsilon_t^{LNGDP}, \varepsilon_t^{REX}$ *and* ε_t^{IR} are the white noise error term and independent of the dependent variables. The matrix of coefficient is:

$$y_t' = [\Delta NPL_t \quad \Delta LNGDP_t \quad \Delta REX_t \quad \Delta IR_t]$$

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{bmatrix} \varepsilon_t^{NPL} \\ \varepsilon_t^{LNGDP} \\ \varepsilon_t^{REX} \\ \varepsilon_t^{IR} \end{bmatrix} = \begin{pmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{pmatrix} \begin{bmatrix} \mu_t^{NPL} \\ \mu_t^{LNGDP} \\ \mu_t^{REX} \\ \mu_t^{IR} \end{bmatrix}$$

b_i = is a (4x4) matrix of parameter that are non − zero.

ε_i = is a (4x1) column vector of the random disturbance term.

The analysis is carried out in the following order. The first step would be to test for the presence of unit root. This is because most time series in economics exhibit a trend over time and when usually these time series are not stationary (contain unit root). Being non-stationary implies that the mean, variance and covariance is not constant over time. When data contains unit root it means any result accrue to such data will be spurious or nonsensical. Spurious regression implies that the relationship between variables may appear statistically significant, though there is no meaningful relationship among the variables. Hence, the whole idea for unit root test is to search for data generating process (DGP) namely:

(a) Pure random walk meaning no intercept and no time trend items:

$$\Delta y_t = \delta y_{t-1} + \sum_{t=1}^{p} \alpha_t \Delta y_{t-1} + \varepsilon_t \qquad ...5$$

(b) Random walk with drift meaning intercept and no time trend item:

$$\Delta y_t = \alpha + \delta y_{t-1} + \sum_{t=1}^{p} \alpha_t \Delta y_{t-1} + \varepsilon_t \qquad ...6$$

(c) Random walk with drift and time trend meaning intercept and time trend item:

$$\Delta y_t = \alpha + \gamma t + \delta y_{t-1} + \sum_{t=1}^{p} \alpha_t \Delta y_{t-1} + \varepsilon_t \qquad ..7$$

There are various methods for testing unit roots such as Augmented-Dickey Test (ADF), extension to the dickey fuller test for example Pantula tests, Phillips Peron tests, Kwaitowski-Phillips-Schmidt-shin (KPS), Elliot-Rothenberg-stock point optimal (ERS) as Ng-Perron tests. This study will use ADF, PP and KPSS test for unit root.

The second step would be to conduct co-integration test to determine whether the variables will converge in the long run to some sort of equilibrium. The Johansen co-integration test is applied in order to establish any cointegrated equations. Since this will be done in the vector autoregressive (VAR) framework, the first step uses first difference as shown below:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + ... + A_n Y_{t-n} + \varepsilon_t \qquad ...8$$

Whereas, Y_t is lag length n $(p \times 1)$ vector endogenous variable, then first difference changes below:

$$\Delta Y_t = \sum_{j=1}^{n=1} \pi_j \Delta Y_{t-j} + \pi Y_{t-n} + \varepsilon_t \qquad ...9$$

whereas π_j is a short term adjusting coefficient to explain short-term relationship, π is long term shock vector that includes long term information that shows the existence long term equilibrium relationship. Moreover rank of π decides the number of cointegrated vector. π has three hybrids:

(a) $rank(\pi) = n$, then π is full rank, meaning all the variables are stationary series in the regression (Y_t)

(b) $rank(\pi) = 0$, then π is null rank, meaning variables do not exhibit cointegrated relationship.

(c) $0 < rank(\pi) = r < n$, then some of variables exist r cointegrated vector.

The Johansen co-integration approach uses rank of π to distinguish the number of cointegrated vector and examine rank of vector in testing how many of non-zero of characteristic roots exist in the vector. There are two statistic processes for co-integration.

(i) Trace test:

$H_0 : rank(\pi) \le r$(at most r integrated vector)

$H_1 : rank(\pi) > r$(at least r+1 integrated vector)

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$$

T is sample size, $\hat{\lambda}_i$ is estimated of characteristic root. If test statistic rejects H_0 that means variables exist at least r+1 long term cointegrated relationship.

(ii) Maximum eigenvalue test:

$H_0 : rank(\pi) \le r$(at most r integrated vector)

$H_1 : rank(\pi) > r$(at least r+1 integrated vector)

$$\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$$

If test statistics accepts H_0 that means variables have r cointegrated vector. This method starts testing from variables that do not have any cointegrative relationship which is r=0. Then test has added the number of cointegrative item to a point of no rejecting H_0 that means variables have r cointegrated vector.

The third step would be to conduct causality test. Economic models often assume different hypotheses about variables' relationship but yet unsure about variables' cause and effect relationship. In econometrics causality basically refers to ability to forecast or predict. Granger (1969) developed model based on lead and lag relations in forecasting. Granger used twin factors of VAR to find variables' causal relationship. The VAR can be considered as a means of conducting causality tests, or more specifically Granger causality tests. It assumes two series X_t and Y_t that define those messages set.

$$X_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} X_{t-1} + \sum_{i=1}^{k} \alpha_{2i} Y_{t-1} + \varepsilon_{1t} \qquad \ldots 10$$

$$Y_t = \beta_0 + \sum_{i=1}^{k} \beta_{1i} X_{t-1} + \sum_{i=1}^{k} \beta_{2i} Y_{t-1} + \varepsilon_{2t} \qquad \ldots 11$$

To determine the variables' relationship the following test are conducted on the coefficients.

(i) $\alpha_{2i} \neq 0 \textit{ and } \alpha_{1i} = 0$: meaning Y lead X or X lag Y.

(ii) $\beta_{1i} \neq 0 \textit{ and } \beta_{2i} = 0$: meaning X lead Y or Y lag X.

(iii) $\alpha_{2i} = 0 \textit{ and } \beta_{1i} = 0$: meaning both variables are independent.

(iv) $\alpha_{2i} \neq 0 \textit{ and } \beta_{1i} \neq 0$: meaning both variables are interactive each other and have feedback relationship.

There are different situations under which Granger causality test can be applied. These include;

(a) A simple bivariate Granger causality that involves two variables and their lags.

(b) A multivariate Granger causality that involves more than two variables and it is most applicable where more than one variable can influence the results.

(c) Granger causality can also be tested in a Vector Autoregressive (VAR) framework where a multivariate model is extended to test for simultaneity of all included variables.

The standard practice is that the main uses of the VAR model are the impulse response analysis and forecast error variance decomposition. The impulse response function which function traces the response of the endogenous variables to one standard deviation shock or change to one of the disturbance terms in the system. Variance decomposition is an alternative method to the impulse response functions for examining the effects of shocks to the dependent variables. This technique determines how much of the forecast error variance for any variable in a system, is explained by innovations to each explanatory variable, over a series of time horizons (Stock & Watson, 2001:106).

3.2 Data, Data Sources and Data Measurements

The data used in this paper are quarterly data for the period 2001:Q1 to 2014:Q2. Secondary data were obtained from the Bank of Namibia's various statutory publications and Namibia Statistical Agency's statutory publications. The variables are non-performing loans (NPL), gross domestic product (LNGDP), interest rate (RR) and inflation rate (IR).

4. Empirical Analysis and Results

4.1 Unit Root Test

Table 1 shows the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test statistic. The results show that NPL is stationary in levels, meaning it is integrated of order zero. The variables REX, LNGDP, IR and RR only became stationary after being differenced once, meaning they are of order of integration 1.

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

Variable	Model Specification	ADF	PP	ADF	PP	Order of Integration
		Levels	Levels	First Difference	First Difference	
NPL_t	Intercept	-2.70*	-2.69*	-6.05**	-6.00**	0
	Intercept and trend	-3.57**	-3.64**	-6.11**	-6.11**	0
REX_t	Intercept	-2.25	-2.25	-5.65**	-6.10**	1
	Intercept and trend	-2.22	-2.22	-5.63**	-6.06**	1
$LNGDP_t$	Intercept	-0.70	-0.75	-10.28**	-10.23**	1
	Intercept and trend	-2.78	-2.70	-10.19**	-10.14**	1
IR_t	Intercept	-3.09	-2.32	-3.98**	-4.07**	1
	Intercept and trend	-3.09	-2.26	-3.96**	-4.47**	1
RR_t	Intercept	-2.02	-1.43	-4.02**	-3.97**	1
	Intercept and trend	-2.61	-2.37	-3.93**	-3.87**	1

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 VAR Stability Condition

It is important to determine whether VAR satisfy the stability condition based on the roots of the characteristic polynomial. If there is unstable VAR, the results of impulse response function and variance decomposition will be invalid. 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 as shown in tables 2 and 3.

Table 2: Roots of Characteristic Polynomial (first model)

Root	Modulus
0.977773	0.977773
0.809031 - 0.216424i	0.837479
0.809031 + 0.216424i	0.837479
0.610073 - 0.345389i	0.701058
0.610073 + 0.345389i	0.701058
-0.451024	0.451024
0.258477 - 0.201534i	0.327759
0.258477 + 0.201534i	0.327759

Source: Author's compilation using Eviews.
Note: No root lies outside the unit circle. VAR satisfies the stability condition.

Table 3: Roots of Characteristic Polynomial (second model)

Root	Modulus
0.984981	0.984981
0.760067 - 0.213137i	0.789385
0.760067 + 0.213137i	0.789385
0.666629 - 0.362169i	0.758658
0.666629 + 0.362169i	0.758658
0.117061 - 0.391384i	0.408515
0.117061 + 0.391384i	0.408515
-0.364707	0.364707

Source: Author's compilation using Eviews.
Note: No root lies outside the unit circle. VAR satisfies the stability condition

4.3 Selection of Optimal Lag

The optimal lag length of 4 was chosen based on the available criteria information as shown in tables 4 and 5 respectively.

Table 4: Optimal lag length (first model with ROA)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-248.1341	NA	0.281923	10.08536	10.23833	10.14361
1	-43.60069	368.1601	0.000150	2.544028	3.308837	2.835271
2	-6.238948	**61.27326***	**6.47e-05***	**1.689558***	**3.066214***	**2.213797***
3	3.293373	14.10783	8.66e-05	1.948265	3.936769	2.705499
4	21.84802	24.49214	8.33e-05	1.846079	4.446430	2.836308

Source: Author's compilation using Eviews
** indicates lag order selected by the criterion*

Table 5: Optimal lag length (second model with ROE)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-362.1590	NA	26.97401	14.64636	14.79932	14.70461
1	-180.7800	326.4821	0.036239	8.031202	**8.796011***	8.322446
2	-155.8449	40.89363	0.025685	7.673796	9.050453	**8.198035***
3	-146.8315	13.33982	0.035106	7.953261	9.941765	8.710494
4	-120.5647	**34.67225***	**0.024818***	**7.542587***	10.14294	8.532815

Author's compilation using Eviews
** indicates lag order selected by the criterion*

4.4 Testing for Co-integration

The results for the Johansen co-integration test based on trace and maximum Eigen values test statics are presented in tables 6 and 7 respectively. The results for both test statistics show at least one cointegrating equation. Hence, the null hypothesis of no co-integration could not be rejected for the first model. Furthermore, this implies that long run analysis can be conducted by estimating a VECM model.

Table 6: The Johansen co-integration test based on trace and maximal Eigen value (first model)

Maximum Eigen Test				Trace Test			
H_0: rank = r	H_a: rank = r	Statistic	95% Critical Value	H_0: rank = r	H_a: rank = r	Statistic	95% Critical Value
r = 0	r =1	33.49	27.58**	r = 0	r >=1	58.16	47.86**
r <=1	r = 2	14.98	21.13	r <= 1	r >= 2	24.67	29.80
r <=2	r = 3	8.66	14.26	r <= 2	r >= 3	9.69	15.49
r <=3	r = 4	1.03	3.84	r <= 3	r >= 4	1.03	3.84

Source: Author's compilation and values obtained from Eviews
Note: Both Max-Eigen value and Trace tests indicates 1 cointegrating equation at the 0.05 level (**).

Table 7 show the results for the second model. Both test statistics shows no cointegrating equation. Therefore, only short run analysis can be conducted by estimating a VAR model.

Table 7: The Johansen co-integration test based on trace and maximal Eigen value (second model)

Maximum Eigen Test				Trace Test			
H_0: rank = r	H_a: rank = r	Statistic	95% Critical Value	H_0: rank = r	H_a: rank = r	Statistic	95% Critical Value
r = 0	r =1	19.60	27.58	r = 0	r >=1	37.89	47.86
r <=1	r = 2	9.86	21.13	r <= 1	r >= 2	18.30	29.80
r <=2	r = 3	7.96	14.26	r <= 2	r >= 3	8.44	15.49
r <=3	r = 4	0.49	3.84	r <= 3	r >= 4	0.49	3.84

Source: Author's compilation and values obtained from Eviews
Note: Both Max-Eigen value and Trace tests indicates no cointegrating equations at the 0.05 level (**)

4.5 Long Run Model

The long run model presented below is only for the first model where there is existence of co-integration. The long run equation is:

NPL = -8.400 + 0.881LNGDP – 0.392RR + 0.055IR (first model with interest rate)

(4.174) (-6.085) (1.816) (t-statistics)

The results show that LNGDP and RR are significant in explaining non-performing loans, while inflation rate is not.

4.6 Granger Causality

The results of the Granger-causality for the four-variable VAR are presented in table 8 below. The results show that there is unidirectional causality running from interest rate to non-performing loans. However, all the other variables do not help to predict non-performing loans.

Table 8: Granger causality tests for non-performing loans (first model)

	Dependent Variable in Regression			
Regressor	NPL	LNGDP	RR	IR
NPL	0.00	0.80	0.75	0.75
LNGDP	0.55	0.00	0.61	0.20
RR	0.00**	0.82	0.00	0.12
IR	0.99	0.20	0.33	0.00

Source: Author's compilation and values obtained from Eviews
*Notes: ** means rejection of the null hypothesis at 5%*

Table 9 shows the results for Granger causality for the second model. The variable of interest is causality between non-performing loans and the macroeconomic variables. Hence, the interpretations are focused on that. The results shows that all the variables can help predict non-performing loans in the short run.

Table 9: Granger causality tests for non-performing loans (second model)

	Dependent Variable in Regression			
Regressor	NPL	LNGDP	REX	IR
NPL	0.00	0.75	0.09*	0.16
LNGDP	0.03**	0.00	0.00**	0.31
REX	0.01**	0.38	0.00	0.40
IR	0.05*	0.25	0.03**	0.00

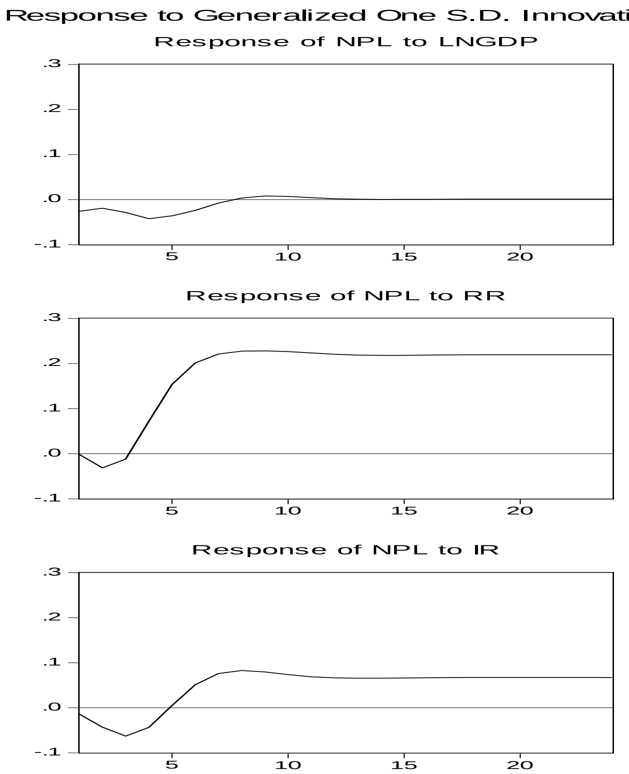
Source: Author's compilation and values obtained from Eviews
*Notes: ** and * means rejection of the null hypothesis at 5% and 10% respectively*

4.6 Impulse Response Functions

The results for the IRF show how non-performing loans (NPL) respond to shocks in the macroeconomic variables. Figure 1 shows the response of NPL to innovations in the LNGDP, IR and RR. The response of NPL to LNGDP is negative and temporary effects which stabilises around the 7 quarter and go back to its initial equilibrium. This is in line with economic theory that during the expansion phase of the economy, there tend to be relatively low number of NPLs, as borrowers face a sufficient stream of income to service their debts. The opposite applies when there is recessionary cycle. The negative relationship between the two variables was also found in studies by Khemraj and Pasha (2009), Messai and Jouini (2013), Prasanna (2014) as well as Nursechafia and Abduh (2014).

The response of NPL to shocks in interest rate is positive and permanent effects. This is consistent with economic theory that an increase in interest rate worsen debt burden as a result of increased interest payment, resulting in high number of NPLs. These findings are similar to those of Messai and Jouini (2013). Furthermore, the response of NPL to shocks in inflation rate results in a positive response and permanent effect. Higher inflation affects income or profit for consumers/producers. Consequently, this affects their ability to honour their debt obligations whin in turn increases the chances of high defaults or NPLS. Adebola, Yusoff and Dahlan (2011) study also found a similar relationship.

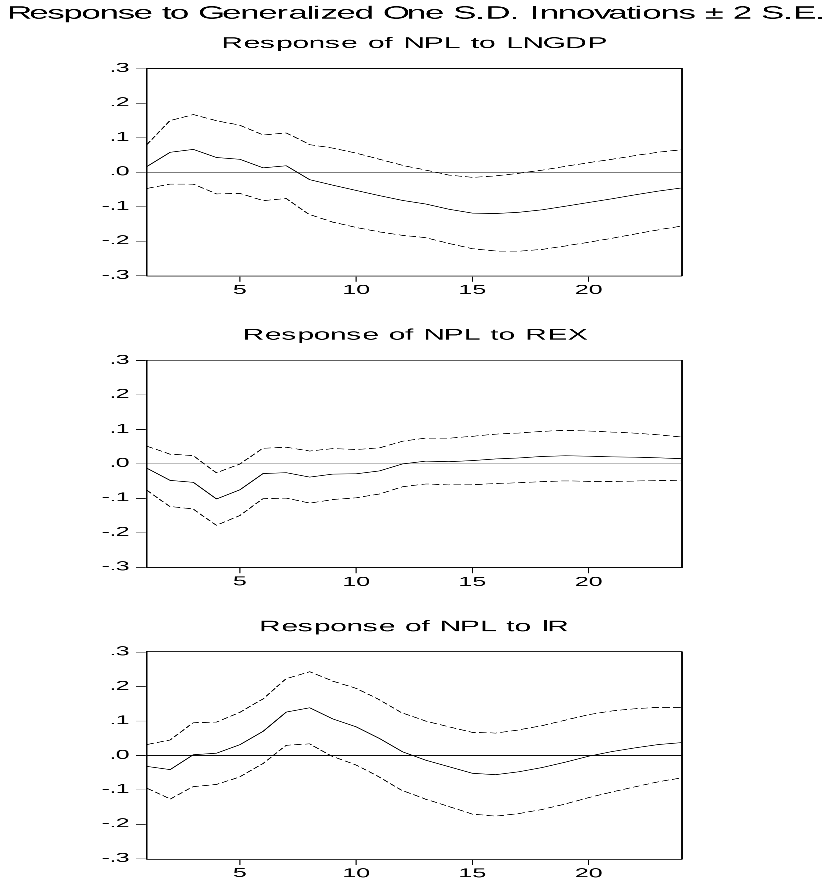
Figure 1: Impulse response functions for non-performing loans (first model)



Source: Author's compilation using Eviews

Figure 2 below shows the response of NPL to shocks in LNGDP, IR and REX. The results for the IRF shows a response of small magnitude of NPL to shocks in LNGDP, which later became negative and permanent as it is in the case of the first model. Moreover, the response of NPL to shocks in exchange rate started of negative but short-lived and turned positive and permanent. The study by Akinlo and Emmanuel (2014) also found a positive relationship between NPL and exchange rate in Nigeria. On the contrary, the response of NPL to shocks in inflation cannot be made out as it is fluctuating between positive and negative grid.

Figure 2: Impulse response functions for non-performing loans (second model)



Source: Author's compilation using Eviews

4.7 Forecast error variance decomposition

Table 10 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 with RR increasing their contributions as soon as at six quarters and increases drastically as forecast horizon extends.

Table 10: Variance Decomposition of non-performing loans (first model)

Variance Decomposition of NPL				
Quarter	NPL	LNGDP	RR	IR
1	100	0	0	0
6	40.26	2.26	49.12	8.36
12	18.15	0.91	78.22	2.73
18	14.24	0.61	83.37	1.77
24	12.53	0.49	85.63	1.35

Source: Author's compilation and values obtained from Eviews

Table 11 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 with LNGDP, REX and RR increasing their contributions as soon as at six quarters. The contributions of both LNGDP and IR gained more momentum as the forecast horizon extends in comparison with that of REX.

Table 11: Variance Decomposition of non-performing loans (second model)

Variance Decomposition of NPL				
Quarter	NPL	LNGDP	REX	IR
1	100	0	0	0
6	71.78	6.98	16.15	5.09
12	48.41	11.27	11.95	28.36
18	35.80	33.82	8.97	21.40
24	32.48	38.93	8.52	20.07

Source: Author's compilation and values obtained from Eviews

5. Conclusion

This study examined the macroeconomic determinants of non-performing loans in Namibia. The study was based on quarterly data covering the period 2001:Q1 to 2014:Q2, utilizing the technique of unit root, co-integration, Granger causality, impulse response functions and forecast error variance decomposition. The results for co-integration found a long run relationship between non-performing loan and log of gross domestic product, interest rate and inflation rate. The results for Granger causality found unidirectional causality from interest rate to non-performing loan in the long run. Moreover, there is also unidirectional causality running from all the macroeconomic determinants to non-performing loans in the short run. The results of the impulse response functions revealed that all the macroeconomic determinants plays a role in determining non-performing loans, while in the short run only log of gross domestic product and exchange rate. This suggests that the macroeconomic environment is very critical for non-performing loans in the Namibian context. Hence, the study recommends that the macroeconomic environment should continue to be monitored as it has linkage to many economic sectors including the banking sector. These results could be enriched with disaggregated data. Future studies should consider that as an avenue for improvement.

References

Abid, L., Ouertani, M. N. & Zouari-Ghorbel, S. 2014. 'Macroeconomic and Bank-Specific Determinants of Household' Non-Performing Loans in Tunisia: a Dynamic Panel Data', *Procedia Economics and Finance*, 13: 58-68.

Adebola, S. S., Yusoff, W. S. B. W. & Dahalan, J. 2011. 'An ARDL Approach to the Determinants of No-Performing Loans in Islamic Banking System in Malaysia', *Kuwait Chapter of Arabian Journal of Business and Management Review*, 1(2): 20-30.

Ahmad, F. & Bashir, T. 2013. 'Explanatory Power of Macroeconomic Variables as Determinants of Non-Performing Loans: Evidence from Pakistan', *World Applied Sciences Journal*, 22(2): 243-255.

Akinlo, O. & Emmanuel, M. 2014. 'Determinants of Non-Performing Loans in Nigeria', *Accounting & Taxation*, 6(2): 21-28.

Andongo, J. & Stork, C. 2005. 'Factors Influencing the Financial Sustainability of Selected Microfinance Institutions in Namibia', Namibian Economic Policy Research Unit.

Badar, M. & Javid, A. Y. 2013. 'Impact of Macroeconomic Forces on Non-performing Loans: An Empirical Study of Commercial Banks in Pakistan', *WSEAS TRANSACTIONS on BUSINESS and ECONOMICS*, 1(10): 40-48.

Bank of Namibia. 2014. *Financial Stability Report*. Windhoek.

Bonilla, C. A. O. 2012. 'Macroeconomic Determinants of the Non-Performing Loans in Spain and Italy', Unpublished Master's Thesis, University of Leicester.

Brownbridge, M. 1998. 'The Cause of Financial Distress in Local Banks in Africa and Implications for Prudential Policy', UNCTAD/OSG/DP/132.

Dimitrios, P., Angelos, L. T. V. & Vasilios, L. M. 2010. 'Macroeconomic and Bank Specific Determinates of Non-performing Loans in Greece's, Comparative Study of Mortgage, Business and Consumer Loan Portfolios', Bank of Greece working paper No 118.

Enders, W. 2004. *Applied Econometric Time Series*. Hoboken: John Wiley & Sons, Inc. 2nd Ed.

Farhan, M., Sattar A., Chaudhry, A. H. & Khalil, F. 2012. 'Economic Determinants of Non-Performing Loans: Perception of Pakistani Bankers', 4(19): 87-99.

Faward, A. & Taqodus, B. 2013. 'Explanatory Power of Bank Specific Variables as Determinants of Non-Performing Loans: Evidence from Pakistan Banking Sector', *World Applied Sciences Journal*, 22(9): 1220-1231.

Geletta, W. N. 2012. 'Determinants of Non-performing Loans: The Case of Ethiopian Banks', Unpublished Master's Thesis, University of South Africa.

Gezu, G. 2014. 'Determinants of Non-performing Loans: Empirical Study in Case of Commercial Banks in Ethiopia', Unpublished Master's Thesis, Jima University Business and Economic College.

Granger, C. W. J. 1969. Investigating Causal Relations by Econometric Models and Cross-spectral Methods', *Econometrica*, 37(3): 424-438.

Joseph, M. T., Edson, G., Manuere, F., Clifford, M. & Michael, K. 2012. 'Non-Performing Loans in Commercial Banks: A Case of CBZ Bank Limited in Zimbabwe', *Interdisciplinary Journal of Contemporary Research in Business*, 4(7): 467-488.

Khemraj, T. & Pasha, S. 2009. 'The determinants of non-performing loans: an econometric case study of Guyana', Munich Personal RePEc Archive.

Makri, V., Tsagkanos, A. & Bellas A. 2014. 'Determinants of Non-Performing Loans: The Case of Eurozone', *Panoeconomicus*, 2: 193-206.

Messai, A. S. & Jouini, F. 2013. 'Micro and Macro Determinants of Non-performing Loans', *International Journal of Economics and Financial Issues*, 3(4): 852-860.

Nursechafia, N. & Abduh, M. 2014. 'The Susceptibility of Islamic Banks' Credit Risk towards Macroeconomic Variables', *Journal of Islamic Finance*, 3(1): 23 – 37.

Ouhibi, S. & Hammami, S. 2015. 'Determinants of Non-performing Loans in the Southern Mediterranean Countries', *International Journal of Accounting and Economic Studies*, 3(1): 50-53.

Prasanna, K. P. 2014. 'Determinants of Non-Performing Loans in Indian Banking System', 3rd International Conference on Management, Behavioral Sciences and Economics Issues. Singapore.

Salas, V. & Saurina, J. 2002. 'Credit Risk in Two Institutional Regimes: Spanish Commercial and Savings Banks', *Journal of Financial Services Research*, 22(3): 203-224.

Stock, J. H. & Watson. M. W. 2001. 'Vector Autoregressions', *Journal of Economic Perspectives*, 15(4): 101-115.