The Anatomy of Credit Risk in Lesotho: Empirical Perspectives on Measurement and Determinants

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Abstract— It has been observed in Lesotho that there is a significant increase in general credit expansion by the commercial banks since 2011 to present (2017) and this boosts economic growth in different dimensions. Eventually, however, every credit-induced economic boom comes to an end when one or more important sectors of the economy default on their debt obligations. Even though this poses significant risks, the existing credit risk measurement techniques in the commercial banks in Lesotho, as with other developing and developed countries, still measure credit risk on a relative scale. That is, they use the traditional balance sheet models to estimate credit risk. The key shortcoming of these methodologies is the failure to account for the inherent dynamism in risk. As a result, this study uses the volatility measures, the GARCH (1,1), BL-GARCH (1,1,1) and the TBL-GARCH (1,1,1) to estimate credit risk. The TBL-GARCH (1,1,1) model proved superior to both the GARCH (1,1) and the BL-GARCH (1,1,1) implying that the threshold effects have an important impact on credit risk measurement.

The study further investigated the determinants of credit risk at three banking clusters, namely; industry, top-two banks and the bottom-two banks. At the industry cluster, the results indicate that credit growth and previous bad loans increase credit risk while profitability has a moderating effect. At the top-two banks, interest rates, credit growth, previous bad loans and economic growth reduce credit risk. Furthermore, at the bottom-two banks, credit risk is reduced by the interest rates, profitability and economic growth. However, it tends to be increased by management inefficiency, credit growth and previous non-performing loans.

Index Terms— Credit Risk, Volatility, SUR

1 Introduction

BANKS are among the most prominent financial intermediaries in developing countries. One of their key roles in the economy is to mobilise domestic resources from surplus sectors and channel them to deficit sectors to spur economic growth. Inevitably, in this process, the bank faces credit risk due to the uncertainty associated with borrowers' loan repayment ability. Fiedler (1971) defines credit risk as a forward-looking concept that focuses on the probable incidence of credit difficulties in the future. On the other hand, the Basel Committee on Banking Supervision defines credit risk as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with the agreed terms. This kind of risk is the most important amongst all major risks facing the bank (Andriani and Wiryono, 2015).

The Bank for International Settlements (BIS) (1999), states that credit risk must be effectively managed. Therefore, the goal of credit risk management is to maximise the bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. The BIS further explains that effective credit risk management is a critical component of a comprehensive approach to risk management and it is essential to the long-term success of any banking organisation.

Credit risk management in the banking industry has come under increasing scrutiny after the 2007- 2008 financial crisis. Financial institutions experienced financial crises as a result of inefficient credit risk management systems characterised by high levels of speculative lending and concentration of credit in non-performing sectors of the economy. According to Adu (2014), ineffective credit risk management practices, and poor asset quality also continue to dominate bankruptcy topics in the banking industry as a result of relaxed credit standards, poor portfolio risk management and lack of attention on changes in economic conditions that weaken the credit position of the banks. Effective credit risk management is thus, unachievable without appropriate credit risk measurement. Appropriate credit risk measurement, according to Bhatia (2005), helps achieve and maintain an active credit portfolio. It also assists in setting appropriate concentration and exposure limits as well as in setting hold-targets on syndicated loans and risk-based pricing. Furthermore, it support the improvement of risk and return profiles of the credit portfolio, the evaluation of risk-adjusted performance of business lines and the validation of loan loss reserves. In this connection, credit risk measurement lies at the epicentre of effective credit risk management.

1.2 Problem Statement

The Central Bank of Lesotho (CBL) has observed a significant upsurge in general credit extension by the commercial banks since 2011 to present (CBL, 2016). Duncan (2011) indicates that in the process of credit expansion, consumers borrow and spend more, and businesses also borrow and invest more. Consumption and investment growth, therefore, create jobs and expand income and profits. Moreover, credit expansion tends to cause an increase in asset prices, thereby boosting the net-worth of the public. Eventually, however, every credit-induced economic boom ends when one or more important sectors of the economy defaults on their debt obligations. A well-remembered event where rapid credit-growth proved

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disastrous is the 2007/8 global financial crisis.

In the context of Lesotho, the observed credit-growth calls for tighter credit risk management. This underscores the need for appropriate credit risk measurement. The credit risk measurement techniques that are used by commercial banks in Lesotho measure credit risk on a relative scale. This is not unique because some developing and developed countries also follow a similar practice (BIS, 2006). That is, they use traditional balance sheet models to estimate credit risk. Such models are purely accounting-based and are generally recognized for their relative simplicity. They utilise static measures of credit risks such as the ratio of non-performing loans to gross loans (NPLs), ratio of loan loss provisions to total assets (LLPs) and the ratio of risk-weighted assets to total assets (RWAs). For example, Berger and DeYoung (1997) use a single-dimensional technique to approximate credit risk. The technique uses traditional measures of credit risk such as income statement indicators like non-performing loans. This approach was later followed by other studies (See Vodova, 2003; Castro, 2012). Other recent studies extend the idea further by using loan loss provisions and the risk weighted assets (see Appendix 1.2). However, a serious limitation of these measures is that they are static. Risk, on the other hand, is a dynamic concept and cannot be adequately measured using static measures such as simple ratios constructed from specific bank income statement and/or balance sheet items. Such measures are unable to capture the inherent dynamism in risk. They view "default as a discrete event that takes place within a fixed time period rather than as a time-dependent process sensitive to changing conditions" (Glennon and Nigro, 2011). This implies that techniques that capture variability of balance sheet risk measures are more appropriate. For example, Delechat et al. (2009) use the coefficient of variation (CV) to capture this variability. Nevertheless, Motelle and Biekpe (2014) argue that static measures of variability such as the standard deviation and the coefficient of variation are still incapable of capturing risk dynamism. They recommend application of GARCH-based models to take care of this shortcoming.

This study contributes to the stock of knowledge on the subject of credit risk measurement by addressing three key questions: Given that balance sheet models are not able to capture the dynamic nature of credit risk, can the standard generalised autoregressive conditional heteroscedasticity (GARCH) and bilinear (BL-GARCH) models address this shortcoming? Can the threshold bilinear-GARCH model assist risk managers to determine whether risk has been overestimated or underestimated? What are the determinants of credit risk - measured using dynamic techniques?

1.3 Objectives of the study

The study sets out to achieve three objectives as follows:

- To determine the suitability of the standard GARCH, BL-GARCH and TBL-GARCH models as dynamic measures of credit risk;
- To ascertain whether the TBL-GARCH model can be used to determine whether credit risk has been overestimated or underestimated; and
- To identify the determinants of credit risk –measured using the most suitable GARCH extension model.

1.4 Hypothesis of the study

Hypothesis 1

The TBL-GARCH (1,1,1) model outperforms both the standard GARCH (1,1) and the BL-GARCH (1,1,1) models in the measurement of credit risk.

Hypothesis 2

The TBL-GARCH model can be used to determine whether credit risk has been over or underestimated.

Hypothesis 3

There is a negative relationship between credit risk and effective management. This hypothesis hinges on the fact that poor credit management leads to bad lending, which then gives rise to a bloated portfolio of unpaid loans and high credit risk.

1.5 Motivation of the study

This study aims to fill some gaps in the literature of credit risk management, especially in the context of commercial banks in Lesotho. As explained in the problem statement, the current measurements of credit risk ignore the most important feature of credit risk, that is, its dynamic nature. The study will thus, make an impact on issues surrounding measurement of credit risk, which forms an integral part in effective risk measurement. This study will also be a valuable addition to the existing knowledge, and will provide a platform for further exploration in the field. Moreover, senior management, oversight boards, and investors in financial institutions shall find the study helpful when formulating their credit decisions. The study will also be beneficial to the regulatory bodies in reviewing the scope of credit risk management and strengthening the financial industry credit policies.

1.5 Structure of the study

The thesis is structured as follows: Chapter 1 provides an introduction for the study. This introduction entails the background, the problem statement, the objectives and motivation of the study. Chapter 2 covers the literature on the importance of credit risk management in achieving macro-prudential objectives. It also discusses different credit risk measurements, their merits and flaws. The chapter also encompasses the theoretical framework on credit risk determinants and reviews what other researchers have written on credit risk and its determinants. Chapter 3 deals with the methodology, that is, data and its sources, credit risk measurement model, the determinants of credit risk and lastly, the estimation techniques. Chapter 4 covers the analysis and results, while chapter 5 concludes and offers some recommendations.

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2 LITERATURE REVIEW

Understanding the relative riskiness of different types of credit exposure is essential for both policy-makers designing regulatory capital requirements and for banks, whose main objective is to maximise returns by extending credit at a minimum risk. Failure to fulfil the payment obligations normally gives rise to credit risk. This is the most important risk exposure for banks due to its strong correlation with bank profitability and economic growth in general. Each non-performing loan decreases a bank's profit and equity, which in turn may result in bank failure. That being the case, the regulatory bodies should design appropriate laws and regulations, strengthen supervision of banks, increase borrowers' awareness of the risks involved, enhance political controls and so forth, in order to mitigate credit risk (Ekinci, 2016). This chapter discusses credit risk management in the context of macro-prudential policy, measurement of credit risk using conditional volatility and other models, determinants of credit risk, and concludes by highlighting key aspects of the chapter.

2.1 Credit Risk Management in the Context of Macro-Prudential Policy

2.2.1 Macro-prudential policy framework

According to Financial Stability Board (2011), macro-prudential policy is a policy that uses primary prudential tools (instruments) to limit systemic or system-wide financial risk. This is done to limit the incidence of disruptions in the provision of key financial services that can have serious consequences for the real economy. Before the global financial crisis and a subsequent Eurozone crisis, the primary purpose for traditional central bank policy was price stability in the belief that focusing on price stability would eventually deliver financial stability (Rhu, 2010). At the same time, financial supervision focused on the soundness of individual financial institutions with the expectation that this would ultimately reinforce the stability of the whole financial system. The global financial crisis proved this perception as a fallacy of composition.

It was only discovered after the previously mentioned crises that financial stability cannot be achieved by traditional monetary policy and micro-prudential policy alone. Schoenmaker (2014) indicates that macro-prudential policy operates at the level of the financial system and is concerned with the impact on the wider economy. Its effectiveness depends on the support of the entire financial system. Table 1(a) demonstrates the differences between micro and macro-prudential policy.

Table 1 (a): Comparison of macro-prudential policy and micro-prudential policy

	MACROPRUDENTIAL	MICROPRUDENTIAL
Proximate objective	Limit financial system distress	Limit distress at an individual level
Ultimate objective	Minimizing the costs caused by financial instability	Consumer protection
Risk feature	Endogenous	Exogenous
Correlations and common exposures across institutions	Important	Irrelevant
Calibration of prudential controls	In terms of system-wide risk; top-down	In terms of risks at an individual level, bottom-up

Source: Tomuleasa (2013)

Table 1(b) displays the economic policies and a set of goals and tools used to achieve those goals.

Table 1(b): Economic policies and the set of goals and tools

	Goal	Tool
Micro-prudential policy	Limit distress at an individual level	Leverage ratio, quality/ quantity
Macro-prudential policy	Limit financial system distress	Loan-to-value, debt-to-income, stress test, leverage ratios
Monetary policy	• Price stability • Liquidity management • Lean against financial imbalances	• Key policy rate, standard repos • Policy corridors, interest on reserves • Key policy rate, reserve requirements , FX reserves buffers

Source: Tomuleasa (2013)

According to the Reserve Bank of New Zealand (2013), the objective of macro-prudential policy is to increase the resilience of the financial system and counter instability arising from credit expansion, asset pricing and liquidity shocks. Its instruments vary with the macro-credit cycle and are de-

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signed to provide additional buffers to the financial system. The following prudential instruments can be deployed in the pursuit of macro-prudential policy objective: the countercyclical capital buffer (CCB), adjustments to the core funding ratio (CFR), adjustments to sectoral capital requirements (SCR), and quantitative restrictions on the share of high loan-to-value ratio loans.

The CCB framework is an additional capital requirement that may be applied in times when excess private sector credit growth is judged to be leading to a build-up of system-wide risk. Banks can meet the CCB requirement by reducing their voluntary capital buffers, leaving the overall capital ratios unchanged. They can also raise capital, through equity issues or higher retained earnings. They can further moderate the risk-weighted assets, by reducing exposures that include lending.

On one hand, the CFR adjustments are intended to reduce the vulnerability of the banking sector to disruptions in the funding markets by ensuring certainty of funding during times of market pressure and reducing rollover risk on the stock of wholesale funding. In addition to that, adjustments to the SCR would require banks to hold extra capital against a specific sector or segment in which excessive private sector credit growth is judged to be leading to a build-up of system-wide risk. As with the CCB, SCRs provide a temporary additional cushion against potential loan losses but to a particular sector.

2.2.2 Implications of macro-prudential policy for credit risk management

Laker (2006) argues that banking is a dynamic business in which new opportunities and threats are constantly emerging. For that reason, macro-prudential policy works on the fundamental premise that the primary responsibility for financial soundness and prudent risk management within a bank, rests with its board of directors and senior management. The board has the obligation to understand the risk profile of the bank, determine the bank's risk tolerance, approve its risk management strategy and policies, and ensure that management is monitoring the effectiveness of risk controls. Laker (2006) also indicates that there is a general possibility that some banks will fail. Nevertheless, the Basel Accord introduced in 1988 and the improvements that followed, attempt to minimise, to the extent possible, the likelihood of failure by implementing a risk-based capital adequacy regime. The regime serves two purposes. First, in its preventative role, it provides a strong incentive to the banks to set, manage and maintain appropriate risk appetites. Second, in its shock absorber role, it aims to ensure that banks can continue operating soundly through unanticipated problems and losses.

Laker (2006) further advocates that credit risk management framework must be both dynamic and up to date with regular review in order to detect early warning signals. There are three ordinary methods used to mitigate and manage credit risk. The first one is limiting, which is a process whereby the limits (in terms of amount) are placed for certain types of lending. The second one is pooling of risks in which the level of risk can be minimised by combining a large number of similar risks. The third one is diversification of the credit portfolio by lending to households, small businesses, larger industrial corporations, agribusinesses, resource companies and many others. However, to do this effectively, banks need good systems to classify loans according to type, major risk drivers such as loan purpose, loan-to-valuation ratio and level of documentation on debt serviceability. It is only with this data that banks become more aware of what determines potential credit losses and how they can be minimised.

Even though it is greatly emphasised that capital adequacy requirements are necessary for macro-prudential effectiveness, Pogach (2016) outlines some important limitations of capital adequacy requirements. The author notes that increased capital requirements are most commonly translated into steady state output reductions through higher loan spreads and decreased investment. Moreover, yet less frequently, capital regulation affects loan supply not only through changes in loan spreads, but also through changes in underwriting standards or credit rationing. Another important consideration includes the possibility of the extent to which banks pass through increased costs of capital requirements to their borrowers. As such, effective credit risk management can only be achieved through strong integration between macro-prudential policy, micro-prudential policy and monetary policy. This integration thus relates to the fundamental requirement in effective credit management, which is credit risk measurement. Fiedler (1971) underlines that credit risk measurement is the most important step in achieving effective credit risk management. The Basel II also attempts in this regard, to contest the existing credit risk measurement techniques in that they assume a relative scale, yet the current economic challenges require absolute risk measures.

2.3 Measurement of Credit Risk

2.3.1 Use of conditional volatility models

Bu and Liao (2013) indicate that there are currently two core approaches to credit risk modelling. One is called the reduced form approach, which considers credit default as an exogenous event. The other one is a structural approach that was first developed in Merton (1974). The Merton model assumes that a firm's asset return follows a geometric Brownian motion with a constant volatility. However, this assumption of constant volatility of asset returns has a long history of criticism. Adrian and Rosenberg (2008), Choi and Richardson (2012), note that the volatility of a firm's asset returns change through time. Other studies have shown that the assumption of constant volatility is too restrictive and causes the Merton model to estimate credit risk with a large bias. For example, Jones et al. (1984) found that Merton model overestimates bond price risk. Ogden (1987) shows that Merton model underestimates the bond yield spread. Furthermore, Tarashev (2005) submitted that

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the probability of default generated by this model is significantly less than the empirical default rate. As a result, Rohde and Sibbertsen (2014) combine the Merton (1974) model with conditional volatility models, which were primarily introduced by Engle (1982) to address these limitations with the view that volatility of asset return is stochastic in nature.
According to Rohde and Sibbertsen (2014), the accurate modelling of asset return volatility is crucial for the valuation of credit risk since high volatilities give rise to a high possibility of heavy amplitudes of the asset price processes. Accounting for the stylized facts of financial time series, that is, heteroskedastic volatilities along with volatility clustering make the class of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models an appropriate technique for modelling the volatility of asset returns.

2.3.1.1 *Auto Regressive Conditional Heteroskedasticity (ARCH) Model*

The concept of volatility and its measurement (Poon and Granger, 2003), are crucial due to their application in risk management, asset pricing & portfolio analysis as well as monetary policy decision making. The ability to appropriately measure volatility plays a key role in pricing derivative instruments and managing risk in banks. In order to measure volatility, some studies, such as Delechat et al (2009), use the Coefficient of Variation (CV). However, this technique was long criticised for its inability to capture the dynamism in volatility. As an improvement in this regard, Engle (1982) developed a time varying technique called the ARCH model to capture the dynamic nature of volatility. The model is autoregressive in squared returns of an asset and is underpinned by the fact that the next period's volatility is conditional on current information. It is also characterised by heteroskedasticity in the sense that conditional volatility varies over time.

According to Engle (2001), if OLS technique is applied to this type of data, the parameter estimates will be unbiased but, they will be inefficient. Engle (1982) advocated that the conditional variance of ε_t from a standard linear regression can be estimated as follows:

$$Var(\varepsilon_t) = \delta_t^{\,2} = \alpha_0 + \alpha_1 \varepsilon^2{}_{t-1} + \cdots + \alpha_p \varepsilon^2{}_{t-p} \qquad (1)$$

Equation (1) basically represents the ARCH model, which estimates the variance of the residuals conditional on their past values. The lagged $\varepsilon^2{}_t$ are the ARCH terms and p represents the order such that (1) is referred to as ARCH model of order p, that is, ARCH (p). The ARCH can be interpreted as volatility shocks from previous periods.

2.3.1.2 *The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) Model*

Bollerslev (1986) noted some shortfalls about the ARCH model and proposed the GARCH model. The first shortfall is that at times, the ARCH model yields negative parameter values, which are unrealistic in the context of volatility. Another shortfall is that the ARCH model fails to incorporate past unpredictable values of volatility, which play a vital role in determining current volatility. Furthermore, ARCH assumes that the variance of tomorrow's return is an equally weighted average of the squared residuals from the last x days. The assumption of equal weights is unattractive because it ignores the fact that recent events would be more relevant in the estimation of current volatility and therefore should be assigned higher weights. This led to an extension of ARCH model to GARCH, or Generalized ARCH model, first developed by Bollerslev (1986).

$$\delta_t^{\,2} = \alpha_0 + \alpha_1 \varepsilon^2{}_{t-1} + \cdots + \alpha_p \varepsilon^2{}_{t-p} + \lambda_1 \delta^2{}_{t-1} + \cdots + \lambda_q \delta^2{}_{t-q} \qquad (2)$$

The (p, q) in parentheses is a standard notation in which p refers to the number of autoregressive lags, or ARCH terms, while q refers to how many moving average lags or GARCH terms are specified. Therefore, the GARCH converts an autoregressive (AR) process into an autoregressive moving average (ARMA) process. Engle (2001) states that such higher-order models are often useful when a long span of data is used, like several decades of daily data or a year of hourly data. The most common specification is GARCH (1, 1) and is specified as:

$$\delta_t^{\,2} = \alpha_0 + \alpha_1 \varepsilon^2{}_{t-1} + \lambda_1 \delta^2{}_{t-1} \qquad (3)$$

Where all parameters are positive, $\lambda_1 > \alpha_1$, and $\alpha_1 + \lambda_1$ is less than but close to 1. Thus, the GARCH models are mean-reverting and conditionally heteroskedastic with a constant unconditional variance. The GARCH (1, 1) is the simplest and most robust of the family of volatility models. However, the model can be extended and modified in many ways.
Even though the estimated model is very useful, Patrick et al (2006) indicate that it cannot measure the leverage effect. That is, it treats the influence of both negative and positive shocks equally, and this is unrealistic. The negative information on stock price always has more pronounced effect on the volatility than positive information. This implies that the symmetric GARCH model does not capture this asymmetric behaviour. In order to address this and other problems, the GARCH model has been extended in several ways.

2.3.1.3 *Extensions of GARCH Model*

There have been a series of extensions to the GARCH model such as the Integrated GARCH (IGARCH) model (Engle and Bollerslev, 1986), GARCH in Mean (GARCH-M) model (Engle, Lilien and Robins, 1987), Exponential GARCH (EGARCH) model (Nelson, 1991), the Power GARCH (PGARCH) model (Ding et al., 1993) and Thresh-hold

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GARCH (TGARCH) model (Zakoian, 1994). Other models continue to be developed in this regard, for example, the Threshold Bilinear GARCH model (TBL-GARCH) in Choi, M. et al. (2012). This model shall be discussed in detail in the methodology.

Engle and Bollerslev (1986) realised that a typical GARCH model, which assumes an exponential decay in the correlation between the conditional variance and its past values, fails to account for the fact that in reality this process of decay is slow. Consequently, past shocks to volatility would affect future volatility in the long run. Engle and Bollerslev's (1986) therefore came up with the IGARCH model designed to account for this effect. If the autoregressive polynomial in (3) has a unit root, then the model is IGARCH (1,1). Thus, the IGARCH models are unit root GARCH models and the kev feature is that the impact of past squared shocks $(\eta_{t-i} = \delta^2_{t-i}\varepsilon^2_{t-i} - \delta^2_{t-i})$ for $i>0$ on $\delta^2_{t-i}\varepsilon^2_{t-i}$ is persistent.

$$\delta_t^{\ 2} = \alpha_0 + \beta_1\delta^2_{\ t-1} + (1 - \beta_1)\varepsilon^2_{\ t-1} \tag{4}$$

Nelson (1991), on the other hand, noticed that volatility of asset prices tends to react differently to shocks, in which case negative shocks tend to have greater impact on volatility than positive shocks. To capture this singularity, Nelson developed an EGARCH model by defining conditional variance in logarithmic form. Since $In\delta_t^2$ is modelled, then the significant advantage of EGARCH model is that even if the parameters are negative, δ_t^2 will still be positive.
EGARCH model provides information about the asymmetric impact of a shock to volatility by separating the impact of negative shocks from positive shocks. Negative shocks affect future conditional variance more than positive shocks do. This is explained by γ in (5) below. If $\gamma = 0$, then the model is symmetric. If $\gamma < 0$, then positive shocks (good news) generate less volatility than negative shocks (bad news). If $\gamma > 0$, that says positive innovations are more destabilizing than negative innovations.

$$log(\delta_t^{\ 2}) = \omega + \beta log\delta_t^{\ 2} + \alpha\left|\frac{\varepsilon_{t-1}}{\delta_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\delta_{t-1}} \tag{5}$$

Ding et al. (1993) developed a PGARCH model by modelling the standard deviation instead of conditional variance. The model is further characterised by an exponent k to account for asymmetric impact of shocks as shown in (6) below. The PGARCH model makes it easy to have a wider class of power transformations than simply relying on absolute values or squaring the data as it is the case in classical heteroskedastic models.

$$\delta_t^{\ k} = \alpha_0 + \alpha_1(|\ \varepsilon_{t-1}| - \theta_t\ \varepsilon_{t-1})^k + \lambda_1\delta^k_{\ t-1} \tag{6}$$

Zakoian (1994) developed the TGARCH model to capture the leverage effect, which arises from the fact that there is a tendency for the volatility of asset returns to vary inversely with returns. This effect is introduced by including a binary dummy variable in the standard GARCH model, which assigns the value of one for negative shocks and zero for positive shocks. The model is as follows:

$$\delta_t^{\ 2} = \alpha_0 + \alpha_1\varepsilon^2_{\ t-1} + \psi D_t\varepsilon^2_{\ t-1} + \lambda_1\delta^2_{\ t-1} \tag{7}$$

$$D_{t-1} = \begin{cases} 1, & \varepsilon_{t-1} < 0 \\ 0, & \varepsilon_{t-1} \geq 0 \end{cases}$$

Note that if $\psi=0$, TGARCH (1, 1) reduces to GARCH (1, 1). Biekpe and Moore (2000) also identified a shortfall in the GARCH model. Even though the model is renowned of its ability to capture the dynamism of volatility, it loses sight of the structure of the covariance between lagged values of independent variables. The authors argue that this omission is fatal as those variables may play a significant role in determining market volatility. In an attempt to overcome this limitation, the authors specify a simple bilinear GARCH model (BL-GARCH) (p, q, r) as thus:

$$\delta_t^{\ 2} = \delta_0^{\ 2} + \sum\nolimits_{i=1}^{q}\alpha_i\varepsilon^2_{\ t-i} + \sum\nolimits_{j=0}^{p}\beta_j\delta^2_{\ t-j} + \sum\nolimits_{i=1}^{q}{}_j\sum\nolimits_{j=1}^{p}\omega_{ij}\delta_{t-i}\varepsilon_{t-j} \tag{8}$$

Where ε_{t-j} are the past values of the residuals and δ^2_{t-i} are past values of variance of the residuals. For $i \neq j, E(\delta_{t-i}\varepsilon_{t-j}) = 0$, Biekpe (1996) and Motelle and Biekpe (2015). For a general appreciation, a simple BL-GARCH (1, 1, 1) model can be specified as follows:

$$\delta_t^{\ 2} = \gamma + \alpha\varepsilon^2_{\ t-1} + \beta\delta^2_{\ t-1} + \omega\delta_{t-1}\varepsilon_{t-1} \tag{9}$$

According to Diongue et al. (2010), the conditional variance δ_t^2 in (9) is non-negative, and if $\omega = 0$ the BL- GARCH (1, 1, 1) reduces to GARCH (1, 1). The task is to test the hypothesis that the covariance between lagged values of δ_t and ε_t is insignificant in explaining volatility. That is, $H_0 : \omega = 0$.

2.3.2 Other credit risk measurement techniques

2.3.2.1 Balance Sheet Models

Sorge and Virolainen (2006) explain that balance sheet models explore the links between the business cycle and financial accounting items or credit risk indicators. These models are relatively simple and typically linear, using the most relevant macroeconomic variables, such as GDP, inflation, interest rates and unemployment to account for variations in the accounting items. However, Sorge and Viro-

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lainen, (2006) identify several drawbacks. First, they are too simplistic and ignore the possibility of non-linearity in variables, especially in periods of shocks. Second, it is also true that these indicators could be too noisy measures of credit risk due to the fact that the coefficients are obtained from OLS regressions with noisy dependent variables plagued by impression (i.e., the standard errors increase). Third, the balance sheet models do not account for dynamism of credit risk, and it could be said they are backward looking.

The generally used credit risk indicators are; (a) the ratio of non-performing loans (NPLs) to gross loans, (b) the ratio of loan loss provision (LLP) to total assets, (c) the ratio of risk-weighted assets to total assets, (d) the ratio of total loans to total deposits and (e) the ratio of total loans to total assets. Takayasu et al. (2000), indicates that the reason why these indicators are widely used to measure credit risk, especially the NPLs and LLPs is because they received a central focus in analysing how credit risk increased after the 1997 Asian Financial Crisis. It was found that they do have a significant explanation in credit risk. For their wide usage, see Ahmad and Ariff (2007), Das and Ghosh (2007), Castro (2012), BoruLelissa (2014), Andriani and Wiryono (2015) among others.

2.3.2.2 *Value at Risk (VaR) Models*

According to Holton (2002), VaR is a statistical technique that is most commonly used by investment and commercial banks to determine the potential loss in value of a risky asset or portfolio over a specified period for a given confidence interval. Its origins can be traced as far back as 1922 where the New York Stock Exchange imposed capital requirements on member firms. Sorge and Virolainen (2006) argue that this method addresses the possible shortcomings of the balance sheet models in that, it provides a different approach altogether. It captures the likelihood of loss in value of traded portfolios from adverse market movements over a certain period of time. This can then be compared to the available capital and cash reserves to ensure that the losses can be covered without positioning the bank at risk.

However, VaR has limitations too. VaR results cannot be added across portfolios. This shortcoming may become quite restrictive at times of high risk because it does not permit analysis of an individual institution's performance nor the possible contagion effects. Moreover, VaR can be misleading (if misunderstood) and can give a false sense of security especially when it is calculated with the confidence parameter set to 99%. That is, it neglects tail risk. VaR also gets difficult to calculate with large portfolios. Likewise, its different approaches (variance-covariance parametric VaR, Historical VaR and Monte Carlo VaR) can also lead to completely different results with the same portfolio, which makes its representativeness to be questionable (Sorge and Virolainen, 2006).

2.3.2.3 *Micro-data Models*

Kattai (2010) indicates that there is another class of credit risk models crafted around microeconomic variables (client- specific characteristics). The Bank for International Settlements labels this method the Internal Ratings Based Approach to credit risk. This approach uses individual borrower's characteristics such as age, sex etcetera to assess their influence on credit risk. Foglia (2009) further adds that micro-data models detect possible problems in loan portfolios sooner than models based on loan classification data such as non-performing loans or loan loss provisions (balance sheet models). However, as informative as they may be, these models have a major draw-back of the need for datasets that are normally available only to selected institutions.

2.3.2.4 *Stress Tests*

According to Schuermann and Wyman (2012) stress testing is an analysis conducted under unfavourable economic scenarios to determine whether a bank has enough capital to withstand the impact of adverse developments. Its history dates back to the original Basel I Accord of 1988 where it was informally introduced. It was later formally introduced under the Market Risk Amendment of 1995 .
Foglia (2009) advises that this approach has valuable strengths as it is closely aligned to capital planning process, setting of capital buffers and informing decisions on high-level risk appetite. However, it also has some important limitations. Generally, current models are weak in the treatment of key financial system interactions. For example, they only rarely model the impact of funding and market liquidity stresses or the correlation between credit, market, and liquidity risks. Feedback effects are often absent or modelled in an elementary fashion. Over and above that, existing methods are generally unable to endogenously account for cross-border transmission channels for risk, including cross-border contagion between financial institutions. They often ignore potential nonlinearities and structural breaks in estimated relationships. In addition, some approaches focus on a projected conditional mean stress scenario outcome and fail to consider the distribution of the losses that will be borne by individual financial institutions in a real-world stress situation. Stress tests therefore, as Bunn et al. (2005) indicate, are just like VaR. They remain a complement to, rather than a substitute for, broader macro-prudential analysis of potential threats to financial stability.

2.4. DETERMINANTS OF CREDIT RISK

2.4.1. Theoretical framework on the determinants of credit risk

After measuring credit risk, it is imperative to identify its key determinants. There are four (4) main theories that the study that provide the theoretical framework for the determinants of credit risk, namely; Markowitz's (1952) Modern Portfolio Theory (MPT), Sharpe's (1963) Capital Asset Pricing Theory (CAPM), Hamada's (1972) theory on risk and leverage as well as Jensen and Meckling's (1976) Agency Theory.

2.4.1.1. Morden Portfolio Theory

Markowitz's (1952) Modern portfolio theory is a theory on how risk-averse investors can construct portfolios to optimize or maximize expected return based on a given level of market risk, emphasizing that risk is an inherent part of higher reward. It assumes that investors are risk-averse and base their investment decisions on the expected return and risk. It also assumes no transaction costs, a perfect capital market and a single period investment so that an investor only takes an increased risk if compensated by higher expected returns. Equally, an investor who wants higher expected returns must accept more risk. The implication is that a rational investor will not invest in a portfolio if the second-best portfolio exists with more favourable risk-expected return profile. The return on a portfolio is the proportion-weighted combination of the constituent assets' returns, and it is obtained by:

$$E(R_p) = \sum_i w_i E(R_i) \tag{10}$$

Where, R_p is the return on the portfolio, R_i is the return on asset i and w_i is the weighting of component asset i (that is, the proportion of asset i in the portfolio).

2.4.1.2. CAPM

The CAPM, which builds on Modern Portfolio Theory, articulates that price or expected return on an asset is related to its risk-free rate, systematic risk and the expected market risk-premium. It is built on assumptions that all investments are infinitely divisible, and that investors are rational and risk averse. It further assumes that investors are price takers who can borrow or lend without any restrictions at a risk-free market rate, and in an environment where transaction costs are zero and the tax system is neutral. Lastly, there is a perfect capital market where all information is available and costless. Sharpe (1963) therefore, specifies that;

$$E(R_j) = R_f + \beta_j[E(R_m - R_f)] \tag{11}$$

Where, R_j is the expected return on the asset, $j = 1,\ldots,N$; R_f is the risk-free rate of return measured as treasury bill/bond yield; R_m is the expected return for a risky market portfolio; β_j is the individual asset's systematic risk relative to the risky market's portfolio, and $E(R_m - R_f)$ is the expected risk-premium of the risky market portfolio.

The MPT and CAPM applied to a portfolio of bank loans therefore, bring forth an intuition that banks maintain a combination of loans with varying risk levels. For that reason, credit risk can be minimized through loan diversification; in which case an acceptable level of credit risk in a diversified loan portfolio, as Markowitz (1959) indicates; should have a correlation coefficient that is closer to 0 rather than to +1.00. This unfolds that, for risky loans, banks would charge higher interest rates in order to compensate for the high uncertainty involved. This might explain the interest rates as one of the determinants of credit risk.

2.4.1.3. Risk and Leverage Theory

Hamada (1972) came up with a theory that banks as highly-levered firms, must incorporate in their loan pricing, other risk-related costs; for example, tax and bankruptcy cost. Bankruptcy costs will arise if a bank indulges in excessive lending. Thus, increased leverage is likely to affect bank credit risk (this was emphasised by BIS (2014) on the 10th Asia-Pacific meeting on Banking Supervision). Hamada (1972) then provides an equation that relates the beta of a levered firm to that of its unlevered counterpart to determine the cost of capital of a levered firm based on the cost of capital of comparable firms.

$$\beta_L = \beta_U[1 + (1 - T)\emptyset] \tag{12}$$

Where β_L and β_U are the levered and unlevered betas, respectively. T is the tax rate and $\emptyset$ is the leverage (equity-to-asset ratio) of a firm. A higher value of beta deprives a firm of a higher return. This implies that if a firm decides to debt finance, it increases its overall risk by a certain degree as compared to the unlevered counterpart. This theory may therefore explain leverage as one of the determinants of credit risk.

2.4.1.4. Agency Theory

Jensen and Meckling (1976) came up with the agency theory, also referred to as the principal-agent theory (shareholders are here referred to as principals while bank managers are agents). The theory tries to explain the behaviour of agents that intervene in the company's activities and to analyse the impact of these behaviours. The hypothesis is that all stakeholders have specific objectives and interests that are not spontaneously reconcilable and as a result, conflicts may arise.

On this premise, agency conflict may arise when bank managers act in their best interest rather than in the interest of the shareholders. This conflict may result in the possibility of lack of corporate governance, in which case loan approvals may be done without proper vetting and credit scoring. Factors such as management inefficiency or efficiency, as well as non-performing loans, stem from this conception.

2.4.2. Some Empirical Evidence on Key Determinants of Credit risk

2.4.2.1. Modern Portfolio Theory

Despite its theoretical relevance, the MPT has been highly criticised; its simplistic assumptions being a predominant

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bias[3]. Omisore et al. (2012) also indicate that risk, return, and correlation measures used by MPT are based on expected values. This means investors must substitute predictions based on historical calculations of asset return and volatility in the equations. In practice, however, such expected values fail to take account of developments, which did not exist when the historical data were generated.

2.4.2.2. CAPM

With respect to CAPM, Lintner (1965) and Douglas (1969) questioned the validity of the theory based on individual security returns and the risk-return relationship. Their results were against CAPM. Miller and Scholes (1972) further revealed some statistical problems when using individual securities' returns in testing the validity of the CAPM. Choudhary and Choudhary (2010) also examine CAPM for the Indian stock market using monthly stock returns from 278 companies of BSE 500 Index listed on the Bombay stock exchange for the period of January 1996 to December 2009. The findings of this study do not support the theory's basic proposition that higher risk (beta) is associated with higher levels of return. Moreover, Khan et al. (2012) tested the CAPM in Pakistan stock exchange for the period 2006 - 2010 by using ten companies stock. They calculated the beta of each company and its expected return, and then compared the expected return with the actual return. Their findings indicated that CAPM is not applicable to Pakistan stock exchange.

Fama and French (2004) also state that, "…the CAPM, like Markowitz' (1952, 1959) portfolio model on which it is built, is nevertheless a theoretical tour de force. We continue to teach the CAPM as an introduction to the fundamental concepts of portfolio theory and asset pricing, to be built on by more complicated models like Merton's (1973) ICAPM. But we also warn students that despite its seductive simplicity, the CAPM's empirical problems probably invalidate its use in applications."

2.4.2.3. Risk and Leverage Theory

Hamada's Equation is derived by combining the CAPM with the first two propositions of Modigliani and Miller (M&M). However, since both M&M and CAPM rule out default risk, the equation will then, by design, exclude it as well. Consequently, any application of the equation becomes restricted to highly idealised scenarios, whereby interest rates remain constant and equal to the risk-free rate, irrespective of the degree of leverage. This limitation poses significant problems, especially if one were to consider situations where debts are risky, (Cohen, 2008). Bramhandkar and Cheng (2012) also add that a major drawback of the Hamada Equation is its assumption that the cost of debt is equal to the risk-free rate at all levels of debt, and this therefore, makes its application unrealistic in the real world.

2.4.2.4. Agency theory

Eisenhardt (1988) tested the validity of agency theory in 54 retail stores and found the result in favour of theory. Barney (1988) also found supporting results in 32 Japanese electronics firms. Despite these tests and many others[4], Donaldson (1990) criticized the agency theory in that its methodology has no standard approach. The author further argues that the theory is one-dimensional and disregards other research, ideological framework, organizational economics and corporate governance's defensiveness.

2.4.2.5. Studies accounting for both micro and macroeconomic factors

Having examined empirical tests of these major theories, there are other studies that try to find the underlying determinants of credit risk. There are lots of factors that can influence credit risk in commercial banks, but the study is going to be narrowed down to those that the literature has emphasized on their significance. According to Naceur and Omran (2011), banks performance with regard to credit risk depends on various micro and macroeconomic factors. The microeconomic factors are bank specific while macroeconomic factors relate to the external environment. Different approaches have been used in the literature to analyse factors that influence credit risk. Some of the research works focused on microeconomic variables alone, while others provide a separate evaluation of macroeconomic variables, for example, Newaz (2012) and Ravi (2013) respectively. Not many have considered a combination of the two classes.

Microeconomic factors include the bank size, profitability, credit growth, leverage, capital adequacy and management efficiency. Boujelbène and Zribi (2011) state that theoretical arguments suggest a negative relationship between bank size and credit risk based on the justification that larger banks are likely to be more skilled in risk management and also have broader diversification opportunities. Kim and Santomero (1988) suggest a negative relationship between credit risk and capital adequacy requirements in that the requirements channel banks to change the composition of asset portfolios in favour of less risky assets and thus, a less risk-taking behaviour. Boujelbène and Zribi (2011) also advocate that the most profitable banks are the riskiest banks. This is after their results reveal a positive correlation between credit risk and profitability. Garr (2013) suggests a negative association between credit risk and management efficiency or operating efficiency with a view that inefficient management leads to agency costs and reckless lending.

On one hand, macroeconomic factors include among others, the level of economic growth, unemployment, inflation and interest rates. Al-Smadi and Ahmed (2009) believe that favourable macroeconomic conditions contribute to the reduction of banks' credit risk exposure. A favourable macro economy can be an implicit indication of an increase in purchasing power, hence the ability of borrowers to pay their obligations. These factors have been extensively analysed in

[3] Petros (2008) and Zhan (2015) also tested the theory and confirm the inconsistencies.

[4] See Eisenhardt (1989) pages 66- 67

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different studies where they reveal a positive relationship between credit risk and unemployment, interest rates and inflation, but an inverse relationship between credit risk and GDP (for example, Badu et al., 2002, Vodová (2003), Das and Ghosh (2007), and Adu (2015) amongst others).

Ahmed et al. (1998) find a strong positive relationship between loan loss provision and the NPLs. Hence, an increase in LLPs implies an increase in credit risk and deterioration in loan quality. Fisher, Gueyie and Ortiz (2002) find similar results in banks of North American Free Trade Agreement (NAFTA) countries where LLPs are positively related to risk despite being in a different economic setting or stage of development. Ahmad (2003) further observes similar situation with Malaysian banks.

According to Vodová (2003), credit risk emerges because of increases in non-performing loans and macroeconomic instability. Three main banks were assessed for the period 1998 to 2002, and it was found that the share of non-performing loans exceeded 30 % of total loans. Such a huge level of non-performing loans was caused by a combination of several factors working together. A huge demand for loans was approved under insufficiently prepared legislative and under the lack of the necessary knowledge and experience of credit risk management as well as assessment of borrower creditworthiness. The situation was further aggravated by the macroeconomic instability and relatively high level of interest rates.

Ahmad and Ariff (2007) find significant positive relationship between capital buffer (measured by the ratio of total equity to total assets) and bank credit risk in Japan, Malaysia and Mexico, after banks were required to raise their capital requirement in order to absorb potential losses from credit risk. Their findings support the positive nexus evidenced in Berger and DeYoung (1997) between bank capital and credit risk. They also estimated credit risk as a ratio of non-performing loans to total loans. Aver (2008) conducted an empirical analysis of factors affecting credit risk in Slovenian banking system for the period 1995 to 2002 using a multivariate linear regression. The findings confirmed the main hypothesis that certain macroeconomic factors affect credit risk. Unemployment rate, interest rates and stock market index have a major influence on credit risk. Nonetheless, no sufficient relationship was established between credit risk, inflation rate, GDP growth rate and exchange rate.

Boujelbène and Zribi (2011) used the ratio of risk-weighted assets to total assets as an estimate for credit risk (dependent variable) to determine its factors in Tunisia during 1995 – 2008. They included ownership structure as one of the microeconomic factors along with macroeconomic factors and the results suggested that the main credit risk determinants in Tunisia are ownership structure, prudential regulation of capital, profitability, and macroeconomic indicators. Castro (2013), analyses the relationship between macroeconomic development and credit risk in Greece, Ireland, Portugal, Spain and Italy, using dynamic panel data approaches over the period 1997-2011 and finds that there is a significant relationship between credit growth and credit risk.

Garr (2013) on the other hand, estimated credit risk by the ratio of loan loss provisions to total assets to examine bank-specific, industry-specific and macroeconomic factors that influence credit risk in commercial banks in Ghana using unbalanced panel data set from 33 commercial banks covering 1990 to 2010. The findings suggested that credit risk is significantly influenced by management efficiency, GDP per capita, government borrowing and the financial sector development. Tehulu and Olana (2014) used the Generalized Least Squares to investigate bank-specific determinants of credit risk in Ethiopian commercial banks. They used panel data of 10 commercial banks including state-owned and private owned from 2007 to 2011. Variables analysed in this study are bank size, profitability, capital adequacy, bank liquidity, credit growth, operating efficiency, and ownership. The findings revealed that credit growth and bank size have negative and statistically significant impact on credit risk. Whereas, operating inefficiency and ownership have positive and statistically significant impact on credit risk. Finally, the results indicate that profitability, capital adequacy and bank liquidity have negative but statistically insignificant relationship with credit risk.

Adu and Adjare (2015), also examine the determinants of credit risk in commercial banks in Ghana from 2007-2014 using Robust Least Squares regression analysis. They estimated credit risk as non-performing loans to total loans. The findings show a significant positive relation between the bank credit risk and leverage. However, a negative relationship between the credit risk and management efficiency was found. The results further show a significant negative relationship between bank credit risk and profit.

In Zimbabwe, Sandada and Kanhukamwe (2016) used primary data where they interviewed lending managers, heads of credit division, credit analysts, senior and junior bank managers and managing directors. They found that industry factors do not affect credit risk, but macroeconomic and bank specific factors are the most influential. However, the authors did not explain how they measure or quantify credit risk in their paper. Ameur (2016) employed the Generalised Method of Moments technique in the top ten commercial banks in Tunisia for the period 2000-2013. The findings suggest that credit risk in Tunisian banks is significantly influenced by capital adequacy and operational efficiency. That is, banks with adequate capital and efficient management appeared to have low credit risk level.

2.5. CONCLUSION

Credit risk is one of major risks that banks face due to the nature of their business. However, through effective management of credit risk, banks not only support the viability and profitability of their own business, but they also contribute to systemic stability and to an efficient allocation of capital in the economy. To achieve these, it is central that credit risk measurement is appropriate and well undestood.

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3 METHODOLOGY

3.1 DATA ISSUES

The study employs monthly data for the period 2013 to 2016. The data were collected from the Central Bank of Lesotho for all the balance sheet variables in the four commercial banks in Lesotho. For macroeconomic variables, the data were collected from the World Development Indicators (WDI) - a World Bank database. Table 2 provides a summary of variables, their description and data sources.

Table 2: Description of variables and data sources

Model	Variable	Description	Data Source
Model I	1. Credit Risk (r_t)	Volatility of ratio of *NPLs to gross loans.* Volatility of ratio of *LLPs to total assets.* Volatility of ratio of *RWAs to total assets.*	CBL
Model II	2. Inflation *(INF)*	Sustained increase in general price levels.	WDI
	3. Interest rate *(IR)*	Cost of borrowing measured by the prime lending rate.	WDI
	4. Money supply (M2)	Measure of money supply.	WDI
	5. Bank size *(SIZE)*	Natural log of total assets.	CBL
	6. Leverage *(LEV)*	Common equity/total assets.	CBL
	7. Management efficiency *(MGT)*	Total cost/total revenue OR cost-income ratio.	CBL
	8. Profitability *(PFT)*	ROE= net profit/capital.	CBL
	9. Capital adequacy *(CAP)*	Total capital/total assets.	CBL
	10. Credit growth *(CRE)*	Current year loans minus previous year loans/previous year loans.	CBL
	11. Previous NPLs (LNPL)	Lagged NPL values.	CBL

N.B: *NPLs are the non-performing loans, LLPs are the loan loss provisions, and RWAs are the risk-weighted assets.*

It was desirable to include a measure of economic activity in the model. However, GDP data are not available on a monthly basis. The study thus indirectly utilised growth effects from the behaviour of money supply. This decision is based on Friedman (1956) Modern Quantity Theory of Money whereby the assertion is put that money plays a key role in economic growth. Money is demanded for transaction purposes and forms a greater part of wealth. Its circulation in the economy creates a link between producers and consumers in which case a network of different markets is established to facilitate growth. This is supported by a strong positive correlation co-efficient of 87 percent as seen in Appendix 7 and thus justifies the use of M2 as a measure of economic activity.

3.2 MODEL SPECIFICATION

This section specifies the models used to measure credit risk and the determinants of credit risk. Each model was estimated for the industry level, then the top-two banks and lastly, the bottom-two.

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3.2.1 Model I: Measurement of credit risk

In order to measure credit risk, the study follows the modelling methodology of Choi, M. et al (2012) which is the TBL-GARCH. This model comprises of two key components. The first part of the model is the TGARCH. The TGARCH does not only have the ability to capture the asymmetric patterns in volatility, but it also incorporates the threshold effects. The second part is the BL-GARCH which is known for its capability to accommodate shift features in volatility. Therefore, this makes the TBL-GARCH model to be characterized by two sources of asymmetry in volatility; that is, the *threshold-asymmetry* and the *shift-asymmetry*.

In order to obtain the conditional volatility δ_t^2, three credit risk ratios (r_t) are used, namely; the ratio of NPLs to total loans, the ratio of LLPs to total assets and the ratio of risk weighted-assets to total assets.

$$r_t = \gamma_0 + \varepsilon_t \qquad (13)$$

$$\delta_t^2 = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \psi D_t \varepsilon^2_{t-1} + \gamma\, \delta_{t_{t-1}} \varepsilon_{t-1} + \beta \delta^2_{t-1} \qquad (14)$$

Where $\varepsilon_t = \delta_t e_t$ and e_t is a series of independent and identically distributed random variables with zero mean and unit variance for *t= 1,2,…T*.

Equation (14) operates on the assumption that ε_t is the error term and it is normally distributed with zero mean and the variance of δ_t^2. α_0 is the time-invariant component of credit risk. For the model to be meaningful, γ can have values in $(-\infty, \infty)$ while $\alpha_0 > 0$ and the other parameters α_1 and β are often non-negative. Since δ_t^2 is a conditional variance, it must be strictly positive.

The estimation process follows a three-step algorithm. The algorithm first estimates (13) and harvests the residuals. The second step utilises the residuals to estimate a simple GARCH model which helps generate the conditional variance. The last step then utilises the squared residuals and the conditional variance to estimate (14). Recall that the conditional variance is used to measure credit risk.

3.2.2 Model II: Estimation of the determinants of credit risk using data from conditional volatility models

In order to determine the drivers of credit risk, the study adopts Boujelbène and Zribi's (2011) modelling technique specified as follows:

$$\delta_{it}^2 = \alpha + \beta_{1i} INF_{it} + \beta_{2i} IR_{it} + \beta_{3i} M2_{it} + \tau_{1i} SIZE_{it} + \tau_{2i} LEV_{it} + \tau_{3i} MGT_{it} + \tau_{4i} PFT_{it} + \tau_{5i} CAP_{it} + \tau_{6i} CRED_{it} + \tau_{7i} LNPL_{it} + v_{it} \qquad (15)$$

Where credit risk is denoted by δ_t^2 from (14) and v_t is a sequence of N (0; 1) *i.i.d.* random variables. *i* stands for categories *(a)* the industry, *(b)* top-two banks and *(c)* bottom-two banks while *t* is the time period.

3.2.3 Model III: Estimation of the determinants of credit risk using level data

The study adopts Boujelbène and Zribi's (2011) modelling technique. The same technique is also used in Garr (2013).

$$CR_{it} = \alpha_i + \beta_{1i} INF_{it} + \beta_{2i} IR_{it} + \beta_{3i} M2_{it} + \tau_{1i} SIZE_{it} + \tau_{2i} LEV_{it} + \tau_{3i} MGT_{it} + \tau_{4i} PFT_{it} + \tau_{5i} CAP_{it} + \tau_{6i} CRED_{it} + \tau_{7i} LNPL_{it} + v_{it} \qquad (16)$$

Where CR represents credit risk and is measured by three ratios which are (1) the ratio of LLPs to total assets or CR1, (2) the ratio of NPLs to total loans or CR2 and (3) the ratio of RWAs to total assets or CR3. α_i is the time invariant component of credit risk and v_{it} is the error term. This means each CR will be estimated for the categories of the industry, top-two banks and bottom-two banks for *t= 1,2,…T.* , respectively.

Table 2.1 below presents the expected signs and their basis for possible determinants of credit risk. For both inflation rate and interest rates, it is expected that they increase credit risk. This is based on theoretical grounds that inflation erodes the purchasing power of money and thus makes debt-servicing more difficult. An increase in interest rates, likewise, implies that the cost of borrowing becomes burdensome and thus increases the probability of default. On the other hand, economic growth improves economic activity and thus moderates credit risk. With respect to the microeconomic variables, big banks are expected to manage credit risk more efficiently than small banks. Furthermore, the expectation is to find a positive relationship between leverage and credit risk. Highly leveraged or highly indebted banks stand a risk of bankruptcy during a business downturn, and this may result in systemic risk since the banks are interrelated. It is also anticipated that there will be a positive relationship between profitability and credit risk due to the idea that profitability increases the risk appetite of the banks, that is; highly profitable banks normally increase their credit portfolios and credit growth. The previous NPLs should also have a positive relationship with credit risk since they have an impact on the current credit portfolio of a bank.

3.3 TIME SERIES PROPERTIES OF THE VARIABLES

3.3.1 Measurement of credit risk

In order to estimate (14), it is imperative to use stationary time series data. Since most time series data are often alleged to be non-stationary, it is necessary to perform a pre-test for this before conducting any analysis in order to avoid the problem of spurious regression. The study employs the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) to test for stationarity. However, should the two tests yield different results; an additional test which is the Kwiatkowski–Phillips–

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Schmidt–Shin (KPSS) will be used, in which case the decision would be based on a simple majority rule. For the ADF and PP tests, the null hypothesis states that there is unit root, and failure to reject the null shows that the series is non-stationary. With the KPSS, the null hypothesis states that there is no unit root, and failure to reject the null implies that the series is stationary. Based on this representation therefore, all variables presented in *Table 2* are tested for stationarity in levels and first differences using the two tests.

3.3.2 Determinants of credit risk

The study utilises two panel unit-root tests, namely; the Levin, Lin and Chu (LLC) (2002) and Im, Pesaran and Shin (IPS) (2003) tests to assess the stationarity of determinants of credit risk. However, should the two tests yield contradicting results, the ADF- GLS is employed in which case the decision would be based on a simple majority rule. Unlike time series unit root tests, panel data unit-root tests gain power by exploiting both the time-series and cross-sectional dimensions of the data set.

Table 2: Expected signs for possible determinants of credit risk

Determinant	Macroeconomic	Microeconomic	Expected sign	Basis
M2	✓		–	Increases economic activity
Inflation	✓		+	Erodes the purchasing power of money
Interest rate	✓		+	Increases cost of borrowing
Bank size		✓	-/+	Bigger banks are more experienced in risk mgt
Leverage		✓	+	High levels of debt pose the risk of bankruptcy
Management efficiency		✓	-/+	Competent bank managers handle credit risk matters with caution.
Profitability		✓	+	Highly profitable banks have high risk appetite
Capital adequacy		✓	–	Buffers the banks against insolvency
Credit growth		✓	+	High credit growth increases the risk of loss
Previous NPLs		✓	+	Previous NPLs affect the current credit position of the bank

Source: compiled by author*; see Appendix 1.2 for pieces of literature*

3.4 ESTIMATION TECHNIQUES

3.4.1 Measuring credit risk using Maximum Likelihood Estimation (MLE)

In order to estimate credit risk; the study employs Maximum Likelihood Estimation (MLE) technique with a Gaussian likelihood function as suggested by Choi et al. (2012), Gabr and Hashash (2012). For a stationary data set and a specified statistical model, which in this case is the TBL-GARCH specified in (14), MLE selects a set of parameter values in the model that maximize the Gaussian likelihood function. MLE has many attractive properties that involve among others, the ability to estimate the coefficients of models with complex functional relationships and nonlinear specifications of the dependent variable.

3.4.2 Estimation of the determinants of credit risk using Seemingly Unrelated Regression (SUR) model

The seemingly unrelated regression estimation technique is utilised to analyse the determinants of credit risk in commercial banks of Lesotho. The SUR estimator is somehow similar to the Generalised Least Squares estimator. It is has the smallest variance as compared to the OLS estimator (thus, it is more efficient). Since the idea is to estimate the determinants of credit risk for the industry, top-two banks and the bottom-two banks, the three equations may appear distinct individually in terms of data series, but there may be a relationship amongst them. These equations can be used to examine the jointness of the distribution of disturbances. In this case, it seems reasonable therefore, to assume that the error terms associated with the equations are contemporaneously correlated so that the equations are “seemingly” unrelated or are simultaneous regressions rather than independent relationships. Hence, SUR can estimate parameters of each cluster in a manner that successfully accounts for the contemporaneous characteristics of the error term.

3.4.3 Estimation of the determinants of credit risk at levels using the Generalised Least Squares (GLS)

The Generalised Least Squares (GLS) estimation technique is utilised to analyse the determinants of credit risk in commercial banks of Lesotho. The GLS is almost similar to SUR estimator. It gains power over the OLS estimator since it has the smallest variance, thus, it is more efficient. The Feasible GLS could also be used; unfortunately, it would produce misleading results since it requires large sample size in order to be meaningful. Therefore, all the estimates are based on GLS regressions after corrections of heteroskedasticity using White Heteroskedasticity Consistent Standard Errors and Covariance technique. This technique is adopted from Ahmad and Ariff (2007) with admiration that it has the ability to minimize the effects of heteroskedasticity and serial correlation problems that almost every financial data is plagued with.

4 DATA ANALYSIS AND DISCUSSION OF RESULTS

The study uses a three-step analytical approach to study credit risk and its determinants. The first step involves the examination of the time series properties of variables in the respective clusters, namely; industry, top-two banks and the bottom-two banks. In the second step, the study addresses the first objective, that is, the measurement of credit risk. The data is fitted into the three credit risk models and the diagnostic tests are conducted to select the appropriate model. As the final step, the study uses the measures of credit risk computed in the previous step as the dependent variable to address the objec-

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tive of investigating the determinants of credit risk in Lesotho. This objective is further extended to include the analysis of the determinants of credit risk using the three credit risk indicators (ratio of LLPs to total assets, ratio of NPLs to total loans and ratio of RWAs to total assets) at levels or single-dimensionally. The idea is to conduct robustness checks against the volatility approach. The rest of the chapter is organised as follows: section 4.2 summarises the findings on measurement of credit risk. Section 4.3 and 4.4 provide the results on the determinants of credit risk while section 4.5 concludes.

4.2 MEASUREMENT OF CREDIT RISK USING CONDITIONAL VOLATILITY MODELS

4.2.1 Time series properties of the variables

The first step in the estimation process is to test for stationary in the data series in order to avoid the risk of spurious regressions. All variables in their respective categories were tested for stationarity using the ADF and PP. The decision rule is that the variable is considered stationary if it passes both tests. However, should the two tests yield contradicting results, an additional test (KPSS) would be used, in which case the decision will be based on a simple majority rule. At the industry level, both the ratio of non-performing loans to gross loans and the ratio of loan loss provisions to total assets are integrated of order zero, that is, I(0) stationary. The ratio of risk-weighted assets to total assets, on the other hand, is I(1) stationary. For the top-two banks and bottom-two banks, the three variables are I(0) stationary. Table 4 summarises the results.

4.2.2 Diagnostic tests

To decide which model is appropriate to measure credit risk between the GARCH (1, 1), BL-GARCH (1, 1, 1) and TBL-GARCH (1, 1, 1), the study first determines the level of significance of the coefficients of the GARCH, bilinear GARCH and threshold-GARCH terms. If the GARCH term is the only significant, GARCH (1, 1) is chosen. Likewise, if the bilinear GARCH term is also significant, the BL-GARCH (1, 1, 1) is chosen regardless of whether the GARCH term is significant or not. The TBL-GARCH (1, 1, 1) would also be preferred if the threshold GARCH term is significant regardless of whether GARCH or bilinear GARCH are significant or not. Second, the preferred model is one with the minimum Akaike information criterion (AIC). Third, an appropriate model is also chosen on its ability to produce the lowest standard error of regression and the ability to yield the highest log likelihood. Finally, it also lies with careful judgement, on the decision of the researcher whether to ignore crucial information given by an extra variable on the basis that the diagnostics are not fully satisfactory. Specifically, in this study, risk is a delicate phenomenon which no single bank can leave unattended regardless of how small the impact is or may be. The decision would be different if the objective was to improve sales or profitability measurement.

Therefore, based on the judgement of the researcher, and still considering the importance of other diagnostic tests, the conclusion is reached from Table 5 that the TBL-GARCH (1,1,1) model outperforms both the GARCH (1,1) and BL-GARCH (1,1,1). This outcome indicates that the threshold effects and the co-variance between lagged values of the standard errors and the residuals contain crucial information in measuring credit risk. Therefore, the TBL-GARCH (1,1,1) is an appropriate model for measuring credit risk. The results build on the findings of Motelle and Biekpe (2014) who found the BL-GARCH (1,1,1) to be suitable for modelling financial instability[5].

Table 4: Unit root test results

Variable	Cluster	ADF		PP		KPSS	Decision
		Levels	*1st Difference*	*Levels*	*1st Difference*	*Levels*	
NPLs	*Industry*	*-3.435* (0.002)*		*-3.064* (0.004)*			*I(0)*
	Top 2	*-3.116* (0.004)*		*-2.431** (0.030)*			*I(0)*
	Bottom 2	*-3.093* (0.004)*		*-3.214* (0.003)*			*I(0)*
LLPs	*Industry*	*-1.882*** (0.068)*		*-1.737*** (0.097)*	*-4.803* (0.000)*		*I(0)*
	Top 2	*-2.953* (0.006)*		*-2.977* (0.004)*			*I(0)*
	Bottom 2	*-1.883*** (0.068)*		*-1.586 (0.141)*		*0.063* (0.000)*	*I(0)*
RWAs	*Industry*	*-1.429 (0.162)*	*-4.570* (0.000)*	*-1.608 (0.102)*	*-6.985* (0.000)*		*I(1)*
	Top 2	*-2.251** (0.031)*		*-2.358** (0.036)*			*I(0)*
	Bottom 2	*-2.035** (0.050)*		*-2.009*** (0.053)*			*I(0)*

Source: Own computation. Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance. NPLs stands for the ratio of non-performing loans to gross loans, LLPs stands for the ratio of loan loss provisions to total assets and RWAs designates the ratio of risk-weighted assets to total assets.

4.2.3 Discussion of results

When using the ratio of NPLs to gross loans as proxy for credit risk, the results from Table 5 indicate that the covariance between the lagged values of the standard deviation and the residuals is insignificant and therefore the BL-GARCH (1,1,1) model is eliminated, leaving the comparison between standard GARCH (1,1) and TBL-GARCH (1,1,1). Based on the diagnostic tests therefore, the model with lowest AIC, lowest standard error of the regression and highest log likelihood is the TBL-GARCH (1,1,1). The results further indicate that the

[5] The volatility of the ratio of credit (private sector) to GDP was used in Motelle and Biekpe (2014) as a candidate measure of credit risk at the macroeconomic level.

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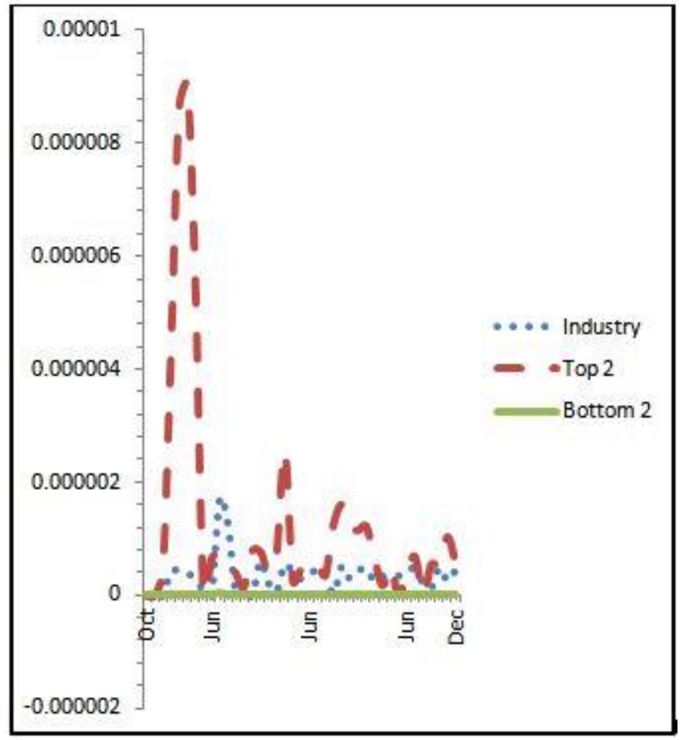
threshold term $D_t \varepsilon_{t-1}^2$ amplifies credit risk by 0.76 percent at 1 percent level of significance. The implication is that if this key term is omitted in favour of either BL-GARCH (1,1,1) or simple GARCH (1,1) models, credit risk will be underestimated by 0.76 percent on average. When using the ratio of LLPs to total assets as proxy for credit risk, the preferred model after eliminating the standard GARCH (1,1) is the TBL-GARCH (1,1,1) based on the significance of key terms and diagnostic tests. As a result, at 1 percent level of significance, credit risk is amplified by 3.53 percent and its omission may result in underestimating credit risk by 3.53 percent on average. When using the ratio of RWAs to total assets as proxy for credit risk, the diagnostic tests favour the BL-GARCH (1,1,1) model. However, the preferred model is the TBL-GARCH (1,1,1) since this model builds on BL-GARCH (1,1,1) and that the threshold term is significant and has a dampening effect on credit risk by 0.012 percent on average. Thus, choosing BL-GARCH (1,1,1) against TBL-GARCH (1,1,1) would overestimate credit risk by 0.012 percent on average. Clearly, accounting for the threshold GARCH term has an important implication in credit risk measurement. Appendices 3 and 4 summarise the results for the top-two banks and the bottom-two respectively.

Appendix 5 compares the volatility clustering of the ratio of non-performing loans to gross loans at three banking categories. For example, the volatility is highest in the bottom-two banks but moderate and stable in the top-two banks and the industry level, especially in the third quarter of 2013 and the firstquarter of 2014. This indicates that smaller banks had high non-performing loans during this period, implying unattractive credit books. Afterwards, the volatility remains stable at all levels as a result of tighter regulation from the Central Bank of Lesotho to curb unsecured lending as well as a noticeable improvement in credit risk management in the banks.

With respect to the volatility of the ratio of loan loss provisions to total assets, it can be observed from Fig. 1 that the volatility in the bottom-two banks remains relatively unbroken while it declines in line with the volatility of non-performing loans in the top-two banks. This is attributable to the fact that, in most cases, there is a strong positive correlation between movements in non-performing loans and provisions allocated for such losses. However, this correlation is not seen in the last quarter of 2013 and the first quarter of 2014. The expectation was to find corresponding spikes in the bottom-two banks. It was discovered from the data that one of the two banks underprovided for bad loans in this period, as a result, the volatility remains low. The purpose of loans loss provisions is to minimise the impact of loss resulting from non-performing loans, therefore, the observation explained above gives an indication that such a bank felt a significant impact of loss

Fig. 1: Volatility of the ratio of loan loss provisions to total assets



Source: Author

The results further indicate that the volatility of the ratio of risk-weighted assets to total assets is lowest at both the industry level and the top-two banks. However, for the bottom-two banks the volatility is high and shows some interesting spikes; especially in the first two quarters of 2014 (see Fig. 2). This observation may be a result of holding a portfolio of high-risk assets such as equities, commodities, high-yield bonds and currencies in pursuit of higher returns. Such returns, however, may be relatively unsustainable and achieved with products which, under a corona of "financial innovation", offer a very high return-risk ratio due to inappropriate valuation of risks and pricing. As with the non-performing loans and loan loss provisions, the volatility of risk-weighted assets has also droppedfrom2015.

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Table 5: Measurement of credit risk at the industry level

Model	NPLs			LLPs			RWAs		
	GARCH(1,1)	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*	*GARCH(1,1)*	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*	*GARCH(1,1)*	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*
ε^2_{t-1}	0.380* (0.000)	0.375* (0.000)	0.375* (0.000)	1.288* (0.000)	1.285* (0.000)	1.287* (0.000)	1.131* (0.000)	1.128* (0.000)	1.135* (0.000)
δ^2_{t-1}	0.500* (0.000)	0.506* (0.000)	0.506* (0.000)	0.001 (0.383)	0.003** (0.013)	0.001 (0.212)	0.006 (0.153)	0.011* (0.002)	0.012* (0.004)
$\delta_{t-1}\varepsilon_{t-1}$		2.295 (0.9380)	2.382* (0.000)		3.962* (0.000)	0.004 (0.993)		0.268* (0.000)	0.241* (0.001)
$D_t\varepsilon^2_{t-1}$			0.757* (0.002)			3.527* (0.001)			-0.012*** (0.059)
S.E. of regression	0.012	0.007	0.007	0.001	0.001	0.001	0.384	0.285	0.313
Akaike info criterion	-6.017	-7.031	-6.996	-11.700	-12.030	-12.084	0.977	0.410	0.622
Log likelihood	116.315	133.066	133.430	224.307	225.553	227.557	-16.068	-4.377	-7.195
Decision	*TBL-GARCH*			*TBL-GARCH*			*TBL-GARCH*		

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance

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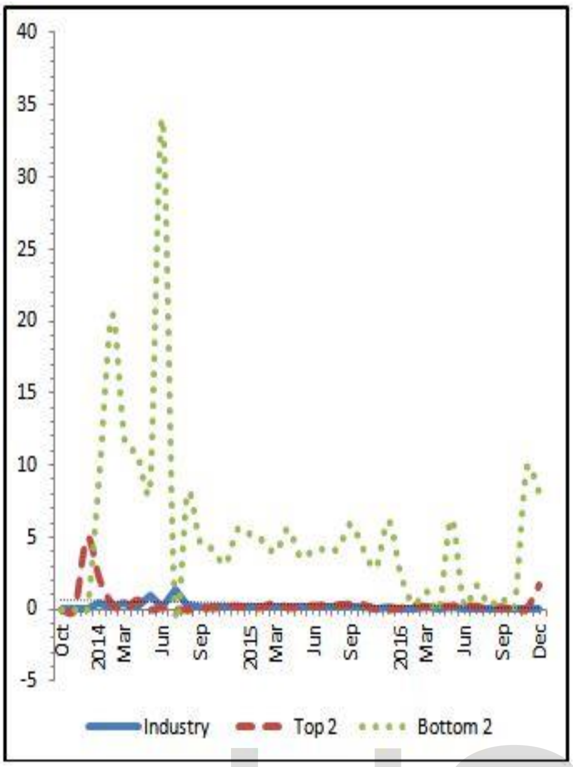
Fig. 2: Volatility of the ratio of risk-weigted asset



4.3 DETERMINANTS OF CREDIT RISK

4.3.1 Unit root tests

Appendix 6A summarises the results and shows that all credit risk indicators (dependent variables) are integrated of order zero. Appendix 6B displays all bank-specific and macroeconomic variables. All the variables are I(0) except size. To investigate the determinants of credit risk using traditional approach, the data series were tested for unit root using time series unit root tests namely; ADF, PP and KPSS. Appendix 10 provides the results.

4.3.2 Choice of appropriate model

The study further utilises a pair-wise correlation matrix to assess if the variables are plagued with multicollinearity. Appendix 8 provides the results and shows that interest rate, money supply, size and capital adequacy are the most strongly correlated variables. Moreover, it can also be observed from appendix 7 that as expected, there is a strong positive correlation between GDP and money supply (M2). Therefore, this justifies the usage of broad money as a proxy for economic growth.

4.3.3 Discussion of results

The results from SUR estimation are summarised in Appendix 9. The subsequent section discusses the results for each group of determinants, that is, macro and microeconomic variables. It is important to highlight that almost all studies in Appendix 1.2 have either used the ratio of NPLs to total loans or ratio of LLPs and RWAs to totals assets to study the determinants of credit risk. However, this study differs from the rest since it utilises all significant credit risk indicators to assess the drivers of this kind of risk. Therefore, should any of the determinant be significant under any indicator, they will indeed be deemed as influential.

4.3.3.1 Macroeconomic Effects

At the industry level, macroeconomic variables were found to be insignificant. However, at both the top-two banks (when the ratio of NPLs to gross loans is used) and bottom-two banks (when the ratio of RWAs to total assets is used), the results indicate that interest rates have a significant negative relationship with credit risk. This may perhaps nullify the perception that one of the reasons why loans do not perform is due to high interest rates. Moreover, based on this, it would be reasonable to infer that the interest rates in Lesotho are relatively low and thus create a platform for investment and growth, ceteris paribus. Likewise, economic growth (when the ratio of LLPs to total assets in Top-two and when both the ratio of LLPs and RWAs to total assets in Bottom-two banks are used), significantly reduces credit risk as anticipated. This validates the concept that sustained economic growth increases the ability to pay of borrowers, and thus reduces default risk. Das and Ghosh (2007), Aver (2008) and Garr (2013) amongst others, also found the same outcome.

4.3.3.2 Microeconomic Effects

At the industry level (when the ratio of NPLs to gross loans is used), credit growth and previous bad loans increase credit risk on average. This outcome supports Castro (2013) and BoruLelissa (2014). Credit growth, as has been indicated in preceding chapters, holds both the positive and detrimental effects to the economy. So, to thrive, both the regulator and the banking industry need to join forces to establish reasonable limits to minimise credit risk exposure. Profitability (when the ratio of RWAs to total assets is used) has a moderating effect on credit risk on average. This may imply that instead of extending more credit, the banks retain their earnings to pursue growth or increase their capital buffers. In either endeavour, this indicates that profitability in banks creates a riskless economic environment, which then attracts more borrowers. Furthermore, the results show that small as it is; the size of the banking industry in Lesotho has a significant moderating effect on credit risk on average.

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The findings are in line with Das and Ghosh (2007), Garr (2013) and Ameur (2016).

In the top-two banks (when the ratio of NPLs to gross loans is used), the results indicate that credit growth significantly reduces credit risk. The inference may be that these banks have a controlled appetite and operate within their specified credit extension ceilings. The previous credit books also reduce credit risk (when the ratio of NPLs to gross loans is used). Even though this outcome contradicts theory, it may possibly mean that the top-two banks sufficiently provide for bad loans so much that the impact of loss is insignificant. When the ratio of NPLs to gross loans is used, the results further conform to the theory that leverage increases credit risk. This may rationalise the need for bigger banks to revisit their leverage positions or perhaps the regulator should place a stricter limit on the relative level of debt that can be used to finance the banks' assets. It was evidenced from the 2007-2008 global financial crises that leverage ratios were not given enough attention because of the misconception that large banks are "too big to fail".

In the category of bottom-two banks, the results show that profitability reduces credit risk when both the ratio of LLPs to totals assets and ratio of NPLs to gross loans are used. However, it can be observed that management inefficiency significantly increases credit risk when the ratio of NPLs to gross loans is used. This outcome supports Ahmad and Ariff (2007) and therefore implies that there is a need to equip bank managers with more advanced credit risk management trainings and workshops. Moreover, the results indicate that credit growth (when RWA and NPLs are used) and previous bad loans (when NPLs are used) increase credit risk. Castro (2013) also found a positive relationship between credit risk and both variables. On the other hand, capital adequacy (when NPLs are used) and leverage (when RWAs are used) contradict the expectations.

4.4 DETERMINANTS OF CREDIT RISK USING THE TRADITIONAL APPROACH

The results in this section are provided in Table 6 below.

4.4.1 Macroeconomic effects

At the industry level, interest rates and inflation have no influence on credit risk. Economic growth, on one hand, has a negative relationship with credit risk as expected when using the ratio of NPLs to total loans and ratio of RWAs to total assets. This confirms the concept that sustained economic growth increases the ability to pay of borrowers, and thus reduces default risk. Das and Ghosh (2007), Aver (2008) and Garr (2013) amongst others, also found the same outcome.

At the top-two banks, interest rates have no impact on credit risk. Furthermore, and surprisingly so, economic growth increases credit risk when the ratio of RWAs to total assets is used. The results further indicate that inflation has a moderating effect on credit risk when the ratio of NPLs to gross loans is used. These results remain the same even in the bottom-two banks and contradict with both the literature and the findings of other studies like the above-mentioned. Interest rates in the bottom-two banks have a positive relationship with credit risk when the ratios of LLPs to total assets and RWAs to total assets are used. This confirms the theory but contradicts the general perception that interest rates in Lesotho are relatively stable.

4.4.2 Microeconomic effects

At the industry level, previous bad loans increase credit risk as expected. However, management inefficiency (when using the ratio of LLPs to total assets) increases credit risk. Does this imply that credit risk managers in these four banks are incompetent? Does it also mean the Central Bank of Lesotho is not doing its part as the regulator? The size of the industry when LLPs and RWAs are used also has an amplifying effect on credit risk. This contradicts general expectations and experience since the banking industry in Lesotho has not presented signs of vulnerability of credit risk in the past.

At the top-two banks, management efficiency reduces credit risk when the ratio of RWAs to total assets is used, and this meets the expectations. Previous bad loans (for all indicators) and credit growth (when RWAs are used) increase credit risk and therefore meet the expectations. However, the results indicate that size of the top-two banks increase credit risk when using ratio of LLPs to total assets. This opposes the philosophy that bigger banks are less susceptible to credit risk than smaller banks. One would also expect capital adequacy to play key in moderating credit risk, nonetheless, the results indicate otherwise when using the ratio of NPLs to total loans.

At the bottom-two banks, previous bad loans significantly increase credit risk as anticipated. Leverage also has a positive relationship with credit risk when the ratios of LLPs and RWAs to total assets are used. The two results are in line with the theory. However, management efficiency or inefficiency opposes the theory and common beliefs that management in the bottom-two banks is less proficient than the top-two banks' management when the ra-

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tio of NPLs to gross loans is utilised. Furthermore, credit growth also contradicts the theories and expectations when the ratios of NPLs to gross loans and RWAs to total assets are used.

4.5 CONCLUSION

This chapter aimed to address two main issues, namely; credit risk measurement and the determinants of credit risk. It was found under credit risk measurement that the TBL-GARCH (1,1,1) is superior than other volatility models tested and was thus decided to be the appropriate model for credit risk. This model brings valuable contribution as it shows by how much credit risk has been under/overestimated. On top of the fact that the study utilised the volatility approach to measure credit risk, it further used a combination of the most crucial credit risk indicators being the ratio of LLPs to total assets, the ratio of RWA to total assets and the ratio of NPLs to gross loans. This approach differs from those of other studies where credit risk was approximated by the relative measure of ratio of non-performing loans to total loans or loan loss provisions (see Appendix 1.2). For robustness checks, nonetheless, the study further analysed the determinants of credit risk using the same relative or traditional measures. It was found that most of the results contradict both the theory and findings from other studies, for example; economic growth and inflation in the top-two and bottom-two banks.

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Table 6: Summary of GLS regression results

Determinant	**Industry (traditional approach)**								
	A			*B*			*C*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	-0.004** (0.036)	-0.001 (0.670)	0.380 (0.723)	-0.064 (0.108)	0.007 (0.129)	7.718* (0.001)	0.022 (0.732)	0.007 (0.422)	14.961** (0.011)
INTRATE	-0.001 (0.179)	-0.004 (0.359)	-0.135 (0.211)						
MGT	0.007** (0.017)	0.001 (0.507)	1.324 (0.424)	0.004 (0.112)	0.003 (0.446)	0.600 (0.742)	0.005* (0.000)	0.002 (0.578)	-0.842 (0.621)
PFT	-0.018 (0.772)	-0.005 (0.159)	-0.542 (0.236)	-0.003 (0.560)	-0.006 (0.340)	-0.286 (0.349)	-0.041 (0.937)	-0.049 (0.327)	-0.639 (0.198)
CRED	0.164 (0.108)	0.006 (0.442)	0.115 (0.784)	0.014 (0.152)	0.012 (0.345)	0.359 (0.404)	0.016 (0.112)	0.007 (0.624)	0.267 (0.724)
LNPL	0.003 (0.201)	0.123** (0.029)	0.017* (0.001)	0.009 (0.496)	0.003** (0.034)	0.029* (0.000)	0.002* (0.004)	0.082 (0.185)	0.022* (0.002)
M2				-0.036 (0.463)	-0.001*** (0.094)	-0.922* (0.001)			
INF				0.026 (0.142)	0.017 (0.472)	0.002 (0.901)			
SIZE							0.047** (0.047)	-0.001 (0.394)	0.957** (0.019)
CAP									
LEV									
n	39	39	39	39	39	39	39	39	39
R^2	0.76	0.62	0.60	0.83	0.55	0.80	0.79	0.52	0.50
D-Watson	1.82	1.860	2.26	1.85	1.12	2.18	1.79	1.88	2.00
$X^2(2)$	16.864 (0.002)	252.79 (0.012)	105.909 (0.010)	23.665 (0.007)	190.609 (0.041)	43.250 (0.040)	15.44 (0.004)	249.93 (0.005)	101.26 (0.012)

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Determinant	Industry (traditional approach)					
	D			*E*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	*-0.031* (0.104)	*-0.003* (0.384)	*0.113* (0.886)	*-0.041**** (0.056)	*-0.002* (0.428)	*-0.003* (0.998)
INTRATE						
MGT	*0.043**** (0.085)	*0.004* (0.334)	*0.420* (0.685)	*0.057*** (0.044)	*0.004* (0.388)	*0.602* (0.689)
PFT	*-0.077* (0.885)	*-0.001* (0.325)	*-0.510* (0.169)	*0.036* (0.552)	*-0.003* (0.675)	*-0.174* (0.619)
CRED	*0.088* (0.309)	*0.009* (0.289)	*0.322* (0.626)	*0.012* (0.186)	*0.001* (0.562)	*0.120* (0.873)
LNPL	*0.027** (0.004)	*0.011**** (0.082)	*0.011** (0.009)	*0.031** (0.000)	*0.031**** (0.075)	*0.013** (0.008)
M2						
INF						
SIZE						
CAP	*-0.026* (0.119)	*-0.030* (0.249)	*-3.514* (0.103)			
LEV				*0.024* (0.152)	*0.004* (0.444)	*5.739* (0.203)
n	39	39	39	39	39	39
R^2	0.81	0.66	0.79	0.78	0.59	0.73
D-Watson	1.82	1.30	2.04	1.80	1.94	2.03
$X^2(2)$	14.58 (0.006)	206.38 (0.015)	138.46 (0.085)	14.178 (0.008)	223.301 (0.003)	149.127 (0.041)

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance

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Determinant	Top 2 Banks (traditional approach)								
	A			*B*			*C*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	*0.114* (0.799)	*-0.002* (0.728)	*1.789* (0.171)	*0.013* (0.423)	*-0.023* (0.123)	*-23.841*** (0.034)	*0.049* (0.261)	*-0.132*** (0.039)	*5.096* (0.625)
INTRATE	*-0.030* (0.300)	*0.007* (0.125)	*-0.024* (0.776)						
MGT	*0.039* (0.671)	*-0.035* (0.832)	*-2.441* (0.283)	*0.010* (0.396)	*0.031* (0.151)	*6.244* (0.160)	*-0.080* (0.991)	*-0.003* (0.800)	*-1.489* (0.287)
PFT	*-0.028* (0.175)	*-0.008* (0.206)	*0.184* (0.763)	*-0.025* (0.291)	*-0.005* (0.604)	*0.548* (0.545)	*-0.023* (0.359)	*-0.001* (0.728)	*-0.414* (0.429)
CRED	*-0.019* (0.713)	*-0.050* (0.566)	*1.939*** (0.037)	*-0.053* (0.915)	*0.004* (0.954)	*0.639* (0.687)	*0.019* (0.974)	*-0.041* (0.594)	*0.061* (0.947)
LNPL	*0.061*** (0.026)	*0.056**** (0.058)	*0.031** (0.063)	*0.062* (0.289)	*-0.098* (0.812)	*-0.054* (0.218)	*0.082**** (0.073)	*0.004* (0.435)	*0.024**** (0.061)
M2				*-0.023* (0.307)	*0.008* (0.735)	*2.271*** (0.049)			
INF				*-0.151* (0.301)	*-0.040*** (0.045)	*-0.084* (0.148)			
SIZE							*-0.032* (0.288)	*0.009** (0.044)	*-0.261* (0.705)
CAP									
LEV									
n	39	39	39	39	39	39	39	39	39
R^2	0.52	0.66	0.55	0.64	0.74	0.51	0.59	0.70	0.55
D-Watson	1.52	1.81	1.52	1.57	1.82	1.62	1.55	1.76	1.63
$X^2(2)$	108.471 (0.027)	711.94 (0.025)	224.95 (0.014)	108.976 (0.022)	709.449 (0.088)	255.05 (0.041)	122.268 (0.028)	740.983 (0.013)	268.818 (0.042)

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Determinant	Top 2 Banks (traditional approach)					
	D			*E*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	*0.034*	*-0.002*	*0.798*	*0.032*	*0.004*	*1.311*
	(0.339)	*(0.826)*	*(0.499)*	*(0.364)*	*(0.599)*	*(0.147)*
INTRATE						
MGT	*-0.038*	*0.004*	*-2.139*	*-0.041*	*-0.004*	*-2.443****
	(0.512)	*(0.798)*	*(0.183)*	*(0.484)*	*(0.767)*	*(0.051)*
PFT	*0.021*	*-0.003*	*-1.029*	*0.022*	*-0.004*	*-0.808*
	(0.190)	*(0.398)*	*(0.116)*	*(0.219)*	*(0.295)*	*(0.171)*
CRED	*-0.057*	*-0.010*	*0.948***	*0.063*	*-0.006*	*1.128***
	(0.832)	*(0.191)*	*(0.033)*	*(0.827)*	*(0.382)*	*(0.029)*
LNPL	*0.009**	*0.000**	*0.009*	*0.001**	*0.000**	*0.012*
	(0.008)	*(0.002)*	*(0.573)*	*(0.001)*	*(0.002)*	*(0.404)*
M2						
INF						
SIZE						
CAP	*-0.015*	*0.003*	*8.634***			
	(0.371)	*(0.912)*	*(0.044)*			
LEV				*-0.013*	*-0.007*	*5.757*
				(0.422)	*(0.772)*	*(0.167)*
n	*39*	*39*	*39*	*39*	*39*	*39*
R^2	*0.69*	*0.54*	*0.53*	*0.55*	*0.60*	*0.59*
D-Watson	*1.51*	*1.84*	*1.58*	*1.51*	*1.83*	*1.60*
$X^2(2)$	*141.155*	*776.152*	*267.748*	*141.738*	*784.69*	*265.847*
	(0.022)	*(0.028)*	*(0.072)*	*(0.066)*	*(0.040)*	*(0.018)*

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance

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Determinant	Bottom 2 Banks (traditional approach)								
	A			*B*			*C*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	*0.017*	*-0.354*	*29.222*	*-0.044*	*-4.580***	*78.389*	*0.046*	*-1.246*	*-191.472**
	(0.496)	*(0.289)*	*(0.114)*	*(0.349)*	*(0.015)*	*(0.202)*	*(0.908)*	*(0.344)*	*(0.002)*
INTRATE	*0.019***	*0.015*	*2.792**						
	(0.020)	*(0.267)*	*(0.002)*						
MGT	*0.032*	*0.202*	*-1.187*	*-0.017*	*-0.098*	*2.640*	*-0.017*	*-0.018*	*15.209*
	(0.191)	*(0.532)*	*(0.944)*	*(0.344)*	*(0.846)*	*(0.862)*	*(0.455)*	*(0.966)*	*(0.395)*
PFT	*-0.064*	*0.134*	*-4.456*	*-0.057*	*0.327*	*-7.814*	*-0.079*	*0.078*	*-5.209*
	(0.202)	*(0.349)*	*(0.706)*	*(0.104)*	*(0.156)*	*(0.502)*	*(0.105)*	*(0.695)*	*(0.705)*
CRED	*0.067*	*-0.977**	*-22.754****	*0.034*	*-0.700**	*20.071*	*0.086*	*-1.037**	*17.675*
	(0.554)	*(0.002)*	*(0.075)*	*(0.624)*	*(0.001)*	*(0.101)*	*(0.445)*	*(0.001)*	*(0.239)*
LNPL	*0.002***	*0.005**	*0.494**	*0.039***	*-0.007*	*0.488***	*0.004***	*0.004*	*0.640**
	(0.045)	*(0.003)*	*(0.007)*	*(0.034)*	*(0.174)*	*(0.013)*	*(0.011)*	*(0.171)*	*(0.002)*
M2				*0.069*	*0.534**	*-8.925*			
				(0.187)	*(0.008)*	*(0.201)*			
INF				*0.087*	*-0.014***	*-0.234*			
				(0.501)	*(0.032)*	*(0.316)*			
SIZE							*0.014*	*0.094*	*-15.314*
							(0.611)	*(0.345)*	*(0.115)*
CAP									
LEV									
n	*39*	*39*	*39*	*39*	*39*	*39*	*39*	*39*	*39*
R^2	*0.89*	*0.76*	*0.84*	*0.94*	*0.79*	*0.90*	*0.84*	*0.78*	*0.81*
D-Watson	*2.29*	*1.75*	*1.99*	*2.42*	*1.83*	*1.89*	*2.31*	*1.85*	*1.82*
$X^2(2)$	*24.872*	*109.572*	*16.737*	*21.339*	*35.442*	*22.196*	*17.605*	*74.063*	*14.639*
	(0.039)	*(0.016)*	*(0.023)*	*(0.031)*	*(0.020)*	*(0.015)*	*(0.016)*	*(0.082)*	*(0.066)*

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Determinant	Bottom 2 Banks (traditional approach)					
	D			*E*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	*0.022*	*-0.492****	*10.415*	*0.047*	*-0.154*	*-4.545*
	(0.244)	*(0.065)*	*(0.349)*	*(0.115)*	*(0.712)*	*(0.795)*
INTRATE						
MGT	*-0.024*	*-0.498****	*-3.810*	*-0.046*	*0.133*	*8.961*
	(0.249)	*(0.067)*	*(0.726)*	*(0.142)*	*(0.756)*	*(0.619)*
PFT	*-0.055*	*0.032*	*-12.157*	*-0.071*	*0.023*	*1.417*
	(0.106)	*(0.878)*	*(0.248)*	*(0.168)*	*(0.939)*	*(0.917)*
CRED	*0.073*	*-1.162**	*31.931*	*0.041*	*-1.292**	*20.335*
	(0.449)	*(0.002)*	*(0.243)*	*(0.736)*	*(0.002)*	*(0.160)*
LNPL	*0.003**	*0.006**	*0.341**	*0.033**	*0.006**	*0.364**
	(0.001)	*(0.001)*	*(0.001)*	*(0.002)*	*(0.001)*	*(0.000)*
M2						
INF						
SIZE						
CAP	*-0.038*	*-0.202*	*-54.816*			
	(0.102)	*(0.469)*	*(0.204)*			
LEV				*0.043****	*0.394*	*57.607**
				(0.017)	*(0.364)*	*(0.009)*
n	*39*	*39*	*39*	*39*	*39*	*39*
R^2	*0.94*	*0.79*	*0.84*	*0.86*	*0.61*	*0.75*
D-Watson	*2.29*	*1.96*	*2.22*	*2.29*	*2.04*	*1.95*
$X^2(2)$	*28.085*	*48.399*	*16.571*	*20.286*	*25.29*	*27.408*
	(0.079)	*(0.031)*	*(0.025)*	*(0.039)*	*(0.032)*	*(0.012)*

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance

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5. CONCLUSION AND RECOMMENDATIONS

5.1 KEY FINDINGS

The study used the volatility techniques to measure credit risk in the commercial banks of Lesotho. This came upon the realisation of the flaws of current measurement techniques coupled with the awareness that increasing credit expansion in Lesotho, even though it has significant economic growth benefits, also poses systemic risk if the borrowers fail to settle their obligations. The study thus used the TBL-GARCH (1,1,1) model based on both the model selection criteria and careful decision of the researcher to measure credit risk as an improvement. This model captures the dynamism of credit risk and accommodates the impact of threshold effects and asymmetric shifts resulting from either positive or negative shocks. The study further investigated the determinants of credit risk in Lesotho where the findings confirm with the literature. At the industry level, the results indicate that credit growth and previous bad loans increase credit risk while profitability has a moderating effect. At the top-two banks, interest rates, credit growth, previous bad loans and economic growth reduce credit risk. Furthermore, at the bottom-two banks, credit risk is reduced by the interest rates, profitability and economic growth. However, it is increased by management inefficiency, credit growth and previous non-performing loans.

The study further investigated the determinants of credit risk using the traditional approach as a way of robustness check against volatility approach. It was found that most of the variables are insignificant. On top of that, those that are significant contradict the theory and findings from other studies. These outcomes, therefore, track back to the missing puzzle which is dynamism of credit risk.

5.1 RECOMMENDATIONS

Having achieved its objectives, the study further suggests two important recommendations. The first recommendation goes to the regulator as part of macro-prudential regulation. Even though this will require effective change management processes, the study recommends the use of new approach to measure credit risk in the commercial banks of Lesotho, which is the volatility technique. This technique does not only capture the dynamism of different credit risk indicators - which the current measures omit - but it also considers the threshold effects emanating from economic upheavals which virtually every banking industry faces. In addition, the study suggests that more focus be put on the key drivers of non-performing loans since they significantly increase credit risk; perhaps the primary studies would be handy. Related to the issue of non-performing loans is the need for review of loan loss provision requirements as it has been observed that some banks under provide for these losses, and this invites undesirable consequences to their stability. The second recommendation is directed to the banks in their respective clusters. Credit risk at the top-two banks is significantly increased by leverage; as a result, this necessitates the formulation of strategies to reduce their leverage positions. The bottom-two banks need to do two things; first they need to consider management proficiency in issues relating to credit risk. An improvement in this regard can be to invest in advanced credit risk management trainings and workshops for existing resources as well as recruiting credit risk management specialists. This will not only inform better decision-making in credit risk management in banks, but it will also impact positively on the stability and continuity of the banking industry in Lesotho. Second, the study suggests that the bottom-two banks should revisit their credit growth ceilings as well as the management of non-performing loans as these factors may have detrimental effects on their business.

5.2 SUGGESTION FOR FUTURE RESEARCH

Even though it might be technically demanding, it would be appealing if this study is taken further to investigate the duration beyond which it could be said that credit risk is headed for a credit crunch. Furthermore, had it not been of the data challenges and the time frame for the thesis, the study could have incorporated political factors to assess their impact on credit risk. It would therefore be interesting for future research to consider this factor due to the idea that politics play a key role in economic activity and thus affect the ability of borrowers to repay the loans. It would also be interesting to see if there will be any significant changes in the results in general, if a wider data span is utilised.

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LIST OF APPENDICES

Appendix 1.1 A Pedagogical Note on the Anatomy of Risk and its Measurement

The measurement of risk has been a subject of several studies in the literature (Altman and Saunders, 1998; Berger and DeYoung, 1997; Motelle and Biekpe, 2014). According to Altman and Saunders (1998), there are at least four methodological approaches to developing a credit risk measurement technique: (a) the linear probability model, (b) the logit model, (c) the probit model, and (d) the discriminant analysis model. The literature on this subject can be divided into two strands. The first strand uses static measures of risk while the second strand uses dynamic measures. However, Altman and Saunders (1998) underline that while in many cases multivariate accounting-based credit risk models have been shown to perform quite well over many different time periods and across many different countries, they have been subjected to at least two criticisms. First, these models are predominantly based on book value accounting data measured at discrete intervals. Thus, these techniques fail to pick up subtle and fast-moving changes in borrower conditions, that is, those that would be reflected in capital market data. Second, the world is inherently non-linear, and this implies that linear discriminant analysis and the linear probability models may fail to forecast as accurately as those that relax the underlying assumption of linearity among explanatory variables.

Berger and DeYoung (1997) use a single-dimensional technique to approximate credit risk. The technique uses traditional measures of credit risk such as income statement indicators like non-performing loans. This approach was later followed by other studies (See Vodova, 2003; Castro, 2012). Other recent studies extend the idea further by using loan loss provisions and the risk weighted assets (see Appendix 1.2). On the one hand, these measures are static. On the other hand, risk is a dynamic concept and cannot be adequately measured using static measures such as simple ratios of constructed from specific bank income statement and/or balance sheet items. Such measures are unable to capture the inherent dynamism in risk. They view "default as a discrete event that takes place within a fixed time period rather than as a time-dependent process sensitive to changing conditions" (Glennon and Nigro, 2011). This implies that techniques that capture variability of balance sheet risk measures are more appropriate. For example, Delechat et al. (2009) use the coefficient of variation (CV) to capture this variability. Nevertheless, Motelle and Biekpe (2014) argue that static measures of variability such as the standard deviation and the coefficient of variation are still incapable of capturing risk dynamism. They recommend application of GARCH-based models to take care of this shortcoming. The omission of volatility, which is one of the fundamental aspects in credit risk measurement, presents a serious drawback to Berger and DeYoung (1997)'s technique of using single-dimension credit risk indicators to measure credit risk.

Although the GARCH models were initially commonly applied to measure volatility of asset returns, other recent studies have exploited their merits to measure volatility of other financial time series other than asset returns. For example, Jin et al (2011) empirically investigate and evaluate various approaches to estimate credit risk using a panel of European banking groups. All models, including the combined Merton/GARCH-MIDAS model and GARCH structural credit risk model were evaluated by comparing their ability to correctly and timely identify changes in credit risk indicators. Despite its hybrid nature, the Merton/GARCH-MIDAS model proved appropriate to measuring credit risk.

Besides credit risk measurement, some studies such as Kresta (2013) employed the GARCH-copula models to estimate currency risk. The author further indicates that it is possible to model other components of market risk namely; interest rate risk, equity risk and commodity risk using the similar technique. Moreover, Motelle and Biekpe (2015) analyse the financial integration and stability in the Southern African Development Community. The study used the BL-GARCH model to measure the risk of financial instability (See also Motelle and Biekpe, 2014).

Consequently, this study uses the GARCH model and its extensions to measure credit risk in Lesotho. In addition, the dynamic measure of credit risk is used as a dependent variable to assess the determinants of credit risk. According to Spuchlakova et al. (2015), volatility of credit risk indicators can be a result of both external and internal factors. The external factors have the biggest impact and are among others, the state of the economy, swings in exchange and interest rates, government policies, while the internal factors are deficiencies in loan policy etc.

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Appendix 1.2 Measurement of Credit Risk

	Description	Formula	Purpose	Source
1	Ratio of Non-performing loans to Total loans	$\frac{NPLs}{Total\ Loans}$	Measures the risk emanating from credit defaults or the inability to repay the loan.	Berger and DeYoung (1997), Vodová (2003), Ahmad and Ariff (2007), Al-Smadi and Ahmed (2009), Castro (2012), Andriani and Wiryono (2015), Adu and Adjare (2015), Ameur (2016)
2	Non- performing loans	$\left(\frac{\mathrm{NPL}it}{1-\mathrm{NPL}it}\right)$	Measures growth in problematic loans. The ratio of problem loans of one period is closely related to that of the previous period.	Das and Ghosh (2007)
3	Loans given to the non-banking sector/gross loans to the non-banking sector	$\frac{NBs\ Loans}{Total\ NBs\ Loans}$		Aver (2008)
4	Ratio of risk-weighted assets to total assets	$\frac{Risk\ weighted\ assets}{Total\ assets}$	Determines the minimum amount of capital that must be held by banks and other institutions to reduce the risk of insolvency	Boujelbène and Zribi (2011)
5	Probability of default	$\pi(x)=\frac{e^{B_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}}$	Provides an estimate of the likelihood that a borrower will be unable to meet its debt obligations.	Jonathan (2012)
6	Ratio of loan loss provision to total assets	$\frac{Loan\ loss\ provision}{Total\ assets}$	An expense set aside as an allowance for uncollected loans and loan payments.	Amhed et al. (1998),Garr (2013), BoruLelissa (2014), Tehulu and Olana (2014) Fisher, Gueyie and Ortiz (2002) Garr (2013)
7	Ratio of net Interest income to total assets	$\frac{Net\ interest\ income}{Total\ assets}$	Measures how much interest income the bank earns from its assets.	
8	Value at Risk	Various methods. It estimates how much a certain portfolio can lose within a certain period at a given confidence level.		Holton (2002),
9	Stress testing	Various approaches. It determines whether a bank has enough capital to withstand the impact of adverse economic developments.		Schuermann and Wyman (2012)

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Appendix 2: Determinants of Credit Risk

Determinant	Macroeconomic	Microeconomic	Nature of relationship	Source
GDP	✓		–	Das and Ghosh (2007), Aver (2008), Boujelbène and Zribi (2011), Castro (2012), Garr (2013), BoruLelissa (2014), Ameur (2016) and others
Inflation	✓		+	
Unemployment	✓		+	
Interest rate	✓		+	
Bank size		✓	–	Das and Ghosh (2007), Garr (2013), BoruLelissa (2014), Tehulu and Olana (2014), Adu and Adjare (2015), Ameur (2016
Leverage		✓	+	Adu and Adjare (2015)
Management efficiency		✓	–	Ahmad and Ariff (2007), Das and Ghosh (2007), Tehulu and Olana (2014), and others
Profitability		✓	+	Boujelbène and Zribi (2011), Tehulu and Olana (2014), Andriani and Wiryono (2015)
Capital adequacy		✓	–	Ahmad and Ariff (2007), Tehulu and Olana (2014), Andriani and Wiryono (2015), Ameur (2016
Credit growth		✓	+	Castro (2013), BoruLelissa (2014), Tehulu and Olana (2014), Andriani and Wiryono (2015),

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Appendix 3: Measurement of Credit Risk in the Top 2 Banks

Model	NPLs			LLPs			RWAs		
	GARCH(1,1)	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*	*GARCH(1,1)*	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*	*GARCH(1,1)*	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*
ε^2_{t-1}	0.855* (0.000)	0.859* (0.000)	0.976* (0.000)	0.303* (0.000)	0.296* (0.000)	0.309* (0.000)	0.340* (0.000)	0.338* (0.000)	0.334* (0.000)
δ^2_{t-1}	-0.057 (0.135)	-0.047*** (0.078)	-0.073*** (0.074)	0.627* (0.000)	0.640* (0.000)	0.646* (0.000)	0.624* (0.000)	0.643* (0.000)	0.643* (0.000)
$\delta_{t-1}\varepsilon_{t-1}$		1.471* (0.000)	0.573 (0.149)		7.325* (0.000)	7.454* (0.000)		0.369* (0.000)	0.395* (0.000)
$D_t\varepsilon^2_{t-1}$			-0.110** (0.049)			-0.028 (0.326)			0.018*** (0.059)
S.E. of regression	0.062	0.043	0.059	0.001	0.001	0.001	0.425	0.228	0.234
Akaike info criterion	-2.666	-3.366	-2.732	-10.839	-11.312	-11.276	1.176	-0.041	0.032
Log likelihood	52.648	65.267	53.172	207.943	212.270	212.608	-20.338	3.763	3.413
Decision	*TBL-GARCH*			*BL-GARCH*			*TBL-GARCH*		

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance.

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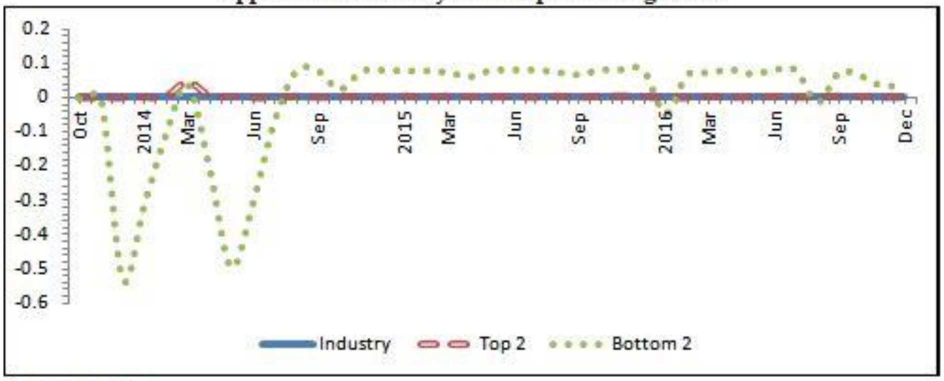
Appendix 4: Measurement of Credit Risk in the Bottom 2 Banks

Model	NPLs			LLPs			RWAs		
	GARCH(1,1)	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*	*GARCH(1,1)*	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*	*GARCH(1,1)*	*BL-GARCH(1,1,1)*	*TBL-GARCH(1,1,1)*
$\varepsilon^2{}_{t-1}$	*1.492* (0.000)*	*1.492* (0.000)*	*1.492* (0.000)*	*1.494* (0.000)*	*1.494* (0.000)*	*1.493* (0.000)*	*0.889* (0.000)*	*1.492* (0.000)*	*0.913* (0.000)*
$\delta^2{}_{t-1}$	*-0.033* (0.000)*	*-0.033* (0.000)*	*-0.033* (0.000)*	*0.032* (0.000)*	*0.032* (0.000)*	*0.032* (0.000)*	*-0.012 (0.363)*	*-0.033* (0.000)*	*-0.013 (0.2825)*
$\delta_{t-1}\varepsilon_{t-1}$		*0.373** (0.011)*	*0.338** (0.016)*		*0.000 (0.610)*	*1.274** (0.020)*		*0.373* (0.011)*	*0.121* (0.004)*
$D_t\varepsilon^2{}_{t-1}$			*0.163** (0.037)*			*0.003** (0.036)*			*-0.026** (0.019)*
S.E. of regression	*0.077*	*0.072*	*0.068*	*0.000*	*0.000*	*0.000*	*2.264*	*0.072*	*1.904*
Akaike info criterion	*-2.233*	*-2.346*	*-2.426*	*-15.650*	*-15.604*	*-15.863*	*4.523*	*-2.346*	*4.228*
Log likelihood	*44.427*	*46.392*	*48.877*	*291.526*	*291.669*	*289.526*	*-83.943*	*46.392*	*-74.211*
Decision	***TBL-GARCH***			***TBL-GARCH***			***TBL-GARCH***		

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance.

Appendix 5: Volatility of Non-performing Loans



Source: Author

Appendix 6A: Unit Root Results for Credit Risk

Indicator	Industry	Top 2 Banks	Bottom 2 Banks
	TBL- GARCH	*TBL-GARCH*	*TBL-GARCH*
Ratio of loan loss provisions to total assets	*-5.014** *(0.001)*	*-2.785*** *(0.011)*	*-6.283** *(0.000)*
Ratio of non-performing loans to gross loans	*-3.400**** *(0.066)*	*-5.685** *(0.000)*	*-3.618*** *(0.042)*
Ratio of Risk-weighted assets to total assets	*-6.401** *(0.000)*	*-4.558** *(0.004)*	*-5.588** *(0.000)*
Decision	***I(0)***	***I(0)***	***I(0)***

Source: Own computation.

The order to integration was decided using ADF test. P-values are in parentheses and (*), (**) and (***) indicate 1%, 5% and 10% significance level.

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Appendix 6B: Unit root test results

Variable	LLC		IPS		ADF-GLS		Decision
	Levels	1st diff	Levels	1st diff	Levels	1st diff	
Size	-0.754* (0.000)		-1.211 (0.642)	-4.908* (0.000)	9.705 (0.138)	57.601* (0.000)	I(1)
Leverage	-0.879* (0.000)		-3.324** (0.020)				I(0)
Mgt-efficiency	-1.295* (0.000)		-1.515 (0.523)	-6.793* (0.000)	13.180* (0.040)		I(0)
Profitability	-0.274* (0.000)		-5.234* (0.000)				I(0)
Capital adequacy	-0.784* (0.000)		-2.072 (0.225)	-4.127* (0.000)	19.556* (0.003)		I(0)
Credit growth	-1.362* (0.000)		-5.281* (0.000)				I(0)
Previous Npls	-0.986* (0.000)		-3.374* (0.000)				I(0)
Interest rate	-0.766* (0.000)		-2.576* (0.023)				I(0)
Inflation	-0.675* (0.000)		-2.437* (0.041)				I(0)
M2	-0.689 (0.000)		-4.408 (0.000)				I(0)

Source: Own computation.

(*) and (**) indicate rejection of the null hypothesis of non-stationarity at 1% and 5% level of significance respectively. Figures in parentheses are probability values.

Appendix 7: Correlation results between GDP & M2

	GDP	M2
GDP	1.000000	0.874214
M2	0.874214	1.000000

Source: Own computation.

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Appendix 8: Correlation Analysis

	INTRATE	INFLN	M2	SIZE	LEV	MGT	PFT	CAP	CRED	LNPL
	INDUSTRY									
INTRATE	1.000									
INFLN	0.484	1.000								
M2	0.820	0.084	1.000							
SIZE	0.818	0.257	0.874	1.000						
LEV	0.857	0.422	0.574	0.567	1.000					
MGT	0.389	0.573	0.279	0.277	0.250	1.000				
PFT	-0.064	-0.049	-0.215	-0.288	0.127	-0.298	1.000			
CAP	0.918	0.566	0.626	0.722	0.867	0.314	-0.067	1.000		
CRED	-0.228	0.180	-0.337	-0.398	-0.103	-0.080	0.001	-0.175	1.000	
LNPL	0.246	-0.027	0.440	0.410	0.119	0.114	-0.206	0.114	0.074	1.000
	TOP-TWO BANKS									
INTRATE	1.000									
INFLN	0.483	1.000								
M2	0.820	0.084	1.000							
SIZET	0.685	0.248	0.764	1.000						
LEVT	0.822	0.154	0.679	0.336	1.000					
MGTT	0.370	0.669	0.273	0.283	0.019	1.000				
PFTT	-0.035	-0.089	-0.128	-0.329	0.131	-0.182	1.000			
CAPT	0.763	0.109	0.607	0.226	0.991	-0.033	0.158	1.000		
CREDT	0.118	0.065	0.100	-0.072	0.239	0.047	0.129	0.253	1.000	
LNPLT	0.248	-0.025	0.443	0.415	0.127	0.228	-0.202	0.078	0.044	1.000
	BOTTOM-TWO BANKS									
INTRATE	1.000									
INFLN	0.483	1.000								
M2	0.820	0.084	1.000							
SIZE	0.884	0.188	0.869	1.000						
LEV	0.759	0.506	0.441	0.565	1.000					
MGT	0.017	-0.132	0.003	0.075	-0.032	1.000				
PFT	-0.078	0.048	-0.280	-0.144	0.160	-0.373	1.000			
CAP	0.855	0.628	0.558	0.562	0.780	-0.011	-0.041	1.000		
CRED	-0.302	0.166	-0.421	-0.399	-0.135	-0.097	0.276	-0.224	1.000	
LNPL	0.244	-0.028	0.439	0.275	0.099	-0.144	-0.134	0.112	0.060	1.000

Source: Own computation.

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Appendix 9: Determinants of Credit Risk

Determinant	Industry								
	A			*B*			*C*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	-22.552 (0.707)	-89.789** (0.0158)	39.542 (0.392)	-39.365 (0.557)	-88.366** (0.027)	121.92* (0.004)	-42.227 (0.608)	-73.638 (0.123)	184.612* (0.001)
INTRATE	4.633 (0.313)	-0.107 (0.950)	-2.892 (0.199)						
MGT	33.566 (0.152)	-7.964 (0.560)	-25.342 (0.159)	16.920 (0.450)	-7.619 (0.551)	-1.514 (0.907)	18.571 (0.404)	-6.879 (0.585)	-9.736 (0.479)
PFT	-2.423 (0.669)	-5.053 (0.137)	-7.039 (0.112)	-4.333 (0.466)	-4.436 (0.196)	-1.635 (0.636)	-4.589 (0.421)	-5.060 (0.124)	-6.168*** (0.086)
CRED	-6.854 (0.398)	14.345* (0.005)	5.252 (0.398)	-2.037 (0.798)	13.849* (0.005)	-3.032 (0.516)	-1.926 (0.807)	13.855* (0.004)	-1.011 (0.836)
LNPL	-1.517 (0.754)	6.758** (0.024)	-1.610 (0.665)	-1.410 (0.780)	6.079** (0.042)	-0.539 (0.854)	-0.466 (0.929)	7.231** (0.020)	1.938 (0.549)
M2				3.189 (0.463)	0.771 (0.756)	-12.694* (0.000)			
INF				0.430 (0.462)	0.286 (0.393)	0.217 (0.523)			
SIZE							1.230 (0.813)	-1.541 (0.603)	-13.565* (0.000)
CAP									
LEV									
n	36	36	36	36	36	36	36	36	36
R^2	0.12	0.28	0.16	0.08	0.30	0.49	0.06	0.29	0.41

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Determinant	**Industry**					
	D			*E*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	-10.252 (0.866)	-91.152** (0.016)	41.086 (0.393)	-17.478 (0.773)	-87.087** (0.019)	37.423 (0.425)
INTRATE						
MGT	35.905 (0.136)	-8.957 (0.523)	-18.772 (0.316)	24.769 (0.266)	-6.549 (0.606)	-19.098 (0.256)
PFT	-2.936 (0.600)	-5.137 (0.126)	-5.904 (0.186)	-5.317 (0.340)	-5.146 (0.119)	-5.295 (0.219)
CRED	-5.339 (0.494)	14.485* (0.003)	2.816 (0.644)	-3.989 (0.603)	13.866* (0.004)	3.310 (0.575)
LNPL	-2.599 (0.605)	6.925** (0.025)	-2.152 (0.585)	-1.300 (0.789)	6.462** (0.029)	-1.854 (0.620)
M2						
INF						
SIZE						
CAP	76.084 (0.116)		-10.977 (0.768)			
LEV				64.769 (0.143)	13.733 (0.590)	-34.766 (0.302)
n	36	36	36	36	36	36
R^2	0.12	0.28	0.12	0.11	0.29	0.14

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance

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Determinant	**Top-two banks**								
	A			*B*			*C*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	-1.339 (0.978)	112.78** (0.030)	-21.112 (0.641)	63.495*** (0.089)	-0.858 (0.983)	-4.580 (0.897)	118.361** (0.036)	20.816 (0.745)	-12.759 (0.816)
INTRATE	0.529 (0.818)	-5.196** (0.031)	0.425 (0.845)						
MGT	-4.600 (0.606)	-2.974 (0.742)	-13.532 (0.116)	-3.759 (0.654)	-2.803 (0.767)	-12.150 (0.144)	-3.060 (0.717)	-2.227 (0.816)	-13.160 (0.131)
PFT	-0.965 (0.755)	-1.108 (0.723)	-2.060 (0.483)	0.587 (0.845)	2.314 (0.496)	-3.356 (0.257)	-2.852 (0.347)	2.958 (0.388)	-2.302 (0.452)
CRED	5.736 (0.396)	-20.504* (0.005)	7.959 (0.217)	-1.487 (0.789)	-23.597* (0.001)	1.801 (0.740)	-4.411 (0.428)	-23.064* (0.001)	3.416 (0.543)
LNPL	-0.803 (0.838)	-9.480** (0.023)	2.332 (0.532)	-0.735 (0.813)	-0.648 (0.857)	-3.787 (0.218)	1.165 (0.740)	-0.251 (0.950)	-2.438 (0.496)
M2				-7.251** (0.041)	0.450 (0.907)	6.351 (0.165)			
INF				0.339 (0.451)	-0.531 (0.298)	0.378 (0.390)			
SIZE							-9.280 (0.043)	-1.474 (0.769)	3.222 (0.474)
CAP									
LEV									
n	36	36	36	36	36	36	36	36	36
R^2	0.08	0.37	0.13	0.19	0.31	0.19	0.17	0.29	0.10

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Determinant	Top-two banks					
	D			*E*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	*30.926*	*-0.391*	*16.425*	*31.398*	*-3.582*	*15.062*
	(0.388)	*(0.991)*	*(0.631)*	*(0.383)*	*(0.920)*	*(0.660)*
INTRATE						
MGT	*-3.557*	*-2.378*	*-12.999*	*-3.550*	*-2.419*	*-13.016*
	(0.690)	*(0.787)*	*(0.136)*	*(0.691)*	*(0.785)*	*(0.134)*
PFT	*-0.946*	*2.301*	*-3.118*	*-0.966*	*2.273*	*-3.176*
	(0.759)	*(0.452)*	*(0.297)*	*(0.755)*	*(0.460)*	*(0.287)*
CRED	*-1.177*	*-34.3**	*0.403*	*-1.565*	*-33.886**	*-0.103*
	(0.873)	*(0.000)*	*(0.955)*	*(0.832*	*(0.000)*	*(0.988)*
LNPL	*-3.474*	*-0.376*	*-0.728*	*-3.512*	*-0.114*	*-0.616*
	(0.241)	*(0.897)*	*(0.796)*	*(0.239)*	*(0.969)*	*(0.827)*
M2						
INF						
SIZE						
CAP	*-36.947*	*158.026***	*39.190*			
	(0.557)	*(0.015)*	*(0.517)*			
LEV				*-33.857*	*163.518***	*49.670*
				(0.620)	*(0.021)*	*(0.448)*
n	*36*	*36*	*36*	*36*	*36*	*36*
R^2	*0.07*	*0.39*	*0.10*	*0.07*	*0.38*	*0.11*

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance

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Determinant	Bottom-two banks								
	A			*B*			*C*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	*-24.748*	*-31.428**	*45.753*	*-86.349****	*1.087*	*113.17****	*-33.661*	*3.223*	*45.874*
	(0.577)	*(0.001)*	*(0.318)*	*(0.083)*	*(0.783)*	*(0.052)*	*(0.466)*	*(0.356)*	*(0.396)*
INTRATE	*2.149*	*0.552*	*-7.284**						
	(0.311)	*(0.172)*	*(0.002)*						
MGT	*3.805*	*4.892*	*-14.447*	*-7.050*	*0.874*	*8.685*	*-2.229*	*1.096*	*1.816*
	(0.733)	*(0.026)*	*(0.212)*	*(0.474)*	*(0.278)*	*(0.448)*	*(0.828)*	*(0.164)*	*(0.880)*
PFT	*-7.723*	*-0.600*	*-3.709*	*-11.331***	*0.356*	*3.101*	*-9.589****	*0.500*	*1.456*
	(0.168)	*(0.565)*	*(0.514)*	*(0.034)*	*(0.398)*	*(0.605)*	*(0.081)*	*(0.221)*	*(0.817)*
CRED	*0.740*	*-0.597*	*5.694****	*5.177*	*0.452****	*-1.542*	*2.620*	*0.281*	*1.772*
	(0.168)	*(0.323)*	*(0.088)*	*(0.105)*	*(0.084)*	*(0.672)*	*(0.403)*	*(0.237)*	*(0.629)*
LNPL	*0.213*	*1.981**	*-2.540*	*0.809*	*-0.197*	*-3.553*	*1.399*	*-0.347*	*-3.808*
	(0.952)	*(0.006)*	*(0.488)*	*(0.812)*	*(0.479)*	*(0.371)*	*(0.706)*	*(0.219)*	*(0.383)*
M2				*-7.051***	*0.054*	*-8.397***			
				(0.022)	*(0.822)*	*(0.019)*			
INF				*-0.214*	*-0.031*	*-0.019*			
				(0.580)	*(0.335)*	*(0.966)*			
SIZE							*3.997*	*-0.465*	*-0.045*
							(0.429)	*(0.226)*	*(0.994)*
CAP									
LEV									
n	*36*	*36*	*36*	*36*	*36*	*36*	*36*	*36*	*36*
R^2	*0.13*	*0.56*	*0.32*	*0.23*	*0.31*	*0.23*	*0.12*	*0.32*	*0.10*

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Determinant	Bottom-two banks					
	D			*E*		
	LLPs	*NPLs*	*RWAs*	*LLPs*	*NPLs*	*RWAs*
Constant	*-19.578*	*3.539*	*43.949*	*-7.673*	*1.485*	*7.123*
	(0.666)	*(0.276)*	*(0.410)*	*(0.867)*	*(0.676)*	*(0.886)*
INTRATE						
MGT	*3.181*	*2.042***	*0.332*	*-2.449*	*1.012*	*5.103*
	(0.790)	*(0.021)*	*(0.981)*	*(0.808)*	*(0.201)*	*(0.640)*
PFT	*-8.088*	*-0.763****	*1.044*	*-11.749***	*0.563*	*7.114*
	(0.157)	*(0.063)*	*(0.874)*	*(0.043)*	*(0.201)*	*(0.245)*
CRED	*1.147*	*0.254*	*1.931*	*1.691*	*0.374*	*2.242*
	(0.632)	*(0.247)*	*(0.590)*	*(0.566)*	*(0.109)*	*(0.483)*
LNPL	*-0.155*	*-0.446*	*-3.538*	*-0.796*	*-0.197*	*-0.674*
	(0.967)	*(0.100)*	*(0.420)*	*(0.828)*	*(0.493)*	*(0.865)*
M2						
INF						
SIZE						
CAP	*13.002*	*3.397***	*-4.583*			
	(0.503)	*(0.018)*	*(0.840)*			
LEV				*16.712*	*-0.687*	*-37.816***
				(0.196)	*(0.489)*	*(0.010)*
n	*36*	*36*	*36*	*36*	*36*	*36*
R^2	*0.11*	*0.39*	*0.10*	*14*	*0.30*	*0.26*

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance

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Appendix 10: Unit root test results

Variable	Cluster	ADF		PP		KPSS	Decision
		Levels	*1st Difference*	*Levels*	*1st Difference*	*Levels*	
NPLs	*Industry*	-3.435* (0.002)		-3.064* (0.004)			I(0)
	Top 2	-3.116* (0.004)		-2.431** (0.030)			I(0)
	Bottom 2	-3.093* (0.004)		-3.214* (0.003)			I(0)
LLPs	*Industry*	-1.882*** (0.068)		-1.737*** (0.097)			I(0)
	Top 2	-2.953* (0.006)		-2.977* (0.004)			I(0)
	Bottom 2	-1.883*** (0.068)		-1.586 (0.141)	-4.803* (0.000)	0.063* (0.000)	I(0)
RWAs	*Industry*	-1.429 (0.162)	-4.570* (0.000)	-1.608 (0.102)	-6.985* (0.000)		I(1)
	Top 2	-2.251** (0.031)		-2.358** (0.036)			I(0)
	Bottom 2	-2.035** (0.050)		-2.009*** (0.053)			I(0)
Size	*Industry*	0.946 (0.905)	-7.449* (0.000)	-1.168 (0.222)	-7.635* (0.000)		I(1)
	Top 2	-0.478 (0.814)	-7.106* (0.000)	-1.390 (0.153)	-6.733* (0.000)		I(1)
	Bottom 2	2.416 (0.995)	-5.678* (0.000)	0.982 (0.914)	-5.291* (0.000)		I(1)
Lev	*Industry*						I(1)
		0.401	-7.229*	-1.447	-7.281*		
	Top 2	(0.795)	(0.000)	(0.138)	(0.000)		I(1)
		1.099	-7.265*	0.323	-5.833*		
	Bottom 2	(0.926)	(0.000)	(0.569)	(0.000)		I(1)
		-1.193	-7.420*	-2.154	-6.538*		
		(0.609)	(0.000)	(0.130)	(0.000)		
Mgt	*Industry*	0.266 (0.764)	-9.007* (0.000)	-3.700* (0.000)	-8.993* (0.000)	2.014*** (0.091)	I(0)

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	Top 2	0.441 (0.805)	-6.204* (0.000)	-2.018*** (0.042)	-6.129* (0.000)	0.177** (0.032)	I(0)
	Bottom 2	-0.228 (0.604)	-9.318* (0.000)	-4.463* (0.000)	-9.279* (0.000)	1.212* (0.034)	I(0)
Cap	*Industry*	0.505 (0.820)	-6.113* (0.000)	-0.866 (0.341)	-6.161* (0.000)		I(1)
	Top 2	0.949 (0.906)	-7.277* (0.000)	-0.574 (0.469)	-7.277* (0.000)		I(1)
	Bottom 2	0.013 (0.681)	-5.455* (0.000)	-1.145 (0.230)	-5.399* (0.000)		I(1)
Cred	*Industry*	-3.324* (0.001)	-8.010* (0.000)	-4.095* (0.000)	-6.873* (0.000)	0.129*** (0.085)	I(0)
	Top 2	-6.658* (0.000)	-11.134* (0.000)	-7.229* (0.000)	-7.277* (0.000)	0.122*** (0.067)	I(0)
	Bottom 2	-3.118* (0.003)	-8.709* (0.000)	-3.696* (0.000)	-8.709* (0.000)	0.165** (0.040)	I(0)
Lnpl	*Industry*	0.019 (0.683)	-7.814* (0.000)	-1.588 (0.1057)	-1.659*** (0.091)		I(1)
	Top 2	-0.022 (0.684)	-7.769* (0.000)	-1.586 (0.106)	-1.659*** (0.092)		I(1)
	Bottom 2	0.019 (0.683)	-7.944* (0.000)	-1.588 (0.106)	-1.659*** (0.092)		I(1)
Intrate		2.688 (0.998)	-2.550** (0.010)	0.668 (0.861)	-3.092* (0.002)		I(1)
M2		1.915 (0.985)	-6.292* (0.000)	-0.347 (0.560)	-6.898* (0.000)		I(1)
Infln		-0.632 (0.444)	-2.745* (0.006)	-1.982** (0.046)	-6.898* (0.000)	0.416* (0.074)	I(0)

Source: Own computation

Figures in parentheses are the probability values where (*), (**) and (***) denote 1, 5 and 10 percent level of statistical significance. NPLs are the ratio of non-performing loans to gross loans, LLPs are the ratio of loan loss provisions to total assets and RWAs are the ratio of risk-weighted assets to total assets