Micro and Macro Drivers of Credit Risk: The Case of Zimbabwean Banking Industry (2009-2013)

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3.0 MICRO AND MACRO DRIVERS OF CREDIT RISK: THE CASE OF ZIMBABWEAN BANKING INDUSTRY (2009-2013)[9]

Katuka Blessing[10] and Dzingirai Canicio[11]

Abstract

There was troublesome development in non-performing loans since the inception of multiple-currency regime in Zimbabwe. The study investigated determinants of non-performing loans in Zimbabwe using a panel of eight (8) banks. Using decomposed monthly data from 2009 to 2013, a combination of static and dynamic panel regression models were applied. Findings revealed that non-performing loans are influenced by microeconomic, macroeconomic and political factors. Results supported quiet life hypothesis. Based on this hypothesis, we identified that interest rates had strong positive nexus with non-performing loans and that they create a platform that threatens realization of the financial inclusion objective in Zimbabwe due to recurring cycles in Non-performing loans (NPLs).Interestingly both dynamic models managed to capture influence of Government of National Unity (GNU) on NPLs in Zimbabwe. We found negative association between GNU and NPLs and results were in line with our expectations. Negative connection means that GNU had a potential to reduce non-performing loans in banks. Capital adequacy and loan-to-deposit variables have significant influence on credit risk, although the Loan-to-deposits ratio (LTD) variable was only significant in two static models. Macroeconomic factors have influence on non-performing loans and they include unemployment rate, inflations rate and real GDP growth rate. According to study results, real GDP growth rate is significant in dynamic models only. Ability of dynamic models to detect GNU and real GDP growth rate undoubtedly proved how robust and superior dynamic models are over static models. Overall, we found systematic risk to be the major driver of credit risk than idiosyncratic risk. To promote financial inclusion in Zimbabwe, we recommended that banks should review interest rates downwards to levels between 5.78 - 8.1% to reduce borrower default rate by between 20-50%, update credit policies periodically to detect changes in customers' characteristics as well as improving capital adequate ratios which will discourage moral hazard in banks. There is need for banks to shift their credit culture to values driven culture. Current profit and market share driven credit cultures compromises banks' assets quality in the long-run.

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[9]This paper is a revised form of "The Impact of Public External Debt on GDP per capita Growth in the East African Community (EAC) Member countries" presented at the Inaugural Macroeconomic and Financial Management Institute of Eastern and Southern Africa (MEFMI) Research and Policy Seminar, 10 December 2015, Harare, Zimbabwe. The authors gratefully acknowledge the reviewers comments and suggestions, which significantly contributed to improving the quality of this manuscript.

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The views as expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the Bank of Uganda.

[11]The MDRI allows for 100 percent relief on eligible debts by three multilateral institutions—the IMF, the World Bank, and the African Development Fund (AfDF)—for countries completing the HIPC Initiative process.

The Treaty establishing the EAC was signed on 30th November 1999.

3.1 INTRODUCTION

3.1.1 Background of the study

Financial institutions such as banks play linchpin role in an economy[12]. Banks' credit risk profile is therefore a policy concern considering how excessive exposure to credit risk can affect the whole financial system and the economy at large. The 2007-2008 financial crises proved how fast excessive exposure to credit risk can weaken the banking industry as well as the economy. More often, banks are reportedly to have failed as a result of excessive exposure to credit risk through high levels of non-performing assets[13]. Nyamutowa and Masunda (2013) identified that credit risk is among leading risks in commercial banks operating in Zimbabwe. Banks' credit risk profile determines the degree of pollution on bank balance sheet through bad loans and advances on the assets side. High credit risk brings dire outcomes not only to banks but also its customers and other stakeholders as well by exacerbated systemic financial fragility and spill over effects through its contagion effect as well as systemic risk (Panageas, 2010; Acharya et al., 2011; Aiyar, 2012; De Haas et al., 2012; Acharya et al., 2014; Acharya et al., 2015).

Excessive exposure to credit risk led to episodes of bank failures in Zimbabwe both post and prior to adoption of the multi-currency regime and this disrupted financial intermediation as well as the overall development process of the economy[14]. Reserve Bank of Zimbabwe (RBZ) (2015) indicated that the impact of NPLs are, *inter alia*, decline in financial intermediation, erosion of bank assets and capital base, resulting to liquidity challenges and adoption of cautious behaviour, as confidence in financial system declines and all these outcomes negatively impact on financial inclusion in Zimbabwe. It is argued that financial inclusion has an impact on reduction of poverty and income inequality (Burgess and Pande, 2005; Brune et al., 2011; Allen et al., 2013). Credit crunch has a potential to rise as banks with high NPLs become reluctant to take up new risk and create new loans. Unavailability of credit to finance working capital and investments might trigger the second-round business failure and this deteriorates quality of bank loans which results in a re-emerging of banking failure (RBZ, 2015).

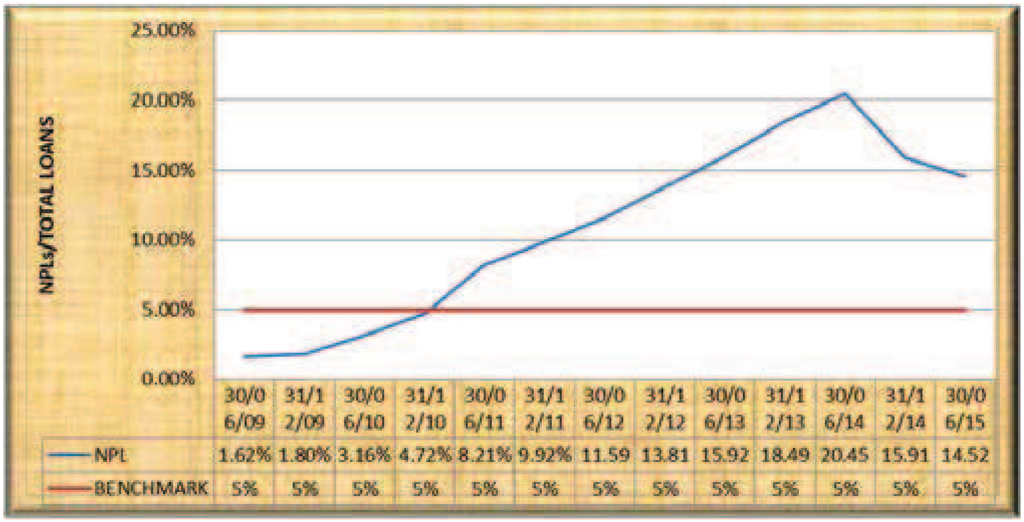
Generally, non-performing loans were on the rise since 2009up to June 2014 (Figure 1).

[12]See, for example, Katuka (2015), Bucur and Dragomirescu (2014). All these authors emphasized on the importance of banks in an economy.

[13]See, for example, RBZ (2006), Waemustafa and Sukri (2015), RBZ (2015), Messai and Jouini (2013), Heffernan (2005) and many others.

[14]For detailed information about post and prior dollarization bank failures, read RBZ (2006), Dzingirai and Katuka (2014) and Mabvure et al. (2012) etc.

Figure 1: Trend of Non-performing loans (2009-2015)



Source: RBZ (2015)

Figure 1 shows that NPLs were on rise since 2009 to June 2014 and that the graph reached a turning point when non-performing loans begin to decline in June 2014 to June 2015. This might be due to reduced lending caused by banks credit risk aversion after the end of the GNU in 2013. Rise in NPLs during GNU was largely driven by aggressive lending that most dominating banks adopted, along with poor risk management systems (Chikoko *et al*., 2012).This is also an indication that credit risk dynamically influences itself once it has gained momentum. Although there was noticeable decline in NPLs since June 2014, the trend decreased at a decreasing rate between December 2014 and June 2015. From the trend, it is clear that the whole banking industry has been operating above thresholds, where NPLs were above 15% but less than 25%. Moreover, from December 2010, NPLs trends were above the Bank of International Settlement (BIS) benchmark of 5%.

Furthermore, RBZ (2015) statistics show that since the adoption of the multiple currencies in 2009, the average daily interest rate, proxied by weighted lending rate recorded a low rate 9.5% in February 2011 and a highest figure of 16.04% in March 2012 with an average of 13.35% over the period 2011-2015. On the other hand, World Bank (2015) statistics showed that the average daily rate for Africa was 8.1%, with daily highest and lowest rates of 19.71% and 5.59%, respectively, whilst for the whole world, it was 5.78% with daily highest and lowest average rates of 60.61% and 3.7%, respectively, for the period 2009-2015.

3.2 PROBLEMS STATEMENT

Banks are key providers of funds to individuals, SMEs and corporates which drive economic growth in developing countries such as Zimbabwe. Figure 1 indicated that the Zimbabwean banking sector's NPLs were above thresholds as well as BIS benchmark. In this regard, it is important to know the drivers of NPLs and how best this cancan be mitigated in order to improve financial inclusion in Zimbabwe which have been found to be critical on poverty eradication. It is also critical to know the specific variables that banks need to keep an eye on to curb credit risk in Zimbabwe. Furthermore, it is useful to assess whether the credit risk currently bedevilling the Zimbabwean banking industry is macro or micro-induced or it is a combination of both.

3.3 RESEARCH OBJECTIVES

- The paper was prepared to achieve the following objectives:
- To identify major internal and external determinants of NPLs in Zimbabwe.
- To determine whether Zimbabwean banking industry's NPLs are macro or micro-induced or it isa combination of both.
- To develop strategies for curbing the increase in NPLs.

3.4 SIGNIFICANCE OF THE STUDY

Limited studies has been conducted to identify factors influencing credit risk in Zimbabwe. Chikoko, Mutambanadzo and Vhimisai (2012), Mabvure et al. (2012) and Mukoki and Mapfumo (2015) made significant contributions to identifying drivers of credit risk in Zimbabwean banking system. However, these studies applied models that were not adequate enough to comprehensively explain the causes of NPLs in Zimbabwe, especially on whether they are idiosyncratically or systematically induced or both. Existing literature gap from the aforesaid studies is that they did not capture the effects of changes in both the political landscape and policies. To our knowledge, no study has employed a dynamic model to study traits of NPLs overtime using Zimbabwean banking industry. Furthermore, identification of credit risk determinants of a more robust panel observation of banks using both static and dynamic econometric modelling helps regulatory authorities, banks and other players in the financial system to devise sound and more informed policies that reduce NPLs as well as preventing possible systemic crises posed by the contagion effect.

3.5 LITERATURE REVIEW

3.5.1 Theoretical Review

Many researchers showed much interest in understanding and testing concentration-fragility and concentration-stability theories. Concentration-fragility hypothesis (CFH) states that highly concentrated banking systems are much more fragile[15]. Under CFH, smaller banks have high chances to assume excessive risk due to high competition. According to Carletti (2005), it is lower margins that worsen excessive risk taking.

Another theory on the level of credit risk has emanates from the structure of the banking industry (Bains, 1951). The theory is known as the structure-conduct-performance (SCP) paradigm. It postulates that the level of non-performing loans is a true reflection of the market structure in which banks operate, that is, incidences of credit and systemic risk are high under monopolistic market structure than under a perfect competition. This is mainly due to inefficiency induced by lack of

[15] Refer to Deltuvaite (2010) and Elferink (2011) for detailed explanation on these two theories.

competition and greediness manifested through excess cost of borrowing above marginal cost (no marginal cost pricing).

Another theory of interest is the quiet life hypothesis developed by Hicks (1935). The theory states that firms with high market power take advantage of gains from non-competitive pricing in more relaxed environment in which less effort is put to minimize cost (Muharrami and Kent, 2009). Through high market power, banks charge high interest rates to cover up for management's slackness. This increases the probability of default by borrowers due to increased chances of adoption of high risk projects. In addition, slack managers would not do diligent vetting of borrowers, since at high cost of borrowing mostly risky borrowers have higher chances of being awarded loans leading to adverse selection and moral hazard incidences.

There are other theories that explain the relationship between cost efficiency and loan quality. Berger and DeYoung (1997) developed theories that explain the efficiency-risk relationship and these theories answer the question of whether banks are bad managers or skimpers. Three hypotheses were developed which are bad management hypothesis, bad luck hypothesis and skimping hypothesis.

Bad management hypothesis posits that low-cost efficiency signals poor managerial practices by bank managers (moral hazard) which also imply inadequate efforts being undertaken to analyse, monitor and control loan resulting in deterioration in loan quality in the long run (Mamonov, 2013). This hypothesis simply explains that low efficiency positively influences NPLs. Poor management may be a result of poor loan appraisal skills. Another possible cause of poor management is inadequate allocation of resources to be used to monitor loans (Podpiera and Weil, 2007).

In Zimbabwe, banks have formal risk reporting structures with each risk factor being analysed independently. This then implies that banks clearly separate all risks into categories hence lower chances of under provisioning resources for loans monitoring. Banks also form credit committees to manage credit risk. In order to ensure that credit risk exposure is within acceptable parameter, banks frequently produce arrears reports, facilities management reports, guarantees reports, insider loans reports, inspection reports, early alert reports and underwriting standards[16]. All these reports provided banks with a clear picture on credit risk hence the need to know why credit risk trended with such systems in place.

A supportive study on the issue of poor managerial practices in credit risk management was developed by Chikoko *et al.* (2012). According to the study, most banks continued to use the credit policies of the Zimbabwe dollar era and this was prominent in local banks, of which all were aggressively lending. Also, banks used reactive rather than proactive approach and these explain poor managerial practices hence matching bad management hypothesis.

[16]Read Nyamutowa and Masunda (2013).These authors explained much on risk categories faced by banks operating in Zimbabwe as well as types of reports there were used in banks to identify and manage credit risk.

Skimping hypothesis is another version of theory that Berger and DeYoung (1997) formulated to explain efficiency-risk relationship. The theory holds that high cost efficiency in the short run leads to deterioration in loan quality in the long run. To improve efficiency in the short term, bank managers may attempt to reduce expenses relating to borrowers' screening process which will eventually erode loan quality due to adverse selection. Skimping hypothesis posits that the amount of resources allocated to monitoring loans affects both NPLs and bank efficiency (Podpiera and Weil, 2007). The authors argued that there is a trade-off between short-term operational costs and long-term NPLs. Specifically, if bank managers strongly emphasize on short term profits, they may be motivated to reduce short term operating expenses by reducing resources allocated to monitoring loans. The overall goal of bank managers, under this hypothesis, is for banks to be perceived as cost-efficient in the short run since they would be using less inputs to produce same output burgeon. The result will be an increase in NPLs in the long run hence leading to the assumption that high cost efficiency should increase NPLs (Podpiera and Weil, 2007). Skimping hypothesis assumes positive relationship between cost efficiency and NPLs.

In Zimbabwe, most banks emphasize on short-term profitability at the expense of long term asset quality. Evidence shows that 40% of banks followed current profits credit culture, 33% are market share driven and 27% are value driven[17]. Clearly banks operating in Zimbabwe have high affinity for short term profitability as explained in skimping hypothesis and this heightens NPLs which affect loans pricing and hence degree of financial inclusion in Zimbabwe, thus exacerbating poverty and retards growth (World bank, 2014; UNDP, 2014).

Another version of theory from Berger and DeYoung (1997) is the bad luck theory which states that adverse macroeconomic conditions reduce the ability of borrowers to honour their debt obligations which erodes loan quality and cause banks to increase expenses devoted to monitoring borrowers (Mamonov, 2013). Berger and DeYoung (1997) cited closure of companies as familiar example of events that may raise NPLs. Applying this knowledge to the Zimbabwean context, most banks have corporate divisions and a lot of companies failed economically and financially and this contributed to a surge in NPLs. Bad luck and bad management hypotheses assume negative efficiency-risk relationship whilst skimping hypothesis assumes positive association. The bad luck hypothesis assumes NPLs arise from external forces which lead to banks incur high loan monitoring cost when dealing with problem loans.

Keeton and Morris (1987) discussed the moral hazard hypothesis which assumes that banks with low capital increases the riskiness of their loan portfolio in response to moral hazard which ultimately spur non-performing loans in the long-run. Berger and DeYoung (1997) found a negative relationship between capital ratios and non-performing loans. Moral hazard hypothesis states that low capitalization in banks leads to an increase in problem loans. Low capitalized banks increase their loan portfolio which builds up problem loans. During and after inception of the new currency regime in Zimbabwe, some banks were undercapitalized but total loans

[17]Read Chikoko, Mutambanadzo and Vhimisai (2012) on banks' credit culture in Zimbabwe.

escalated especially in locally banks. There was excessive insider lending and all these evidenced the existence of moral hazard in the banking industry. Adverse implications are that borrowers enjoyed when the new currency regime was introduced and suffered when NPLs were on rise which led to most groups being financially excluded in accessing financial services, particularly loans.

Generally, bank lending is cyclical implying that it follows movement in economic trends. Pro-cyclicality in lending refers to tendency of banks to lax lending standards during booms and stiffens during downturns (Athanasoglou, 2011). Pro-cyclical credit policy has implications on bank overall risk profile as well as performance. According to pro-cyclical credit policy, past earnings are positively related with problem loans (Belaid, 2014). The theory explains that bank managers advance credit to risky borrowers in order to convince the market for bank's profitability by inflating current earnings at the expenses of future problem loans (Belaid, 2014). The issue of lenient credit policies led to failure of several banks which include Interfin, Genesis and Renaissance to name a few. All these were not adhering to internal lending standards as well as regulatory lending standards and overly led to reduction in the number of financial service providers in the economy with some having their funds frozen during curatorship periods.

The Cognitive dissonance hypothesis states that banks justify past choices even if they had failed. Cognitive dissonance arises from misinterpretation or rejection of currently available information to justify the past choice (Athanasoglou, 2011). Use of Zimbabwean dollar era credit policies during early periods of inception of the multiple-currency regime may explain why banks believed in old credit policies than any new policies.

Empirical Review

The risk that the borrower may not service loans, either in full or not, is credit risk. A great deal of studies identified that bank credit risk is a function of either internal or external forces or a combination of both. Various models were applied in this research area, with some studies employing static models only and these include Poudel (2013), Zibri and Boujelbene (2011). In Zimbabwe, Mukoki and Mapfumo (2015) applied autoregressive distributed lag (ARDL) Bound Test while Chikoko et al (2012) used a survey approach and Mabvure et al (2012) used CBZ case study to explain the determinants of NPLs in Zimbabwe. Beck, Jakubik and Piloiu (2013) and Klein (2013) used a combination of both static and dynamic models.

There are studies that researched on the influence of macroeconomic environment on credit risk (Diaconasu, Popescu and Socolius, 2014; Gitonga, 2014; Castro, 2013; Bucur and Drogomirescu, 2014). Some studies looked into both micro and macroeconomic determinants of credit risk (Messai and Jouini, 2013; Gosh and Das, 2007; RBZ, 2015). In the same line of research, Ganic (2014) conducted a study on the influences of credit risk by incorporating bank-specific variables only. A well comprehensive study was performed by Garr (2013) and the study captured bank-specific, industry-specific and macroeconomic variables.

The commonly discussed macroeconomic determinants are real gross domestic product growth rate, inflation, unemployment rate, exchange rate fluctuations, market interest rate and broad money supply. The general hypothesis is that an increase in real GDP improves incomes for borrowers hence debt servicing capacity which imply reduced credit risk (Zibri and Boujelbene, 2011; Gosh and Das, 2007; Castor, 2012). However, Garr (2013) found positive connection between GDP growth rate and credit risk. A variety of studies rendered GDP growth rate as insignificant determinant of credit risk (Waemustafa and Sukri, 2015; Poudel, 2013; Bucur and Dragomirescu, 2014).

Inflation is also among macroeconomic determinants of credit risk. Several studies indicated that inflation negatively correlated with credit risk (Zibri and Boujelbene, 2011; Waemustafa and Sukri, 2015), while some studies provide mixed evidence. Waemustafa and Sukri (2015) noted that inflation has negative influence in conventional banks but does not influence banks in an Islamic banking model. Negative influence of inflation variable on credit risk implies that high inflation make debt servicing easier than low inflation because under high inflationary environment, the real value of outstanding loans deteriorates. However, this may not hold if the economy decides to quickly switch to using other countries' currencies as well as restating debts in the new currency. Gezu (2014) concluded that inflation does not have any significant impact on credit risk. Some studies found unemployment rate as a significant determinant of credit risk. Diaconasu, Popescu and Socolius (2014) foundthat unemployment rate positively relates to credit risk while Valahzaghard, Kashefi, Alikhani and Hosseini (2012) suggest that the variable does not have any impact on credit risk.

The bank internal environment also has an influence of the levels of credit. The internal drivers include, but not limited to, bank size, loan growth rate, loans to deposits ratio, capital adequacy ratio, and branch network. Literature indicates that big banks are able to control problem loans than small banks. Mukoki *et al*. (2015) explained that the specific determinants of NPLs in Zimbabwe's prominent banks were liquidity, return on equity (ROE), efficiency and interest rate spread. Survey from Chikoko *et al*. (2012) revealed that NPLs were resulting from, *inter alia*, lack of client knowledge, poor ethics and corporate governance, overcommitted clients, weak internal systems, high lending rates and over reliance on balance sheet strength. In terms of the influence of capital adequacy ratio, Makri *et al*. (2014), Hyun and Zhang (2013) and Shingjerji (2013) found negative relationship between capital adequacy ratio and NPLS. On the contrary, Djiogap and Ngomsi (2012) found positive linkage between capital adequacy and NPLs.

In the same area of research, Poudel (2013) and Ganic (2014) found that loan to deposit ratio has no influence on NPLs while Swamy (2012) and Boru (2014) found a negative influence of the aforesaid ratio to NPLs. There are also mixed findings on the effect of lending rates on NPLs. Zibri et al (2011) and Saba *et al.* (2012) found negative association whilst Ranja and Chandra (2003) and Farhan *et al*. (2012) found a positive linkage. Vigiazas and Nikolaidou (2011) used a multifactor model and identified that loan growth rate negatively relates with NPLs. Das and Ghosh (2007) indicated that branch network is an insignificant determinant of NPLs.

Knowledge Gap

A strand of literature in previous studies incorporated almost similar microeconomic and macroeconomic determinants of NPLs in their researches with less citation on the effects of political environment. This paper will add difference to existing literature by incorporating a political stability dummy variable which represents changes in political policies and systems. More so, a string of studies that were performed in Zimbabwe to analyse causes of NPLs applied static models and qualitative approaches which do not capture persistent growth in NPLs hence this paper covered the existing gap by using both static and dynamic models.

3.5.2 Methodologies and Data

This paper focused on microeconomic and external determinants of credit risk using both static and dynamic models. The paper used decomposed 480 monthly panel data observations from eight (8) commercial banks over the multiple currency era 2009-2013. Over this period, irrespective of adopting more stable currencies, nonperforming loans followed an upward spiral trend (see fig. 1). This behaviour on nonperforming is not clear whether it has memory of itself overtime or not. Data from commercial banks' websites is publicly available which addresses confidentiality issues. Eight (8) commercialbanks were selected and analyzed based on data availability. Although our sample was limited by data availability, banks that were selected had a total market share in excess of 70% based on market capitalization and more than half of 13 operational commercial banks by June 2015 (RBZ, 2015).

The variables included to assess systematic credit risk are: external variables to be incorporated are annual real GDP growth rate, annual inflation rate, unemployment rate, annual average lending rates and a political stability binary dummy variable, taking a value of 1 for Government of National Unity (GNU) era and 0 otherwise. We also included microeconomic determinants such as credit-to-deposit ratio and capital adequacy as control variables in the model. Macroeconomic data was generated from RBZ monetary policies, World Bank dataset and global finance website. Microeconomic or Bank specific data was generated from published financial statements obtained from banks' websites.

Static Model

The study performed correlation analysis and panel unit root test tests. Hausman test was performed to select the best model between random effect and fixed effect models. The test was performed under the following hypotheses:

H_0: *Random effect model is appropriate*

H_a: *Fixed effect model is appropriate.*

Hausman test supported the random effect model and we further performed BrueschandPagan LM test for random effects to see whether we selected the best model. Bruesch and Pagan LM Test were performed under the following hypothesis:

H_0: *Pooled regression model is appropriate.*

H_a: *Random effect model is appropriate.*

For the static case, static panel data regression allowed us to study individual behaviour in a repetitive environment (Baltagi, 2008; Cameron and Trivedi, 2009). The static model assumed that non-performing loans as a ratio of total loans disbursed are time invariant overtime that is, they do not have memory or built momentum on itself overtime. Descriptive and multiple regression techniques were used and we adopted the static model used by Poudel (2013) and the specific regression model is as follows:

$$NPL_{it} = \phi_i + \beta_1 RGDP_{it} + \beta_2 INFR_{it} + \beta_3 CAR_{it} + \beta_4 UR_{it} + \beta_5 IR_{it} + \beta_6 LTD_{it}$$
$$+ \beta_7 GNU + \beta_8 t + \varepsilon_{it} \quad --- (1)$$

Where:

Variable	Definition
NPL	Nonperforming loans/ Gross loans
RGDP	[(Current year real GDP/Previous year real GDP)-1]
INFR	Annual inflation rates as given in worldbank database
CAR	[(Tier 1 capital + Tier 2 capital)/ Risk weighted Assets]
UR	Unemployment rate as given in worldbank database.
IR	Average lending rates
LTD	Total loans/ Total deposits
GNU	Government of national unity

$i = 1.2,3,...,N$ are individual commercial banks, $t = 1.2,3,...,T$ represent respective time in months, βs are parameters, ϕ_i denotes the unobserved bank-specific effects such as managerial competency, organisational culture etc., which might correlated or uncorrelated with the regress and ε_{it} is the white noise, independently and identically distributed (IID) error term, that is, it has zero mean, constant variance and is uncorrelated across time and banks. The composite error term w_{it} is constituted by ϕ_i and ε_{it}, that is, $w_{it} = \phi_i + \varepsilon_{it}$. We discussed five static models namely least squares dummy variable (LSDV), pooled or ordinary least squares (OLS), generalized least squares (GLS), fixed effects (FE) and random effects (RE) models in order to shed more light on how they adequately explain NPL drivers in Zimbabwe.

Dynamic Model

Davidson and MacKinnon (2004) asserts that although generalized least squares (GLS), ordinary least squares (OLS) and weighted least squares (WG) have alternative version that are robust under heteroskedasticity disturbances, none of them has acceptable properties when a dynamic structure $(NPL_{i,t-1})$ is introduced in the model.

For the dynamic case, a dynamic panel data regression model is useful when the dependent variable depends on its own past realizations (Holtz-Eakin et al., 1988; Arellano and Bond, 1999; Arellano and Bover, 1995; Blundell and Bond, 1998), that is, if high non-performing loans as a ratio of total loans in the past month lead to even higher ratios in the next month or low ratios in the preceding month caused even much lower ratios in the following month. In order to try to assess whether the ratio of non-performing to total loans disbursed evolve overtime the following dynamic panel regression was usedto perform this task:

$$NPL_{it} = \phi_i + \beta_0 NPL_{i,t-1} + \beta_1 RGDP_{it} + \beta_2 INFR_{it} + \beta_3 CAR_{it} + \beta_4 UR_{it} + \beta_5 IR_{it}$$
$$+ \beta_6 LTD_{it} + \beta_7 GNU + \beta_8 t + \varepsilon_{it} --- (2)$$

Where:

Variable	Definition
NPL	Nonperforming loans/ Gross loans
RGDP	[(Current year real GDP/Previous year real GDP)-1]
INFR	Annual inflation rates as given in worldbank database
CAR	[(Tier 1 capital + Tier 2 capital)/ Risk weighted Assets]
UR	Unemployment rate as given in worldbank database.
IR	Average lending rates
LTD	Total loans/ Total deposits
GNU	Government of national unity

Since $NPL_{i,t-1}$ is correlated with ϕ_i because $NPL_{i,t-1}$ is a function of ϕ_i GLS and OLS procedures give biased and consistence estimators (Greene, 2008). In addition, because the transformed model, when using the deviation form model, the independent variable will be endogenous, that is, the mean of NPL_i is correlated with the mean of ε_i, which indicates that WG estimators are also biased and inconsistent. Alternatively, Blundell and Bond (1998) argued that the so-called "first-difference" transformation to remove bank specific individual effects ϕ_i can be used, but again, the WG and GLS estimators are inappropriate. The reason being that, in the first differenced dynamic model of equation (2), $\Delta NPL_{i,t-1}$ are correlated with $\Delta\varepsilon_{it}$. To solve this problem, we adopted the methodology proposed by Anderson & Hsiao in 1982 to control endogeneity using $\Delta NPL_{i,t-2}$ or $NPL_{i,t-2}$ as Instruments for $\Delta NPL_{i,t-1}$. In fact, according to Holtz-Eakin et al. (1988), lagged levels of the endogenous variable, three or more time periods before, can be employed as instruments and we had more available instruments than unknown parameters if the panel includes three or more time periods. We used the method proposed by Arellano and Bond (1991) that exploited all possible instruments. Using the Generalised Methods of Moments ((GMM) Hansen, 1982)), they found the moment conditions generated by lagged levels of the dependent variables (in this research context $NPL_{i,t-2}$, $NPL_{i,t-3}$, $NPL_{i,t-4}$,...) with $\Delta\varepsilon_{it}$. The estimators obtained are known as difference GMM estimators. Having similarity with all instrumental variables regression, GMM estimators are unbiased. Comparisons of the performance of difference GMM, OLS and WG estimators was done by Arellano & Bond in 1991 using simulations and found that GMM estimators exhibit the smallest bias and variance.

Exceptions

Heteroskedasticity and time invariant independent variable

Different GMM do not provide good estimators if the errors are heteroskedastic, but we found our errors to be homoscedastic and we used one-step GMM estimators since the two-step GMM proposed by Windmeijer in 2005 provide estimators which are robust, but their standard errors will have downward bias. The second possible problem of dummy-variable inclusion (GNU) in the model was resolved by employing the approach proposed by Arellano and Bover (1995) as well as Blundel and Bond (1998) of using system GMM estimators.

Instrument Validation

After the difference and system GMM estimators were obtained, model validity was checked for autocorrelation and instrument subsets validity.

- The importance of detecting serial correlation in the error term was proposed by Arellano and Bond in 1991, after it was observed that its presence invalidates some of the instruments. If ε_{it} are serially correlated of order 1 (AR(1)), then $NPL_{i,t-2}$ is endogenous to $\Delta\varepsilon_{it}$ (due to the presence of $\varepsilon_{i,t-1}$ in the difference), and therefore, $NPL_{i,t-2}$ will be an invalid instrument. To do this task we used the difference $\Delta\varepsilon_{it}$ instead of ε_{it}. Alternatively, we tested autocorrelation of order 1 in level using AR (2) in differences and found that the null hypothesis of no autocorrelation was not rejected, and concludes that validation of instrumental variables was obtained.
- The Sargan test (Sargan, 1958) was used to validate instrument subsets. It was based on the null hypothesis that residuals are uncorrelated with instruments to be used and we found that this hypothesis was not rejected, implying that the validation of instruments was obtained.
- Variables and hypothesized relationships

Table 1 show a list of variables that will be used in the regression analysis along with hypothesized relationships.

Table 1: Definitions of variables and sources

Variable	**Proxy**	**Definition**	**Hypothesised relationship with credit risk**	**Source**	**Data Frequency** *(Decomposed using Eviews 7)*
NPL	Non-performing loans	Nonperforming loans/ Gross loans		Bank statements	Monthly
RGDP	Real GDP growth rate	[(Current year real GDP/Previous year real GDP)-1]	Negative	Global Finance	Monthly
INFR	Annual inflation rate	Annual inflation rates as given in worldbank database	Positive	Worldbank database	Monthly
CAR	Capital Adequacy Ratio	[(Tier 1 capital + Tier 2 capital)/ Risk weighted Assets]	?	Bank statements	Monthly
UR	Unemployment Rate	Unemployment rate as given in worldbank database.	Positive	Worldbank database	Monthly
IR	Interest rates	Average lending rates	Positive	Monetary policy statements	Monthly
LTD	Loan-to-deposit Ratio	Total loans/ Total deposits	Positive	Bank statement	Monthly
GNU	Government of national unity		Negative		Monthly

3.6 DIAGNOSTIC TESTS, DATA ANALYSIS AND RESULTS INTERPRETATION

3.6.1 Descriptive Statistics

Table1 presents common descriptive statistics of both dependant and independent variables.

Statistic	Npl	nnr	rgdp	ltd	Ir	Infr	Car	Gnu
Mean	.089249	5.602	.0908	.6293036	.1118	.00728	.1890625	.8833333
Minimum	0	5.3	.033	.166371	.075	-.077	.1114	0
Maximum	.2185514	6.4	.119	.9637259	.18	.049	.44	1
Observations	480	480	480	480	480	480	480	480
Std Dev	.0563829	.4044215	.0316013	.2156185	.0359953	.0446486	.0672788	.3213576

Table 2: Descriptive Statistics-Dependant and Explanatory variables

Generally descriptive statistics proved that NPLs were above the thresholds. Statistics showed that the average NPL was 8.92%, with a minimum of 0% and a maximum of 21.9%.Zero NPL was attributable to new loans on adoption of multiple-currency regime. This is an indication that NPLs were out of control in the Zimbabwean banking industry considering that non-performing loans level was far much above the prudential benchmark of 5% stipulated in Basel II (Basel, 2004). Research findings showed that the average real GDP growth rate is 9.08% with minimum and maximum values of 3.3% and 11.9% correspondingly. The average loan to deposit ratio is 62.9%. The lowest loan-to-deposit ratio in the Zimbabwean banking industry is 16.6% and a maximum of 96.37%. Statistics revealed that average inflation rate was 0.7% and maximum rate of 49%. In terms of capital adequacy, the study found that average capital adequacy ratio in banks was 18.9%. Minimum capital ratio was 11.14% and a maximum of 44%.

Correlation Analysis

We performed correlation analysis to eliminate variable exhibiting high correlation coefficients so that a reliable model can be produced.

Table 2: Correlation Matrix

	Gnu	car	Infr	Npl	Unr	Rgdp	Ltd	Ir
Gnu	1.0000							
Car	-0.0045	1.0000						
Nfr	0.1259	-0.5051	1.0000					
Npl	-0.7687	-0.3759	-0.1654	1.0000				
Unr	-0.5455	0.5122	-0.0932	-0.3018	1.0000			
Rgdp	0.5848	-0.1240	0.4337	-0.2402	-0.1345	1.0000		
Ltd	-0.0864	-0.6034	0.3137	0.3793	-0.3745	-0.0644	1.0000	
Ir	0.1568	-0.1303	0.2370	0.7147	-0.0617	0.3409	-0.0338	1.0000

Table 2 showed that correlation coefficients for all study variables are within the acceptable range of 0.8 to -0.8, indicating absence of severe multicollinearity. Hence, we considered them in further analysis to be performed before the final model. The highest Pearson correlation of 71.47% was found to exist between NPL and interest rate, while the least one of 0.45% exist between GNU and CAR.

Hausman Test

We performed model specification test to choose between random effect model and fixed effect model.

Table 3: Hausman Test

Variable	(b) Fixed	(B) Random	(b-B) Difference	Sqrt(diag(V_b-V_B)) S.E.
Unr	-.1851021	-.1848862	-.0002158	.0015658
Rgdp	.0646492	.0658991	-.0012499	.0040324
Ltd	-.0159317	-.014533	-.0013987	.0016168
Ir	.2309855	.2312674	-.0002819	.0024854
Infr	-1.597607	-1.598052	.000445	.0110362
Car	-.2665085	-.2661295	-.0003789	.002147
Gnu	3.64e-16	-1.01e-14	1.05e-14	.0001996
Months	1.47e-16	-2.78e-15	2.93e-15	.0000148

H0: Random effect model is appropriate
Ha: Fixed effect model is appropriate.
chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 1.07
Prob>chi2 = 0.9978

According to table 3, the probability value is more that 5% so we accepted the null hypothesis which supports the use of random effect model over fixed effect model.

Panel Unit Root Tests

Table 4: Panel Unit Root Test Results

Harris-Tzavalis			Im-Pesaran-Shin		Fisher-type	
Variable	p-value	Order of integration	p-value	Order of integration	p-value	Order of integration
Car	0.04497**	I(0)	0.000***	I(1)	0.000***	I(1)
Infr	0.0024**	I(0)	0.000***	I(1)	0.000***	I(1)
Ir	0.0001***	I(0)	0.0124**	I(0)	0.000***	I(1)
Ltd	0.04861**	I(0)	0.0245**	I(0)	0.000***	I(1)
Rgdp	0.0000***	I(0)	0.000***	I(1)	0.000***	I(1)
Unr	0.0000***	I(0)	0.000***	I(1)	0.000***	I(1)
Npl	0.0000***	I(0)	0.000***	I(1)	0.000***	I(1)

*NB: *** (**) (*) indicates stationarity at 1%, 5% and 10% respectively*

We performed three panel unit root tests namely Harris-Tzavalis, Im-Pesaran-Shin and Fisher-type to determine whether research data was stationary or not. The test indicated that order of integration of variables varies with the method used but overall it was found that most variables were integrated of order one. These unit root test results indicate that a GMM of a dynamic nature is applicable (Holtz-Eakin et al., 1988; Arellano and Bond, 1999; Arellano and Bover, 1995; Blundell and Bond, 1998, Baltagi, 2008).

Static and Dynamic Models

In our analysis, we performed seven regressions which we categorized into least squares dummy variable (LSDV), pooled or ordinary least squares (OLS), generalized least squares (GLS), fixed effects (FE), random effects (RE), difference generalized methods of moments(DIFFGMM) and system GMM (SYSTGMM). LSDV, OLS, GLS, FE and RE models are static in nature, that is to say, the models provided a snapshot of NPLs at a particular time. DIFFGMM and SYSTGMM are dynamic or time variant model, that is, they capture the evolution of NPLs over time. Diagnostic checks done in this study chose RE as the most appropriate static model, while in the dynamic case, the SYSTGMM was found to be the most appropriate one. Other models were used for robustness checks.

Table 5: Static and Dynamic Regression Results

Var	LSDV	OLS	GLS	FEM	REM	DIFFGMM	SYSTGMM
Unr	-0.1851***	-0.1798**	-0.1798**	-0.1851***	-0.1849***	-0.1478***	-0.1321***
Rgdp	0.0646	0.1169	0.1169	0.0646	0.0659	0.1085***	0.0681***
Ltd	-0.0159	0.0439***	0.0439***	-0.0159	-0.0145	0.0119	0.0102
Ir	0.2310**	0.2520*	0.2520*	0.2310**	0.2313**	0.1775***	0.1661***
Infr	-1.5976***	-1.6055***	-1.6055***	-1.5976***	-1.5981***	-1.3126***	-1.1327***
Car	-0.2665***	-0.1904***	-0.1904***	-0.2665***	-0.2661***	-0.1381***	-0.1402***
Gnu	5.847x10-16	3.665 x10-16	2.238 x10-12	3.642 x10-16	-4.965 x10-15	-0.1778***	-0.1222***
Months	2.287 x10-16	1.556 x10-16	6.630 x10-13	1.468 x10-16	-1.467 x10-15	-0.0464***	-0.060***
Banks							
2	0.0011						
3	0.0376***						
4	0.0208**						
5	0.0840***						
6	0.0003						
7	0.0052						
8	0.0955***						
						0.6422***	0.7657***
Const	1.0974***	1.0391**	1.0391**	1.1279***	1.1256***	0.8612***	0.7760***
N	480	480	480	480	480	464	472
R2	0.6936	0.3099	0.4588				
Adj-R2	0.6837	0.2982	0.4413				

Bruesch & Pagan LM Test for Random Effects H0: Pooled regression model is appropriate. Ha: Random effect model is appropriate. chibar2(01) = 4222.44*** Prob> chibar2 = 0.0000	Sargan Test of Over identifying Restrictions H0: Over identifying restrictions are valid chi2(173) = 103.8371 Prob> chi2 = 0.6035
Test for Serial Correlation for Instrument validation Arellano-Bond test for AR(1) in first differences: z = -4.45 Pr>z= 0.000 Arellano-Bond test for AR(2) in first differences: z = -0.68 Pr>z= 0.536	

NB legend: * p<0.05; ** p<0.01; *** p<0.001

After performing the Hausman test, we further conducted Bruesch and Pagan LM test to choose between pooled and random effect models. The probability value is zero which is less than 5% hence we rejected null hypothesis in favour of the alternative hypothesis. Therefore, we conclude that the random effect is more appropriate in this research than the pooled OLS model. Furthermore, the insignificant Sargan and serial correlation test results indicate that the instruments used are valid.

Robustness Checks

This study used alternative static models namely LSDV, OLS, GLS, and fixed effect andDIFFGMM dynamic model to check whether coefficients were robust. Robustness of study variables was assured by similarity in significance, coefficients and direction of movements of variables in all three static models. Using the Wald and/or F-test for joint significance, we found that all models were equally significant at 1% (i.e. p - value = 0.0000).

Static models (OLS, Fixed Effect and Random Effect)

Bruesch and Pagan LM test for random effects supported the use of random effect model, just as with Hausman test. All static models revealed that unemployment (UNR) negatively correlate with non-performing loans and the variable is statistically significant at 0.1% in LSDV, FEM and REM. In OLS and GLS models, the variable has negative coefficient but significant at 1%. Based on the REM, a unit increasing unemployment increase the bank systematic risk by 18.49%. It conforms to the one found by Hyun and Zhang (2012). These authors explained that negative association between unemployment and NPLs implies that fluctuations in an economy quickly translate to meaningful effects on NPLs. Probably this is because only deserving borrowers have access to loans along with stringent client screening procedures. However, these results are against promoting financial inclusion in Zimbabwe as credit facilities will only be available to smaller population, that is, those employed. In line with Holmstrom and Tirole (1994, 1997) argument, financial exclusion especially of small firms is exacerbated in a financially constrained environment due to reputational risk since they do not have collateral. In addition, bank credit is out of reach since banks cannot afford the cost of monitoring such fragmented markets.

Concerning market interest rates, the study indicated that there is positive relationship between market interest rates and non-performing loans in all static models and the correlation matrix show a positive value of 0.71, an indication that interest rates increases credit risk by 71%. Thisfinding is in line with theoretical expectations and also conformed to findings made by Messai and Jouini (2013). Positive connection implies that an increase in interest rates will result in burgeoning non-performing loans and the variable is significant at 0.1%. According to results, high interest rates erode borrowers' repayment capacity which may delay or avoid realization of interest income resulting in surge in overdue loans with unearned interest. The result is also in line with Hicks' (1935) quiet life hypothesis. Tagging along similar lines of thought, high interest rates presented loan burden to borrowers as most banks were charging high rates averaging 13.35% during the period understudy when compared to world and Africa rates of 5.78 and 8.1% respectively. Banks reviewed lending rates downwards to 11.99% in December 2015 following RBZ directive in September 2015 but these are above both average world and Africa rates. Although Zimbabwean economy is in a liquidity glitch, banks cannot increase their assets and profitability through high lending rates as this might work the other way, which is, eroding bank assets and low profitability due to bad debts written off.

Although Zimbabwean economy has been experiencing negative inflation rate for lengthy period of time, research findings indicated that inflation has negative influence on NPLs in all static and dynamic models and the variable is significant at 0.1% level. Our findings conformed to Waemustafa and Sukri (2015) on the effect of inflation in conventional banks. Negative association indicated that increase in inflation rate results in decrease in credit risk. According to these findings, a high level of inflation makes debt servicing easier by reducing the real value of outstanding loans, provided the loan agreements do not contain variable interest rate clauses leading to compensatory upward adjustment in interest rates. However, although debt servicing becomes easier, banks' assets will deteriorate in real terms.

To shed more light of bank-specific determinants, research results indicated that capital adequacy ratio negatively influence NPLs in Zimbabwe. The variable is statistically significant at 0.1% across all static models and findings are in line with Hyung and Zhang (2013) and Shingjerji (2013). High capital acts as bank safety net in case of contingency events but this study rendered high capital ratios as major driver of NPLs within bank setup or vice versa. From the study, increase in bank capital adequacy reduces NPLs. Bank capital adequacy ratio measures risk taking behaviour of any banking institution and according to results we found the banks with low capital adequacy ratio increase NPLs through moral hazard (risky loans). Evidence has it that most of failed banks were poorly capitalized, as indicated in RBZ publications, which support the view that bank with high capital adequacy ratio is less likely to venture into moral hazard than those with lower ratios. Both 2003-2004 and 2007-2008 Zimbabwean financial crises that Zimbabwean economy experienced were also related to moral hazard that resulted from banks venturing into risky activities. The LSDV results provide much interesting results which are included in all other static model results, that is, banks which have significant contribution to the level of credit risk in the Zimbabwean banking sector. Compared to bank 1, bank 3, bank 4, bank 5 and bank 8 significantly contributes 3.76%, 2.08%, 8.4% and 9.55% respectively of the systemic risk of the Zimbabwean banking sector.

Loan-to-deposit ratio (LTD) increases with non-performing loans. We found that LTD variable was significant in OLS and GLS models but insignificant in other statics models. All our static models rendered real GDP growth rate and GNU variables as insignificant determinants of NPLs in Zimbabwe. In the interest of brevity, NPLs are mainly driven by microeconomic and macroeconomic factors with political stability having no influence, that is, bank credit risk in Zimbabwe a result of both idiosyncratic and systematic risk factors. Systematic risk such as inflation and unemployment play a major impact on credit risk levels. However, these models do not have memory to capture persistent growth in non-performing loans therefore to circumvent this weakness we employed GMM models, which are dynamic in nature.

The Dynamic Model (GMM)

Using Arellano-Bond and Arellano and Bover or Blundell and Bond estimations, we identified that NPLs are a function of microeconomic, macroeconomic, political forces as well as build in momentum in itself. The significance of one-period lagged NPLs indicates that credit risk is a function of its past realization, that is, it evolves overtime. It has been found that 76.57 percent of credits risk in each month is driven by the credit risk in the previous month. The GMM models were significant at 1% and this is an indication that the model is reliable. Similarly, to findings from static models, we identified that average lending rates positively influence NPLs in Zimbabwe. The lending rates variable (IR) is statistically significant at 0.1% in both models which implies that it has much influence on level of credit risk in Zimbabwe. Positive relationship infers increase in lending rates results in increase in non-performing loans and this is in line with theoretical expectations as suggested Farhan *et al*. (2012) and Sakiru*et al.* (2011). In reiteration, high interest rates facilitate best platform for creating bad loans and hindering economic growth as well financial inclusion process in Zimbabwe.

To further explain credit risk determinants in Zimbabwe, research findings highlighted that changes in inflation rate have negative influence on non-performing loans. The study indicated that the inflation variable (INFR) negatively an associate with NPLs and the variable is significant at 0.1%. Surprisingly, both dynamic models found significant relationship between real GDP growth rate and NPLs. According to findings, real GDP increases with non-performing loans and findings are similar to those of Garr (2013). Concerning unemployment, the study suggests negative connection between unemployment rate and credit risk and this was line with findings drawn by Makri*et al.* (2014).

More interestingly we also found out that political stabilityhada negative influence on credit risk. GMM model captured influence of political stability dummy variable which was not recognized in all five static models discussed above. Our political policy dummy variable, Government of National Unity (GNU) has a negative coefficient and is significant at 0.1% level. GMM model suggest that GNU negatively influence bank credit risk profiles. Political stability necessitated by GNU boosted confidence of investors, increasing both employment levels, growth ultimately causing a reduction in credit risk as supported by correlation results in table 3 between GNU, and unemployment, real GDP and non-performing loans of -54.6%, 58.5% and -76.9% respectively.

These results have shown the robustness and superiority of a dynamic model over static model. Variables such as GNU, RGDP and past observationsare significant factors in the dynamic model though insignificant in the static models. There is also a drastic increase in the coefficients of both GNU and month when a dynamic model is adopted. These results imply that most researches which rely on static analysis have a specification bias posed by model under-fitting, and this compromised the reliability of results.According to Greene (2008), Baltagi (2009) and Gujarati (2013), this induces bias, inefficiency and inconsistency of estimators even if the sample size increases indefinitely, that is, they are not asymptotically unbiased and efficient.

3.7 CONCLUSIONS AND POLICY IMPLICATIONS

Conclusions

The Paper Investigated On The Determinants Of Credit Risk In Zimbabwe. Our Paper Suggested That Credit Risk Is Driven By Microeconomic, Macroeconomic And Political Stability Factors, That Is, It's A Combination Of Both Idiosyncratic And Systematic Risk Factors.Dynamic Models Identified That Gnu Has Negative Impact On Npls While All Static Models Rendered The Variable Insignificant, An Indication That Political Instability Exacerbates Systematic Risk Not At A Specific Time But Overtime. Static And Dynamic Models Found That Interest Rates Have positive influence on non-performing loans. High interest rates are direct threat to meeting financial inclusion objectives in economy.

The study identified that increasing capital adequacy ratio reduces credit risk in Zimbabwe. Previous studies indicated that banks with low capital adequacy ratio are likely to suffer increase in NPLs through moral hazard (issuing risky loans). Loans-to-deposit ratio has positive influence on non-performing loans. This ratio detects bank lending culture and most local banks were aggressively lending during the period under study, with most banks having higher ratios. Concerning macroeconomic influence on NPLs, inflation and unemployment negatively relate with NPLs in all static and dynamic models. Real GDP growth rate has apositive influence on NPLs. A negative relationshipbetween inflation and NPLs implies that increase in inflation rate can decrease NPLs. However high inflation rates are never favourable and the 2007-2008 hyperinflation evidences this. During periods of high inflation, real monetary value is lost thus only borrower benefit from rising nominal values.

Dynamic models yield superior results above static models. Some variables which were insignificant in static models become significant in the dynamic model, an indication that only relying of static models induces specification bias, which compromise much on the reliability of results and policy analysis.

Policy Implications and /or Recommendations

Econometric analysis provided a picture on direction and strength of influence of each factor considered in the models and based on findings that were discussed in previous section, we recommend the following:

- The study supported quiet life hypothesis thus we recommend banks operating in Zimbabwe to reduce lending rates to levels between average world and African rates of 5.78% and 8.1% respectively. Reduction in lending rates will improve borrowers' repayment capacity and hence boosting loan repayments which curtail NPLs in banks. Banks cannot increase their assets and profitability through high lending rates as this might work the other way, which is, eroding bank assets and low profitability. Reduction in interest rates will also discourage incentive for moral hazard in borrowers hence lessening chances to defaults. Overlay, the objective of financial intermediation and financial inclusion will be satisfied.
- Banks should endeavour to improve their capital adequacy ratios. According

to the study, low capital adequacy ratio creates incentive for moral hazard thus increasing bank capital would discourage such incentives.

- Banks to periodically monitor loan-to-deposit ratios and also ensure that any expansion in lending activities is adequately supported by capital growth. Banks that operates in Zimbabwe should consider shifting their culture from current profits credit culture to value driven credit culture.
- As part of developing proactive credit risk management systems, banks should periodically update credit policies in order toimprove their screening process in assessing loan applications. A combination of anxiety for current profits and outdated credit policies was adequate enough to justifying trending NPLs.
- Macro and political risks were identified as significant drivers of credit risk in Zimbabwe. Our research proved that inclusive government led to reduction in NPLs hence we recommend the Zimbabwean government to ensure political stability to boost investor confidence through all stakeholder involvement, especially on indigenisation policies and this will stimulate growth, employment and ultimately reduce default rates.
- The central bank must come up with a standard official discount rate. At the moment, the Reserve Bank of Zimbabwe does not have an official discount rate. The current official interest rate is the Weighted Lending Rate which makes it difficult for one to determine the bank margin or spreads as effective metric measure of competition and efficiency of banks to determine drives of credit risk in line with the SCP paradigm, quite life, the competition fragility hypothesis.

3.7.1 Contribution of the study

The study contributed to in-depth understanding of NPLs dynamics by banks and regulatory authorities in that it captured NPLs as a dynamic variable, a unique analysis that has never been performed in the Zimbabwean context.

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Appendices

Table 5: Data used in Figure 1

YEAR	NPL	BIS BENCHMARK
30/06/09	1.62%	5%
31/12/09	1.80%	5%
30/06/10	3.16%	5%
31/12/10	4.72%	5%
30/06/11	8.21%	5%
31/12/11	9.92%	5%
30/06/12	11.59%	5%
31/12/12	13.81%	5%
30/06/13	15.92%	5%
31/12/13	18.49%	5%
30/06/14	20.45%	5%
31/12/14	15.91%	5%
30/06/15	14.52%	5%