DETERMINANTS OF CREDIT RISK ON RESIDENTIAL MORTGAGE LOANS IN SOUTH AFRICA

Applied Research Project

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Declaration

I, Alikho Mbulana, hereby declare that this research report is my own unaided work. Where I have used or referred to the work of others, I have clearly marked as such. The research is submitted in partial fulfilment of the requirements for the degree of Master of Management in Finance and Investments at the University of the Witwatersrand. This research has not been submitted for any degree or examination at this or any other university before.

Abstract

Residential mortgages are an important asset class for banks as these assets provide the majority of bank's income. By the nature of issuing loans to customers, this asset class also presents the greatest risk to the banks and as a result, banks need to constantly evaluate and review credit risk in order to ensure dynamic response strategies that curb losses and achieve sustainable profits. This study aims to investigate factors influencing credit risk on residential mortgage loans in South Africa. A regression analysis was conducted to capture the influence of both macroeconomic and bank specific factors on loans that have been in arrears for less than 89 days and on loans that have been in default for more than 90 days; using monthly data from an undisclosed bank over a period of eight years, 2010 to 2018.

The results show that Housing Price Index, Unemployment, Household Disposable Income, Bank's Capitalization and Operational Efficiency are the only significant determinants for non-performing residential mortgage loans that are less than 89 days.

Credit Quality, Inflation, Unemployment, Household Disposable Income, Bank's Capitalization, Operational Efficiency and are the main determinants of the non-performing residential mortgage loans greater than 90 days.

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CHAPTER ONE: INTRODUCTION

1.1. Introduction

This study is based on the various factors which influence customer default on residential mortgage, pertaining more specifically to residential mortgage loans originated in South Africa. In this chapter, a background to the study will be provided, followed by the overview of the mortgage market in South Africa. Furthermore, the nature and challenges faced by this market will be discussed. Lastly, this section will discuss objectives of the study, along with the problem statement and significance of the study.

1.2. Background

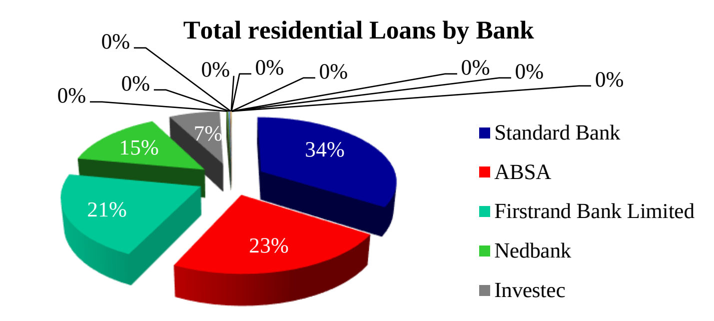
Having contributed 37.5 percent of total credit extended, with mortgage loans contributing 42.2 percent of this as a total of loan types extended by banks in 2018, the household sector plays a significant role within the banking sector as a source of income (South African Reserve Bank, 2019; PWC, 2018). Even though banks may have tightened their credit risk standards post the global recession, as of end of 2019, non-performing loans are averaging around 3.89 percent of the value of loans granted (CEIC, 2019). This indicates that South Africa is not yet totally out of the woods with regards to customer defaults on loans. The percentage is almost half of the number reported ten years ago, when South Africa reached what is reported as an all-time high of 6 percent in 2010 following the 2008/2009 recession (CEIC, 2019). Of paramount interest that affects credit risk is the role of loan strategies that banks take when granting residential mortgages to households, which sometimes involve granting personal loans to applicants in order to bridge the gap created by the lower loan-to-value ratios that banks now require as a means of protecting themselves. Although this strategy aids bank’s position by ensuring customer equity on the loan, the strategy results in increased non-performing loans at an aggregated asset class level.

Understanding the drivers of non-performing residential mortgage loans in South Africa is of critical importance in ensuring that banks maintain good quality assets, optimal efficiency and profitability in their balance sheets. According to Messai and Jouini (2013) weakened quality of bank assets was a key source of the issue noted during the of banking crises, in the banking system these poor quality assets do not only threaten the banking system but could negatively affect economic efficiency, weaken social welfare and produce a weak economy (Gosh, 2015).

1.3. Mortgage Market in South Africa

The South African Reserve Bank defines residential mortgage loans as long-term loans granted to individuals for the purposes of financing the purchase of a home to live in (SARB, 2016). These residential mortgage loans are extended to individuals by a number of banking institutions and other non-bank specialist mortgage finance institutions in South Africa. As at the end of September 2019, the total residential mortgage loans advanced amounted to R1 billion, which equals to 54 percent of overall total credit extended by banks (SARB, 2019). The largest providers of these mortgage loans were: Standard Bank (R348 million), Absa Bank (R235 million), Firstrand Bank (R214 million) and Nedbank (R146 million), as illustrated on Figure 1 below.

Figure 1 Total residential home loans issued per Bank



Source: SARB BA900 (SARB, 2019)

The South African banking sector consists of 36 banks (local and foreign-owned), led by the top four banks, mentioned in paragraph above, in terms of market capitalisation (SARB, 2019). As part of product offering, banks are responsible for and licensed to issue residential mortgage loans to the public. Since 1999, SA Home Loans and OOBA (previously Mortgage SA) are non-bank mortgage finance institution that also operate in South Africa. These banks have been in operation for more than twenty years and have seen the banking market evolve through many challenges, such as the banking crisis in 2008, which saw the SARB adopt the Basel Accords. This additional regulation was adopted in South Africa with the aim of strengthening risk management practices within the banking sector and to “improve banking sector's ability to absorb shocks arising from financial and economic stress” (SARB, 2008).

The banking sector has also seen some breakthroughs through the years, a country that is characterised by a population that predominantly consists of lower income earning households who are not active in the economy. In the recent years, there has been a deliberate effort by the government and banks to increase the level of participation and access to credit by these low income-earning households, through a variety of initiatives and support structures (The Banking Association of South Africa, 2019). In response to these initiatives, banks have had to be innovative and create specific product suites aimed at serving this niche market while still maintaining acceptable exposure and returns. Some of the notable initiatives include a national housing policy that was created in 1994 to give low-income earners access to credit (Human Settlements, 2003). Along with this, in 2005 the South African government created the National Credit Act, which was effected in 2007, with the aim of protecting consumers from unfair practices as they participate in the credit market (National Credit Regulator, 2006).

In South Africa, banks can grant residential mortgage loans to finance existing buildings or vacant land for construction. The average mortgage loan tenure is 20 years and consumers have a choice of financing residential mortgages at fixed or variable interest rate (FNB, 2019). A fixed interest rate is a specific percentage rate that the borrower and the bank agree on the loan amount for a specific period i.e. for the duration of the loan or a particular period during the duration of the loan. A variable interest rate is a fluctuating percentage rate that is linked to the country's prime (market) lending rate as determined from time to time. The prime rate was 10 percent for the last six months of 2019 (SARB, 2019), is used as a benchmark to price mortgage loans; the actual rates between bank and borrower are based on borrower's risk profile and differ for each borrower. The majority of residential mortgage loans in South Africa are predominantly determined at variable interest rates (FNB, 2019). Repayments of these loans are usually in form of monthly instalments, while the amount paid may vary each month, in accordance with movements of the prime interest rate (for variable interest rates).

1.4. Credit Risk

Adopting a definition that is most commonly used in South Africa, the SARB defines credit risk as "the risk that the counterparty to the contract, transaction or agreement may default before the final settlement of the underlying cash flows arising from the said contract, transaction or agreement" (SARB, 2019). Under the Basel III framework, banks are required to measure the well-being of customer repayment profiles using three categories namely a "good book" which reflects customer repayments that are past due by 0 days, "arrears" when repayments are past due for 1 to 89 days and in "default" when repayments are past due for more than 90 days. This study will focus on loans that are in arrears and in default.

Banks monitor customer repayments on a continuous basis and in efforts to manage they arrears book, they flag and contact customers as soon as customers miss a payment, in order to ensure successful recovery of the money outstanding on the loan. The credit agreement signed by the borrower (customer) and lender (bank) gives the Bank a right to call for a full repayment of total loan due when a borrower fails to meet contractual obligations. However, there are various reasons that render the customer unable to meet mortgage repayments in a timely manner, circumstances such as loss of income due to sickness or a loss of a job. Banks understand these circumstances and actually encourage customers to engage with them as soon as there is a difficulty in keeping up with the mortgage loan repayments in order to assess for possible solutions available such as restructuring the outstanding balance or rescheduling the repayment (Absa, 2019; FNB, 2019 and Nedbank, 2019).

The National Credit Act of 2005 also gives customers the right to “apply for a debt review” (National Credit Regulator, 2006) in the event that they are unable to meet their loan obligations due to over-indebtedness. According to this Act, the customer makes this application through a debt counsellor who will evaluate the customer’s financial position and have the customer’s debt restructured, postponed, or rescheduled (National Credit Regulator, 2005). Even though applying for a debt review is a customer’s right, the customer is not allowed to apply for debt review if the bank is already in the process of re-inforcing foreclosure of that loan.

Debt restructure involves extending the period terms on the initially signed credit agreement (Absa, 2019; FNB, 2019; Nedbank, 2019 and National Credit Regulator, 2006); this consequently reduces the amount of monthly payments due from customer, although it increases interest amount in the long-term. A debt reschedule on the other hand means postponing the repayments through arranging with the bank to temporarily relieve the customer from making monthly repayments for a specified period with a promise to pay once the agreed period is over; this also may result in penalty costs added on the loan due to not paying within the initially agreed timeframes. In the event that the customer’s financial position improves while in debt review, the customer has an option to negotiate higher repayments with the bank or settle the loan balance in advance in order to exit the agreement earlier, thereby saving on the remaining high interest payments. The National Credit Regulator (2019) reports a total number of 1.29 million customers that applied for debt counselling between 2007 and June 2019, which indicates a high level of consumer over indebtedness in South Africa.

From the processes explained in paragraph above, the customer has an option of requesting the debt restructure or rescheduling either directly with the bank or with the debt counsellor who acts as an intermediary. However, as opposed to when done with the debt counsellor, with Banks, over indebted customers do not by default, automatically qualify for a debt restructure or reschedule. This option is at a bank’s discretion following minimum requirements that a loan should meet to qualify for such restructure which include reasons for non-payment, period in arrears and whether the customer is making any form of payment in the loan during the period of default. Once a restructure is done, the bank will continue monitoring the customer repayment behavior while the customer is retained under the “default” category. After a number of repayments under the new arrangement to demonstrate customer’s commitment to the restructured arrangement, the bank may decide to move the client’s name from the default category to the “good book”.

From the two options mentioned above, the customer benefits as they retain the property while the bank saves money by preventing foreclosure and costs.
Where customers do not have any form of income and have no prospects of getting sufficient income in the future to fulfil loan repayments, they have an option to approach the lending bank to assist in selling the property through estate agents in the market. Absa offers this process through the “HelpUSell” programme which offers 50 percent write off on the shortfall between the selling price and the outstanding loan amount (Absa, 2019), the discount is only applicable is the financed property is sold via the programme and the customer continues to service their monthly repayments while the property is being sold. FNB also has a similar programme called Quick Sell and they offer up to 25 percent on the shortfall. Similarly, Nedbank and Standard Bank have the Nedbank Assisted Sales Service and EasySell programs and where the borrower sells their property through these programmes, the respective banks offer an interest free loan on the balance of the shortfall for up to 10 years after the original property is sold.

The options mentioned in paragraphs above demonstrate the different shapes and forms currently in place to help banks minimise losses and customers besides the previously traditional process of repossessing the asset, otherwise known as foreclosure, is a cumbersome process. These options are only successful if customers are aware of them and timeously engage with banks when they reach a financial difficulty. However, where customers in default do not communicate or refuse to engage the bank on the arrears and intention thereof, the bank is able to initiate the foreclosure process as a last resort to recover the outstanding amount on the mortgage loan.

A very cumbersome and costly process by nature, the National Credit Act describes foreclosure as a legal procedure where the lender takes possession of the financed property and sells the property in order to realise funds that will settle the outstanding amount on the mortgage loan (National Credit Regulator, 2006). This process is initiated upon the customer defaulting on the contractual obligations of the mortgage loan, normally by failing to make the required payments to service the loan (Brits, 2012). The cumbersome nature is due to the mandatory court proceedings that the bank is required to apply in order to enforce the bank’s “right of sale” clause from the credit agreement. This process is necessary to transfer ownership of the property, by way of a court order and to obtain judgement for the amount due, which will be used as a basis of the sale through a public auction. While the foreclosure is in process, the bank may encourage the customer to sell the property themselves, in order to settle the outstanding loan amount, although in order to protect the minimum amount of proceeds realised from the sale, the bank may stipulate the reserve price for the sale. The sale by customer, if sale price is fair and large enough, provides ability for customer to settle to outstanding debt and still have excess amount that they can use to start over.

If the sale is to be done by the bank, once ownership of property is transferred to the bank by the court order, the bank has an option to sell the property and receive a lumpsum amount that will be used to settle part or the full amount of the outstanding loan. The bank also has an option to keep the property for leasing and receive periodic cash inflows in form of rental income.

The costly nature of a foreclosure process emanates from the various costs that arise in enforcing the process in terms of legal fees, costs to pay sheriffs and advertisements for the auction or fees for estate agents. In addition, there are expenses required in order to sustain the property until it is sod, costs such as expenses towards maintenance, levies, insurance, rates and taxes. Lastly, the costs of carrying a loan in default brings about opportunity costs, as banks are required, as part of capital adequacy requirements, to keep a portion of their funds aside for all non-performing loans in their books (SARB, 2019). This is in addition to the interest income foregone that would have been earned from the non-performing loan had it not been foreclosed.

1.5. Problem Statement

Since non-performing loans are a symptom of a customer's inability to meet their loan repayment obligations, a review of non-performing loans has attracted interest in recent decades. The levels of non-performing loans in South Africa exhibit a notable persistence and highlight an important need to understand and identify robust drivers of non-performing loans. According to Fofack (2005), the rapid build-up in non-performing loans in the Sub-Saharan Africa amplified banking crisis. This finding signifies the important contribution of non-performing loans to bank failures (Reinhart and Rogoff, 2011). Examining factors that influence credit risk is also important in assisting with financial surveillance of the financial sector, as it enables the sector and regulators to identify weaknesses in credit risk management processes and adapt better credit risk management practices (Beck, 2015).

The majority of studies that investigate factors that drive credit risk on residential mortgage loans mostly cover advanced economies, where the level of market efficiencies is more advanced when compared to an emerging economic environment like South Africa. The few studies that have been undertaken on the South African economy mainly focus on macroeconomic factors and largely use cross sectional data. These studies largely ignore bank specific factors that play out at credit origination and throughout the duration of the loan, which may have an impact on credit risk (Fofack, 2005; Havrylchyk, 2010; Mpofu & Nikolaidou, 2018). In addition, those studies that consider bank specific factors, are limited and largely outdated (National Housing Finance Corporation, 2003; Marais, Botes, Pelser & Venter, 2005, Nikolaidou & Vogiazas, 2017). This study is based within the context of South Africa, using on time series evidence and will jointly consider both macroeconomic and bank specific factors, which may give better insights on the research question. These factors will be reviewed on a particular bank, using unique and high-quality bank database that is largely reported on a monthly basis which in turn allows us to draw particular insights that maybe cross sectional studies have not done.. Findings of this study will help banks focus their efforts, in modelling credit risk, on the main drivers that influence nonperforming residential mortgage loans in South Africa. This study aims to establish these factors for the South African economy and covers the most recent period of 2010 to 2018.

1.6. The Main Objective

Given the background and problem statement, the primary objective of this study is to investigate the factors influencing nonperforming on residential mortgage loans in South Africa.

1.7. Significance of the study

As not many studies have been performed on residential mortgage aspect in South Africa, the study will contribute to the existing literature by adding an understanding of the factors that influence persistent levels of non-performing residential mortgage loans in South Africa. By highlighting some of the benefits and pitfalls which are associated with certain strategies employed in managing credit risk; this study provides insights on the manner in which both macroeconomic and bank variables can be used by the banks to improve on their non-performing residential mortgage loans. For policy makers and the government, the findings and recommendations of this study would serve as a guide to improvement of credit risk management as well as the formation of new standards. In addition, the findings of this study would serve as a source of insight for South African banks, regulators, and government; on the opportunities, benefits, and strategies of managing credit risk on residential mortgage loans. This would improve their attitude towards implementation of robust credit risk management policies which my assist in reducing non-performing loans.

1.8. Conclusion

In this Chapter, a background to the study was provided followed by the overview of the mortgage market in South Africa. A discussion on the nature and challenges faced by this market was also outlined together with the objectives of the study, the problem statement and significance of the study. The next chapter discusses existing empirical literature of the factors that have been identified to influence non-performing loans, a backdrop on which this study will be based. Lastly, the chapter will formulate relevant hypotheses of the explanatory variables identified.

CHAPTER TWO: LITERATURE REVIEW

2.1. Overview

The objective of this chapter is to conduct a review of existing literature concerning the different factors that have been found to explain customer defaults on residential mortgage loans. In this chapter an overview of the factors that have been found to influence credit risk on residential mortgage loans will be individually discussed and explained. The hypotheses of explanatory variables will be formulated based on the factors identified from the literature review.

2.2. Empirical Studies

This section discusses and evaluate factors which have been found to influence credit risk on residential mortgage loans. The empirical literature identifies two sets of factors that influence non-performing loans in general, namely, bank specific and macroeconomic factors. Macroeconomic factors are factors that affect a wider general population in an economy and not just a specific category of consumers (Blanchard & Johnson, 2011; Taylor, 2017). These macroeconomic factors are important because unfavorable economic conditions adversely affect a wider community in the economy than factors that only affect a specific niche. Bank specific factors on the other hand are unique factors that are specific to the individual bank such as policy and strategic choices adopted by each bank concerning the management of risk imposed by issuing loans to the public (Louzis, Vouldis & Metaxas, 2012; Ofori-Abebrese, Pickson & Opare, 2016).

2.2.1 Macroeconomic Factors

Macroeconomics is a branch of economics that studies the performance of an economic environment in its entirety, using macroeconomic indicators that have an impact at a broader level. These macroeconomic indicators affect all people that participate in the economy and include factors such as the economic output and income of the nation, the overall price levels of the economy, levels of unemployment and many more (Wilkinson, 2005; Blanchard & Johnson, 2011). In 1987, Keeton and Morris investigated the factors that influenced nonperforming loans in the US banking industry, and through analysis of data from 1979 to 1985 across 2500 banks, the authors showed that macroeconomic conditions contribute vitally in explaining differences in loan losses realised by various banks. In addition, the conduct on banks through advancing high-risk loans was also highlighted in the study as another cause of loan losses. The authors support the notion of implementing diversification policies to mitigate nonperforming loans caused by macroeconomic factors.

Outlined below is the combination of a theoretical understanding and a review of existing literature on the impact that macroeconomic variables have on credit risk for residential mortgage loans.

2.2.1.1. Real Gross Domestic Product

Gross domestic product measures the market value of final output produced in a country or economy. During a good performing economic environment (booming economy), there is an increase in income and revenue levels for both consumers and firms and therefore consumers are able to service their debt obligations. On the contrary, during the downturn in the economy (recession), the level of income decline and consequently, consumers struggle to service their debt obligations thereby increasing non-performing loans. Louzis, Vouldis and Metaxas (2012) agreed with this notion when they conducted a study in the Greek banking industry. The paper showed that banks tend to accumulate credit risk rapidly during a booming economy, which tends to materialise during a recession when the quality of debtors in the bank's loan book reduces. This is in line with a study by Castro (2013) in Greece, Ireland, Portugal and Italy banking systems over the period 1999–2011, who also found that growing GDP levels reduce unemployment which consequently decrease non-performing loans as households will have income to meet their debt obligations. This finding was further confirmed by Abid, et al (2014) in Tunisia and Ghosh (2015) in the Unites States, who found that an improved economy in form of growth in real gross domestic product, reduce non-performing loans for a panel of 50 states in the United States over the period 1984–2013. In summary, almost all studies have found a negative relationship between growth in gross domestic product and nonperforming loans, causing one to expect a reduction in nonperforming loans because of an improvement in gross domestic product which translates into more income for consumers (Khemraj & Pasha, 2009). However, this growth in income also means growth in borrowing capacity of consumers and this, underpinned with bank managers that are overly confident about the wellbeing of the economy during the booming period, could be a dire combination during the difficult times when income tightens.

2.2.1.2. Real Interest Rates

Interest rate is the price charged by banks for taking the risk of lending funds to customers. Interest rates affect the price that customers pay on funds borrowed. Borrowers are required to pay interest on the funds borrowed, over and above the repayment of capital amount borrowed from the bank. Interest rates charged by banks depend on the credit risk profile of each borrower, but the base rate is largely influenced by country regulatory authorities such as monetary and fiscal authorities. A higher interest rate charged on the mortgage loan increases the amount that a customer is required to repay on the loan granted and consequently, inhibits customer's ability to service their debt obligations (Wambui, 2013; Viswanadham, 2015).

In South Africa, Munyai (2010) argued that high interest rates were the biggest problem during the economic recession in 2007 and 2008 even after the country's introduction of the National Credit Act in 2006; citing the resulting impact of default due to over indebtedness.

Various studies have confirmed the aforementioned relationship between interest rates and non-performing loans. Castro (2013) found interest rates to have a positive and statistically significant relationship with credit risk in a panel of five countries (Greece, Ireland, Portugal and Italy). Abid et al (2014) concurred with this finding although a study conducted by Ghosh (2015) reported inconsistent results when the study showed interest rate as an insignificant variable in influencing credit risk on commercial banks and savings institutions for 50 states in the United States.

Wu, Li and Hong (2017) examined determinants of defaults on home loans in Taiwan. The study found interest rate as a crucial factor that contributed to defaults on mortgage loans in Taiwanese commercial banks. A finding that concurred with Louzis, Vouldis and Metaxas (2011) when they reported that because banks charge higher interest rates to customers that have a higher credit risk profile, high interest rates reduce borrower cash flow during recession and increase borrower's repayment obligations. As a result of this notion explained above, it is reasonable to follow that banks that grant higher interest rates would have a higher exposure to nonperforming loans, from the conduct issue of inadvertently lending to bad borrowers in pursuit of higher interest rates charged on these loans. A conduct issue that is more evident in a country that is characterized by a high volume of low-income earning consumers who are charged heavy interest rates while consumers in better financial position enjoy favorable interest rates. In her study, Wambui (2013) agreed that higher interest rates make loan repayments harder and this challenge gets exacerbated when consumers have taken on more debt than they can service (Bosman, 2009). Additionally, on the bank's side, when interest rates are low, banks have been found to increase their risk appetite through increased lending volumes and this consequently fuels inflation (González-Aguado, 2014).

2.2.1.3. Inflation

Inflation rate is the rate at which the average prices for goods in the economy are increasing over time (Blanchard & Johnson, 2011) and is measured as a percentage change in consumer price index, an official measure of inflation in South Africa. Of importance is that inflation is interconnected to interest rate, as interest rates are used in the monetary policy as a tool to control inflation (Wambui, 2013). As inflation reflects changes in general prices of goods, if inflation rises at the same time as interest rates are high, the consumer's ability to service loan repayments becomes hard, as everything becomes expensive. As a result, banks increase lending rates due to the rising probability of default and inflation (Kondo, Perri & Hur, 2013), an evidence that was also supported by Njoki (2014) when she reviewed the influence of interest rates on mortgage credit risk in Kenyan banks.

Various papers have hypothesized a positive relationship between inflation and non-performing loans, as rising prices diminish the purchasing power in an economy, thereby eroding funds available for consumers to meet all their repayment obligations. As inflation rises, consumer income does not always rise at the same time and this creates misalignment that can lead to decreased cash flows for consumers as more funds will be required for the same expenditure item. Vaicondam, Hishan and Shan (2019) studied three macroeconomic factors that influence non-performing loans in Malaysian banks over the period 2009-2018. The paper found a profound positive relationship of an increase in inflation rate to non-performing loans. Mpofu and Nikolaidou (2018) supported this finding, adding that an increase in inflation rate decreases borrower's real income, which consequently weakens the borrowers' capacity to service their debts. Several studies also support this positive relationship between inflation and nonperforming loans (Khemraj & Pasha, 2013; Klein, 2013; Washington, 2014; Abid et al, 2014; Kjosevski & Petkovski, 2017) and as a result, the working class of consumers (employees) tend to require increases in salaries whenever the inflation rate rises, in efforts to maintain the value of their disposable income.

According to Kelin (2013), the level of relationship between inflation on the non-performing loans ratio can be vague, due to the fact that the relationship can take any of the negative or positive impact (Nkusu, 2011). Due to the notion that increased levels of inflation decrease the real value of outstanding debt, which in turn increases the loan serviceability capacity of borrowers. Ghosh (2015) supports this view and further adds a theory reduction in real value of debt stemming from inflation where nominal interest rates remain constant, which in turn lowers non-performing loans. Numerous studies have also confirmed the negative relationship that inflation has to non-performing loans (Ahmad & Bashir, 2013; Touny & Shehab, 2015; Tsumake, 2016; Rajha, 2017; Szarowska, 2018).

On the contrary, other studies found inflation to be insignificant in explaining non-performing loans and Castro (2013) attributes this result to the concept of 'net off' that occurs between real loan values and customer's real income, stating that inflation erodes both values (Alexandri & Santoso, 2015; Asfaw, Bogale & Teame, 2016).

In closing, according to these empirical studies, inflation has an important influence on interest rates and the relationship between inflation and non-performing loans could be either negative, positive or insignificant.

2.2.1.4. Real Income Growth

Closely linked with inflation, the amount of income available to household has been found to be a significant influence of non-performing loans. Ghosh (2015) explains that if nominal income does not increase along with inflation, the amount of funds available to households to service their debt obligations will reduce. In order for consumers to be able to repay their debt obligations, they make use of cash generated from income. Therefore, as inflation rises, consumer's disposable income becomes less and less valuable and this increases the financial strain (Bosman, 2009). Rinaldi and Sanchis-Arellano (2006) supported this negative relationship; analysing household non-performing loans for a panel of European countries, the study concludes that real disposable income is negatively related to non-performing loans. Dash and Kabra (2010) concluded on the same result when they conducted a study on Indian banks over the period of 1998-2009, when income is improved, consumers have funds to settle loans and therefore rates of default decrease. These findings are in line with the economic theory that the more funds available increase the consumer's capacity to service their obligations (Blanchard & Johnson, 2011).

2.2.1.5. Unemployment

The unemployment rate is another macroeconomic factor that affects credit risk and is interlinked with real GDP. Unemployment means loss of income, and this loss of income directly affects a person's ability to generate income and therefore repay debt obligations. On the other hand, growth in real GDP results in increase in employment as firms recruit more labour for production of goods and services (Ifeacho, 2014).Louzis, Vouldis and Metaxas (2011) conducted a study in the Greek banking sector and found that an increase in unemployment rate reduces household income and inhibits borrower's ability to repay their debt obligations. The lack of income therefore contributes to an increase in non-performing loans. Klein (2013) agreed with this negative effect of unemployment and suggests that a decrease in household income increases borrower's debt burden. Numerous studies have also brought similar conclusions on the positive relationship of unemployment to non-performing loans and confirm that households with no jobs lack the ability to repay loans owed as argued by Castro (2013) in Greece, Portugal, Spain and Italy; Messai & Jouini (2013) in Italy, Greece and Spain; Skarica (2014) in Indonesia; Szarowska (2018) in Central and Eastern European (CEE) countries, Mileris (2015) in Lithuanian banks, Tsumake (2016) in Botswana and Mpofu and Nikolaidou (2019) in Sub-Saharan Africa. With an unemployment rate that has been increasing year on year in South Africa during the period under review, it will be of interest to confirm if this variable is a key driver for nonperforming residential mortgage loans.

2.2.1.6. Housing Prices

Empirical studies contend that an increasing level of housing prices improves the value of the property financed, thereby reducing the likelihood of default (Castro, 2013). Studies also show that the boost in the property value helps household get additional access to credit by using the property as collateral (Beck, Jakubik & Piloiu, 2013). The opposite impact also applies on housing prices where declining housing prices lead to negative equity for the property owners, resulting in borrowers owing banks more than the property's worth, this reduces their motivation and ability to service the mortgage loan (Havrylchyk, 2010). During the rise in housing prices, the value of property is used as collateral increases the consumer's borrowing capacity and some consumers are accumulate more debt from this capacity, and encounter pitfalls when property prices drop and repayment obligations become unbearable, resulting in default (Daglish (2009). Ghosh (2015) concurs with the positive influence of housing prices on non-performing loans and further suggests that borrowers are motivated to continue servicing their loans when housing prices increase. Flavin (2002) supports this finding by arguing that home values of the property contributes a major part of household wealth and the wealth benefits from property as an asset are greater than financial assets. Various authors have found that the lending behavior by banks during the booming period in property prices also influences nonperforming loans and consequently suffer the losses during an economic downturn when bad quality borrowers are unable to meet their repayment obligations (Mian and Sufi, 2009; Gimeno and Martinez-Carrascal, 2010; Pesola (2011). In closing, the negative relationship between housing prices and nonperforming loans is in line with the findings by Tajik, Aliakbari, Ghalia and Kaffash (2015) who also found the impact of house price fluctuations to be stronger during economic downturns in the United States.

2.2.2. Bank Specific Factors

Bank specific factors are unique factors that are specific to an individual bank such as policy and strategic choices adopted by each bank concerning the management of risk imposed by issuing loans to the public. According to Keeton & Morris (1987), bank specific behaviors is one of the two causes, in addition to industry conditions, of severe loan issues encountered by banks. These bank specific behaviors are behaviors attributed to taking of risks by banks in pursuit of business and range from the quality of management responsible for managing credit in banks (Louzis, Vouldis & Metaxas, 2012; Marais et al, 2005), ratio of loans in relation to assets (Ghosh, 2015; Nikolaidou & Vogiazas, 2017) credit quality of the banks, bank capitalisation, the size of the banking industry and bank profitability (Ghosh, 2015; Mpofu & Nikolaidou, 2019). Outlined below is the combination of a theoretical understanding and a review of existing literature on the impact that bank variables have on credit risk for residential mortgage loans.

2.2.2.1 Credit growth

Credit growth reflects the growth in the supply of loans by a bank, which in turn is a growth of a bank's loan book. In order to obtain market share on loan portfolios, banks tend to adopt aggressive strategies that grow their loan book quickly and easily. A few authors that have studied this variable highlight the pitfalls of growing a loan book faster as this is often achieved by supplying loans at lower credit standards to customers that have poor credit quality, thereby increasing the possibility of default (Keeton & Morris, 1987; Stern & Feldman, 2004; Moss, 2013; Castro, 2013 and Ghosh, 2015). Although in the short run, the objective of growing the loan book may be achieved, the long-term impact from these strategies is negative (Castro, 2013). This finding is consistent with the later studies by Klein (2013), Chaibi and Ftiti (2015) and Nikolaidou & Vogiazas (2017) who found a positive relationship between credit growth and non-performing loans. In particular, Maddaloni and Peydró (2011) have shown that during the booming expansionary period of the monetary policy when interest rates are low, banks tend to lower their lending standards when screening customers and on collateral requirements, and consequently realise bad quality loans when recession emerge (Jiménez & Saurina, 2006). However, a study by Vithessonthi (2016) investigated the links between credit growth and nonperforming loans in Japan between 1993 and 2013 and found this relationship negative after the financial crisis in 2007. The authors attribute this negative relationship to tightening of lending standards by banks after the financial crisis, which results in high quality customers. The authors did however not test, due to scarcity of data, although acknowledged the possibility that these banks could just be simply not classifying their bad loans correctly. With the introduction of rigid regulation such as the National Credit Act and the Basel provisions, there is a general acknowledgement that the country has had the opportunity to improve on the quality of loans issued by the South African banking market. Linked to credit growth is profitability, several authors have found a positive relationship between credit growth and bank's profitability (Becker & Ivashina, 2014; Allen, Jackowicz, Kowalewski & Kozłowski, 2017) and this has been attributed to returns earned from issuing high risk loans that achieve profitability (Crowley, 2008).

A loan book of the bank consists of various loan asset types such as mortgage loans, credit cards, personal loans, overdrafts. When customer situations are tough, borrowers tend to acquire new additional funds through alternative credit facilities such as overdrafts or personal loans, in order to reduce their mortgage debt and keep their account status satisfactory. Although customers may benefit from this strategy in short term, over time the excessive borrowing will lead to over indebtedness and therefore default.

2.2.2.2 Credit quality of the banks (Loan Loss Provisions)

In terms of accounting standards, if a bank can predict a loss from a loan, the bank needs to make a provision for that loss in the income statement; and if the loan becomes unrecoverable or a bad debt, the provision must be used to reduce the load balance (Angklomkliew, George & Packer, 2009). Credit quality reflects a bank's attitude towards preventing and managing risk (Ghosh, 2015). When analysing the moral hazard theory, Keeton and Morris (1987) argued that banks that have substandard credit quality tend to have higher nonperforming loans, because these banks issue riskier loans in effort to achieve higher profits from charging higher interest rates on loans granted. Keeton and Morris (1987) found that banks that issued high-risk loans ultimately incurred higher losses. Reflected in the loan loss provisions, otherwise known as provision for bad debts, Gosh (2015) found that credit quality influences non-performing loans through impairments, which show provisions made for losses on credit portfolios for those borrowers that have been assessed as unlikely to repay the loans.

2.2.2.3 Bank capitalisation

In the same rationale as the credit quality variable discussed in the paragraph above, according to the moral hazard theory, Keeton & Morris (1987) argued that banks with low equity capital have a tendency of issuing riskier loans, which consequently result in a bank realising higher non-performing loans in pursuit of higher profits. While on the contrary, Rajan (1994) found a positive relationship between bank's capital and non-performing loans, citing reasons that banks with high capital seek loans that have a high probability of default under the protection that comes from the "too-big-to-fail" notion that is provided by high capital as they can absorb shocks from the credit market (Ćurak, Pepur & Poposki, 2013). Measuring the bank's level of capitalisation by the ratio of total equity capital to total assets, Ghosh (2015) agreed with the positive relationship by Rajan (1994) and Ćurak et al (2013) and further explained that banks with more capital tend to employ poor credit policies under the presumption of "too-big-to-fail", which eventually led to increase in non-performing loans. Louzis, Vouldis and Metaxas (2011) differed with this finding, as they found no relationship between the "too-big-to-fail" presumption and non-performing loans in Greece. The authors attributed this finding to the notion that banks that operate in small markets tend to have more regulatory oversight and also, banks in smaller banking markets are susceptible to a more visible reputational risk than peers in larger sized markets – a scenario that relates in the South African context characterized by a small sized banking market.

2.2.2.4 Operating efficiencies

Operating efficiency refers to a bank's ability to deliver services in the most cost-effective way while retaining high quality service offering to customers. In relation to credit risk management, Abid et al (2014) measures this factor by the quality of the management team employed by the bank. Captured under the notion of "bad management" hypothesis, Berger and DeYoung (1997) argue that when banks allocate resources that have poor skills to prevent, control and manage credit risk, tend to have a high cost inefficiencies (decrease in efficiencies) and increased non-performing loans resulting from granting loans that are of bad quality. Consistent with this explanation, Abid et al (2014) further found banks in Tunisia victims of this hypothesis due to insufficient tools embedded to assess customers before granting credit and due to a lack of robust credit monitoring tools to monitor and identify poor performing loans timely. A finding that resonated with the South African environment more than ten years ago when two studies found that lenders did not have strong corporate governance and also allocated weak credit teams to evaluate, grant and monitor credit on behalf of banks (Bah, Faye, & Geh, 2018; Marais et al, 2005; National Housing Finance Corporation, 2003). Several authors around the world have also found evidence in support of the existence of “bad management” hypothesis in terms of cost efficiency’s positive relationship with non-performing loans (Podpiera & Weill, 2008 in transition countries; Louzis, Vouldis, & Metaxas, 2012 in Greece; Ghosh, 2015 in the United States; Alexandri & Santoso, 2015 in Indonesia). Hughes, Lang, Mester & Moon (1995) argued, in a study in Philadelphia, that when bank managers are risk averse, they increase monitoring of the loan book which leads to incurring higher costs and therefore affecting the measure of operating efficiency. Therefore, a less efficient bank may in fact hold a low risk portfolio.

2.2.2.5 Size of the bank

In earlier years, Salas and Saurina (2002) found, in Spanish banks, evidence of negative correlation between the size of the bank and its non-performing loans, citing reasons that a bigger size allows a bank more opportunities to diversify their assets and therefore spread risk exposures. A recommendation that was also given by Keeton & Morris (1987) as a solution to minimise the effect of issuing high-risk loans that tend to wind up non-performing. A later study conducted by Abid et al (2014) reported consistent findings concerning the diversification opportunities available for larger banks. In addition to diversification, the size of the bank also provides a benefit for a bank to manage the issue of information asymmetry which in turn reduces nonperforming loans as a result of having the right human and information resources, while banks of smaller size would not have as much resources to manage credit risk. However, Amuakwa-Mensah and Boakye-Adjei (2015) disagreed with this finding, when they analysed the determinants of non-performing loans in Ghana. The study found a positive correlation on bank size to non-performing loans, suggesting that banks have a higher tendency to expand their credit base as their size increases, thereby increasing the possibility and volume of borrowers defaulting. This result supports Shehzad, de Haan, and Scholtens (2010) who showed that ownership concentration has a negative impact of concentrated ownership of banks when combined with supervisory control and shareholder protection rights. On the contrary, Peric and Konjusak (2017) found the relationship between bank size and non-performing loans insignificant, acknowledging that diversification may not be fully captured by the size of the bank and that the net effect from poor diversification and consequent of non-performing loans maybe zero (Louzis, Vouldis & Metaxas, 2012). This insignificant result can also be interpreted to mean that larger banks are necessarily more effective in screening loan customers when compared to their smaller peers (Khemraj & Pasha, 2009).

2.2.2.6 Bank profitability

Measuring bank profitability by return on assets, Gosh (2015) found a negative relationship between profitability of the bank and non-performing loans, indicating that when banks achieve high profits managers have low incentives to seek high-risk loans as banks are achieving profits already, elsewhere. This finding agreed with Ramlall (2009) who conducted a study in Taiwan and Garcia-Herrero, Gavila & Santabarbara (2006) in China, when they found that high levels of non-performing loans had a negative impact on bank's profitability, due to poor quality of these assets. These results were also consistent with a other studies across the world, such as Bashir (2000) in their study on Middle East, Apergis (2014) on a sample of banks in the United States and with Peric and Konjusak (2017) on Central and Eastern European Countries (CEE). On the contrary, authors in Philadelphia argued that when bank managers are risk-averse they are comfortable trading off reduced earnings for reduced risk, especially when their wealth depends on the performance of the bank (Hughes, Lang, Mester & Moon, 1995). In the later years, Dietrich and Wanzenried (2011) supported the insignificance of the relationship between bank's profitability and nonperforming loans in Switzerland, revealing that the positive effect of credit growth has no bearing effect on bank's profitability; a finding insinuates that banks can comfortably increase profitability and a supply of loans (through credit growth) without worrying about increase in nonperforming loans. Linked to credit growth is profitability, several authors have found a positive relationship between credit growth and bank's profitability (Becker & Ivashina, 2014) and this has been attributed to the practise of issuing high risk loans to achieve profitability.

Based on the literature reviewed in the previous paragraphs, both macroeconomic and bank level factors seem to be influencing non-performing loans in a significant way.

From the literature review, this study selected all six recurring macroeconomic factors that have been found to mostly affect nonperforming loans. The factors selected are relevant to the South African economy and are also considered the main macroeconomic drivers in the country in general; namely: real gross domestic product, real interest rates, inflation rate, unemployment rate, real income growth and housing prices. Six recurring bank specific factors were selected for this study namely: credit growth rate, credit quality (loan loss provisions) bank capitalisation, operating efficiencies, bank profitability and size of the bank.

After considering the variables included in the literature, the next section will formulate hypotheses.

2.3.2. Research Hypotheses

Based on the literature reviewed in the section above, Table 1 below outlines null hypotheses that was formulated:

Table 1: Research Hypotheses

Explanatory Variable	**Hypothesis**
Real GDP growth (RGDP)	H_1: Real GDP growth has a negative relationship with Non-Performing Residential Mortgage Loans. As economic environment improves, consumer income increases and their financial capacity to service their debt obligations. This in turn lowers credit risk levels.
Real interest rate (RINT)	H_2: Real interest rate has a positive relationship with Non-Performing Residential Mortgage Loans. As interest rate levels increase, so does the real value of the debt. This in turn makes repayments required from the borrower more expensive, leading to increased chances of default.
Inflation rate (INFL)	H_3: Inflation rate has a positive relationship with Non-Performing Residential Mortgage Loans. Although conflicting results were provided in the literature, the hypothesis of this study is based on the notion that as inflation levels rise, borrower's income will not be enough to cover all normal expenses thereby increasing the chances of default.
Unemployment rate (UNEMP)	H_4: Unemployment rate has a positive relationship with Non-Performing Residential Mortgage Loans. As unemployment rises, source of income reduces for borrowers resulting to inability to repay their debts.
Housing prices (HPI)	H_5: Housing prices have a negative relationship with Non-Performing Residential Mortgage Loans. As house prices increase, borrowers are more motivated to repay their debts in order to benefit from increased value of the property asset.
Real income growth (DINCO)	H_6: Real income growth has a negative relationship with Non-Performing Residential Mortgage Loans. As real income grows, there are excess funds available to borrowers, resulting in decrease non-performing loans.

Bank Capitalisation (BCAP)	H_7: Bank capitalisation has a negative relationship with Non-Performing Residential Mortgage Loans. Although there are conflicting views from the literature, the hypothesis is based on the theory of the "moral hazard", implying the notion of banks with low equity capital have a tendency of issuing riskier loans thereby increasing opportunity for increased non-performing loans.
Bank Profitability (PROF)	H_8: Bank profitability has a negative relationship with Non-Performing Residential Mortgage Loans. Although conflicting results were provided in the literature, the hypothesis of this study is based on the notion that highly profitable banks have less incentive to issue riskier loans.
Bank operating efficiencies (OPEFF)	H_9: Bank operating efficiencies have a positive relationship with Non-Performing Residential Mortgage Loans. As banks increase operating efficiencies, costs allocated to credit risk management also reduce, increasing chances of non-performing loans.
Credit Growth (CRGTL)	H_{10}: Credit growth has a positive relationship with Non-Performing Residential Mortgage Loans. As banks increase supplying loans, there is a tendency to reduce the pricing on loans, these banks also tend to lower their credit standards in pursuit of credit assets. This strategy increases probability of default by borrowers and the associated volume of defaults.
Bank Credit Quality (Loan Loss Provisions) (CRQUAL)	H_{11}: Credit quality has a positive relationship with Non-Performing Residential Mortgage Loans. An increase in loan loss provisions as a ratio to total loans indicates an increased risk of the bank's loan portfolio and implies an increase in non-performing loans.
Bank Size (SIZE)	H_{12}: Size of the bank has a negative relationship with Non-Performing Residential Mortgage Loans. Larger banks have opportunity and resources to adopt better risk management strategies than smaller banks.

2.4. Conclusion

The purpose of this chapter was to conduct a literature review of the different factors that have been found to influence credit risk on residential mortgage loans. In this chapter, an overview of the mortgage market in South Africa was outlined and discussed. This chapter also discussed the theoretical review of the credit risk concept, followed by the definition as well as determinants of credit risk. Thereafter, the factors that influence credit risk on residential mortgage loans were outlined and explained. Lastly, the hypotheses of explanatory variables was formulated based on the variables identified from the literature review. The next chapter will discuss the research methodology for the study.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1. Overview

Collis and Hussey (2014) define research as a systematic and methodical approach of investigating with a view to increasing knowledge. This chapter will describe the methodology of how the data was collected and will explain the tools used to process and analyse the data. The next section begins by specifying the research population and sample, followed by a discussion on the methods used to collect, test and analyse the data used in the study.

3.2. Research Population

The population of the study is all residential mortgage loans issued by retail banking industry in South Africa.

3.3. Research Sample

The sample used for this study is a non-performing loan book from one of the four big banks in South Africa. As at November 2019 and from figure 1 above, the four big banks collectively contributed 93% of the total loans reflected in the banking industry balance sheet (SARB, 2019). Of the residential mortgage loans in the balance sheet, Standard Bank holds the largest contribution of the residential mortgage loans at 33.77 percent, followed by ABSA 23.11 percent, First National Bank 21.29 percent and Nedbank 14.44 percent. In order to maintain confidentiality the name of the bank whose data is being used for the study is not disclosed.

3.4. Data Collection

Monthly data of current, overdue and foreclosed mortgage loans was obtained from one of the big four banks in South Africa, covering a sample period of January 2010 to December 2018. The time series data was selected because time series investigations are able to provide certain insights that cross sectional investigations may have not. The decision to use time series methodology is in line with the majority of previous and recent studies conducted on the subject, although more frequent that other studies which have used quarterly and yearly data. The period of 2010 to 2018 was selected to capture a normalized stress period post the global banking crisis and pre implementation of IFRS9 expected credit loss model for impairments. From 2018 onwards, the new IFRS9 model required banks to provide for impairment allowance from the time a loan is recorded in the books based on expected losses. A consequence of this new approach, compared to the old approach of IAS39, is an increase in impairment allowances that reflect on bank financial statements (EY, 2017).

Data for bank specific variables was retrieved from the financial records of the bank under review as well as from Bloomberg.

The macroeconomic data used in the study was sourced from the South African Reserve Bank for real interest, while data for real gross domestic product, unemployment and inflation rates were obtained from Bloomberg; the housing price index data was obtained from the FNB online database. Lastly, data for household disposable income was obtained from the World Bank.

Macroeconomic data for unemployment, real GDP and household disposable income is only published quarterly whereas we needed monthly observations, in order to overcome this misalignment, we used a method of Cubic Spline Interpolation to split the data into monthly observations.

Due to the possibility that Macroeconomic and Bank level data for the current period does not necessarily affect non-performing loans in the same period, macroeconomic data was lagged by three periods and by twelve periods for the bank level data.

3.5. Data Description

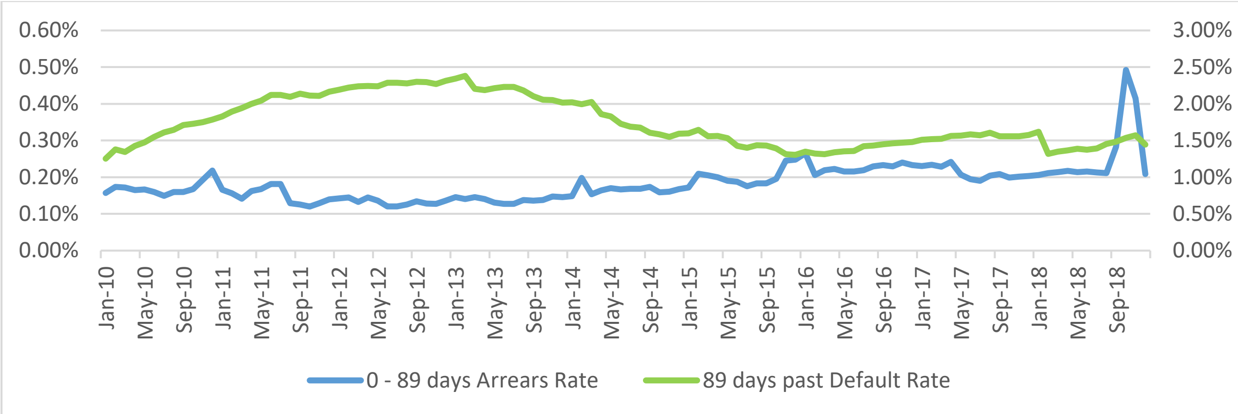
This section gives a detailed description of the data collected and used for the regression analysis that follows. The section will start by explaining and analysing the dependent variable, followed by the description of each independent variable used in the study along with a trend analysis for each variable.

3.5.1. Dependent Variable

The dependent variable is the ratio of non-performing residential mortgage loans to total loans issued, calculated as amount of loan overdue ÷ total amount of loan outstanding. This is a monthly ratio of the total loans in arrears (0 to 89 days past due) and default (>89 days past due), computed using the mortgage loan book of one of the four big banks in South Africa.

Figure 2 below shows a trend analysis of non-performing residential mortgage loans that are in “arrears” for 1 to 89 days and in “default for more than 90 days as a ratio of total loan book of the undisclosed bank, between 2010 and 2018.

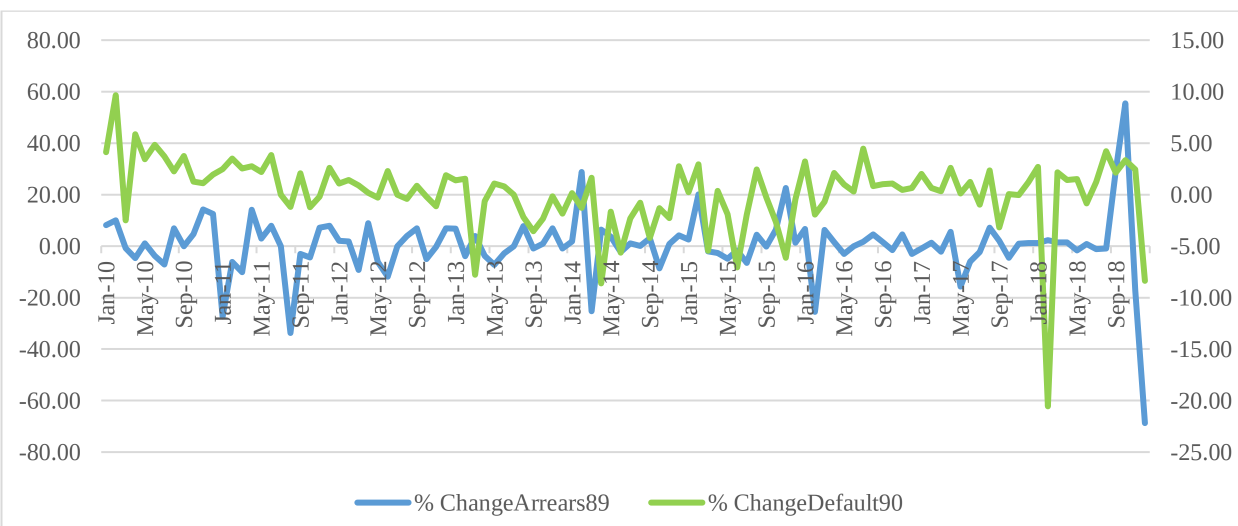
Figure 2: Default rates for residential mortgage loans



The graph on Figure 2 above shows a marginally increasing trend of around one basis point month on month for 0 to 89 day arrears rates until 2011 when the default rate on the category lowered. The default rates for loans past 89 days started increasing in 2011 and were at their highest in 2013 as customers were migrating from the 0 to 89 arrears category. By the second quarter of 2016, the past 89 days default rate had decreased to 1.36% from a high of 2.38% in February 2013. Towards the end of 2018, the 0 to 89 days default rates increased by 74 basis points from a trough of 0.28% in September 2018 to 0.49% in October 2018. This trend indicates a deterioration in the credit quality of the loan book.

Figure 3 below shows the transformed data of the default rates (differenced logit that indicates the monthly percentage change in the default rates - the growth rate); this transformed data exhibits a similar trend as the original data in Figure 2 above over the testing period.

Figure 3 Growth rate of defaults for residential mortgage loans



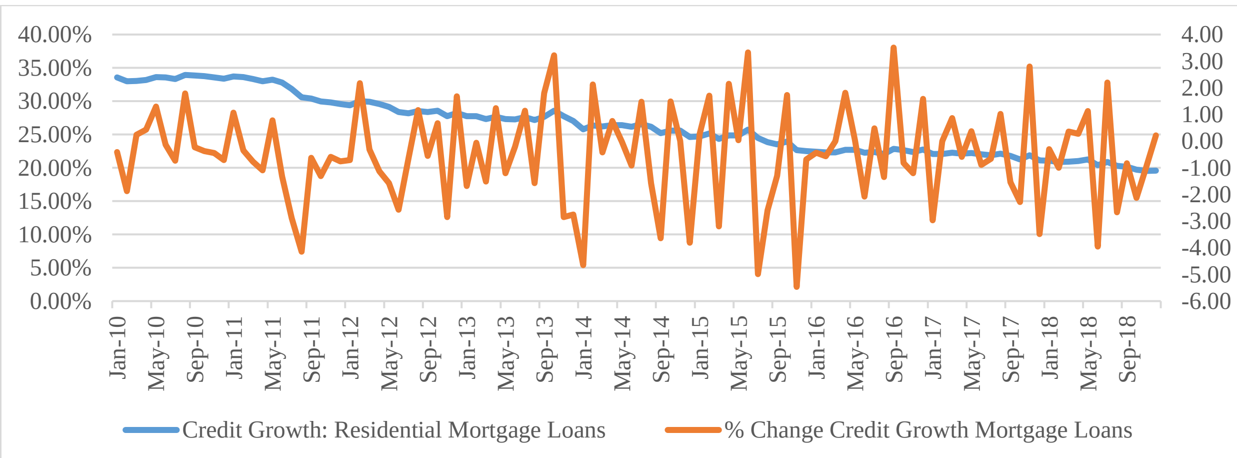
3.5.2. Bank Specific Variables

Figures below show a comparison between the original data values and monthly percentage change in the values for each variable.

3.5.2.1. Credit Growth

Credit growth rate is the rate of change in loans supplied by banks in relation to the banks' total assets. Figure 4 in the paragraph below shows the credit growth rate of residential mortgage loans issued by the bank.

Figure 4: Credit Growth: Residential Mortgage Loans



Measured as a ratio of residential mortgage loans to total assets, the Figure 4 shows a gradual downward trend to 19 percent in December 2018 from a 33.59 percent in 2010.

Figure 5 below, shows the credit growth rate of total loans issued by the bank to the household sector, including residential mortgage loans, measured as a ratio of total loans to total assets.

Figure 5: Credit Growth on Total Loans

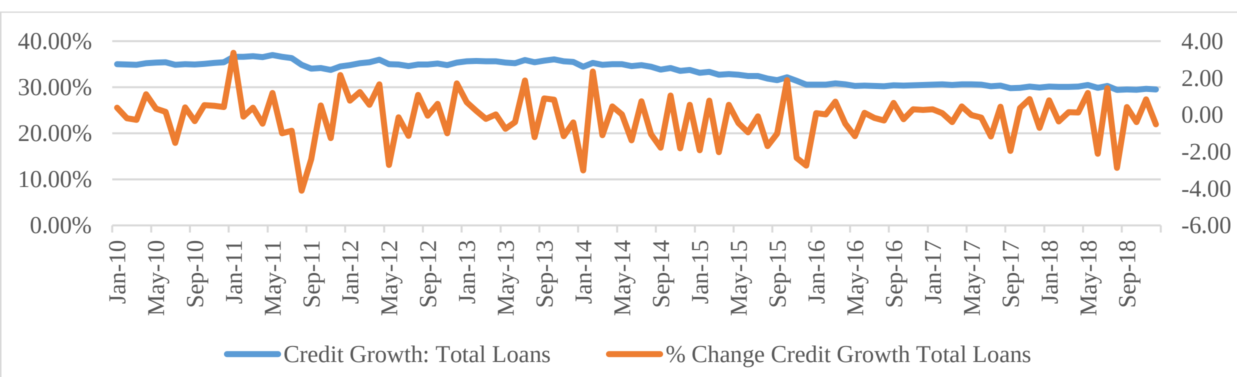


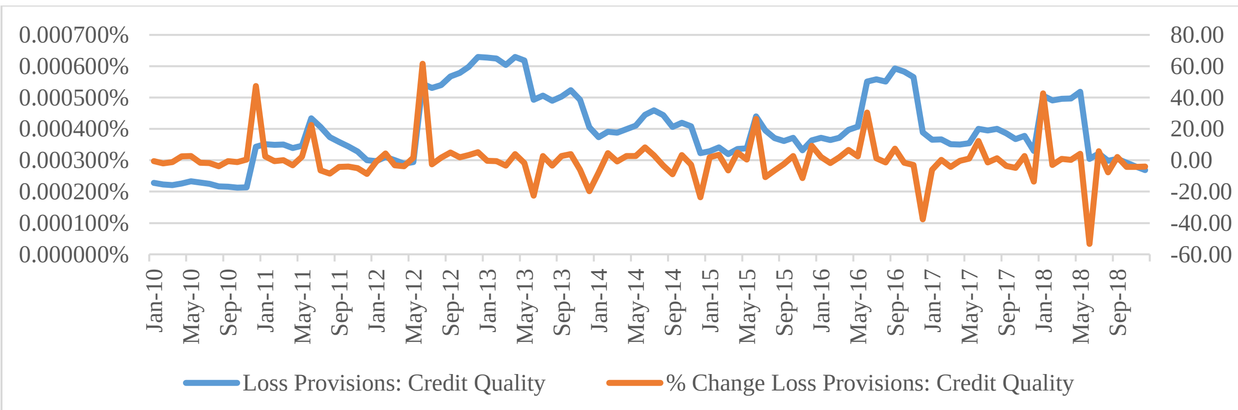
Figure 5 above, shows a stable trend as the ratio floated in the 35 percent region, with 1 percent variability, since 2010. The graph also shows a marginal downward trend from 2014 until 2010, which indicates a net effect from as customers alternate between residential mortgage loans and other loan types.

3.5.2.2. Credit Quality (Loan loss provisions)

Measured as the ratio of loan loss provisions to total loans issued by the bank, credit quality reflects a bank's attitude towards preventing and managing risk (Ghosh, 2015).

Figure 6 in the paragraph below shows the ratio of provisions for loan losses to total assets for the bank under review.

Figure 6: Loss Provisions: Credit Quality



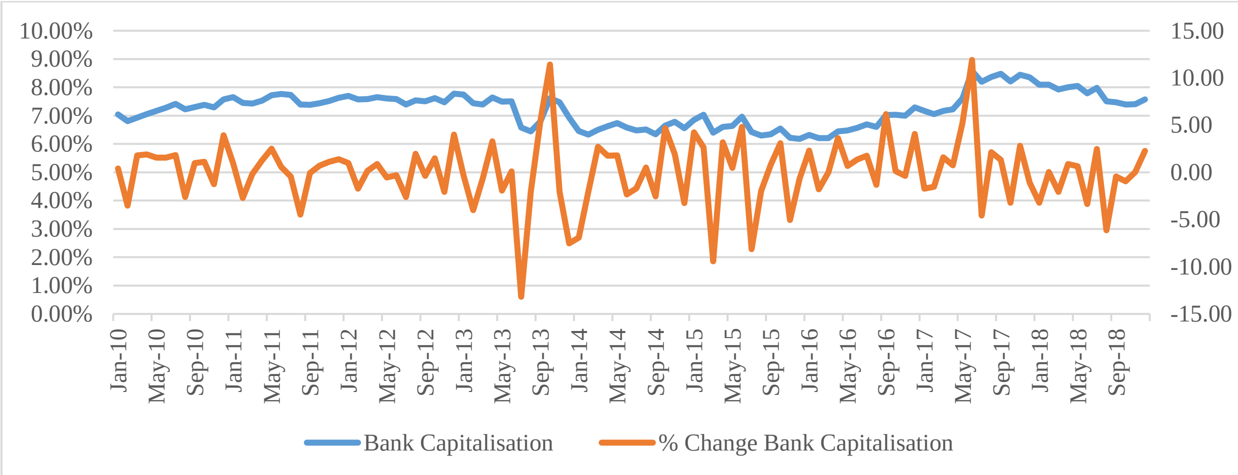
Averaging 0.004 percent between 2010 and 2018, the ratio of loss provisions peaked to 0.0006 percent in 2013 and 2016 while there have been small peaks in between. The growth rate on loss provisions month on month (shown under name '% Change with corresponding numbers on the right side of the equation) also shows the same trend.

3.5.2.3. Bank capitalisation

Bank capitalisation reflects the capital strength of a bank and represents that amount of equity capital in relation to the bank's total assets. This variable is measured by the equity-to-total asset ratio.

Figure 7 below shows that ratio of total bank's equity to total assets was in the 7 percent region from 2010 until January 2014 when it reduced by 1 percent for a short while before going back to the 7 percent average in the second quarter of 2017.

Figure 7: Bank Capitalisation

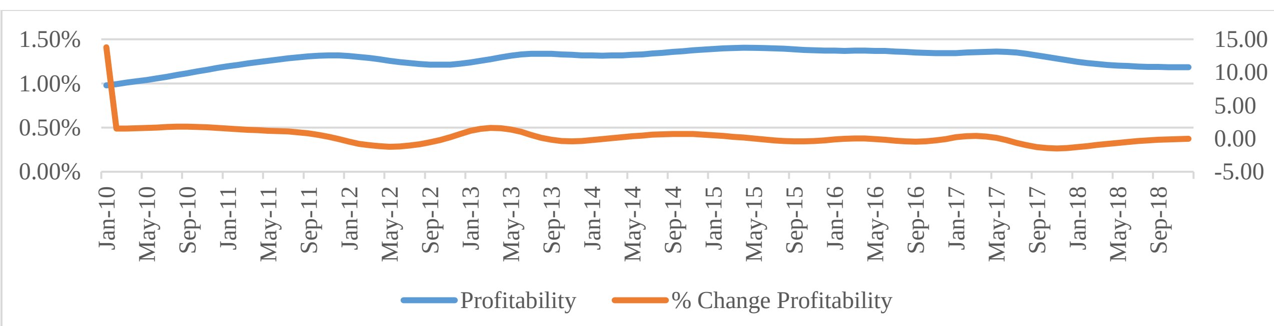


3.5.2.4. Profitability

Profitability is a financial ratio used to measure how a bank uses its assets to generate profits. Loans are assets to a bank and profitability from this asset class is achieved by issuing loans in high volume or loans with high interest income. Profitability by the Return on Assets (RoA) of the bank.

Figure 8 below, captures the bank's profitability from 2010 to 2018. The graph shows a stable trend of the bank's RoA ratio, that has been increasing very marginal increase month on month since 2010.

Figure 8: Bank Profitability

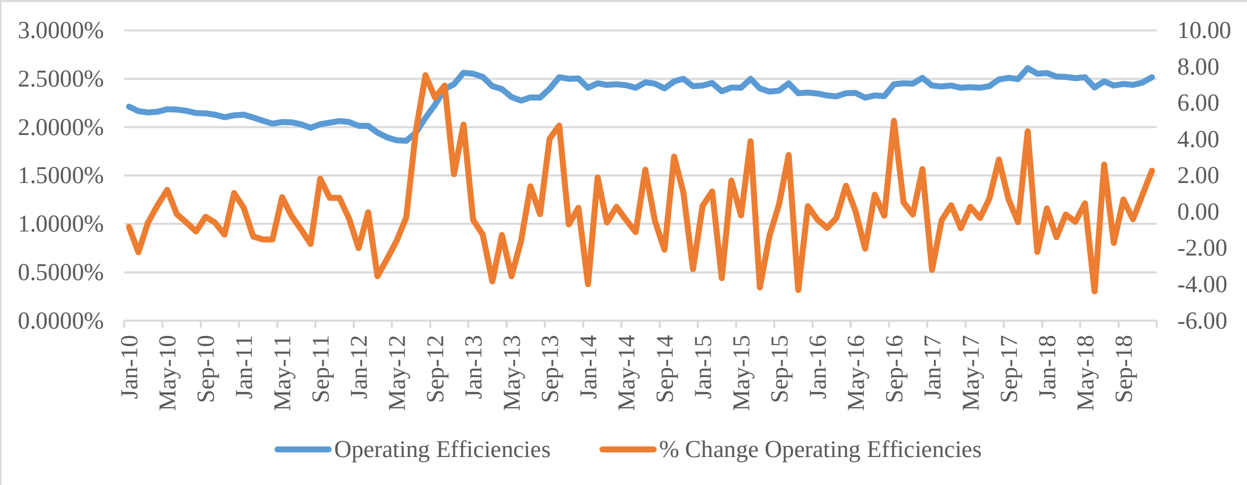


3.5.2.5. Operating efficiencies

Measured as a ratio of non-interest expenses adjusted for labor and fixed costs, divided by total assets, operating efficiencies reflect the bank’s efforts to manage costs.

Figure 9 below, shows the trend analysis of operating efficiency ratio of the undisclosed bank.

Figure 9: Operating Efficiencies

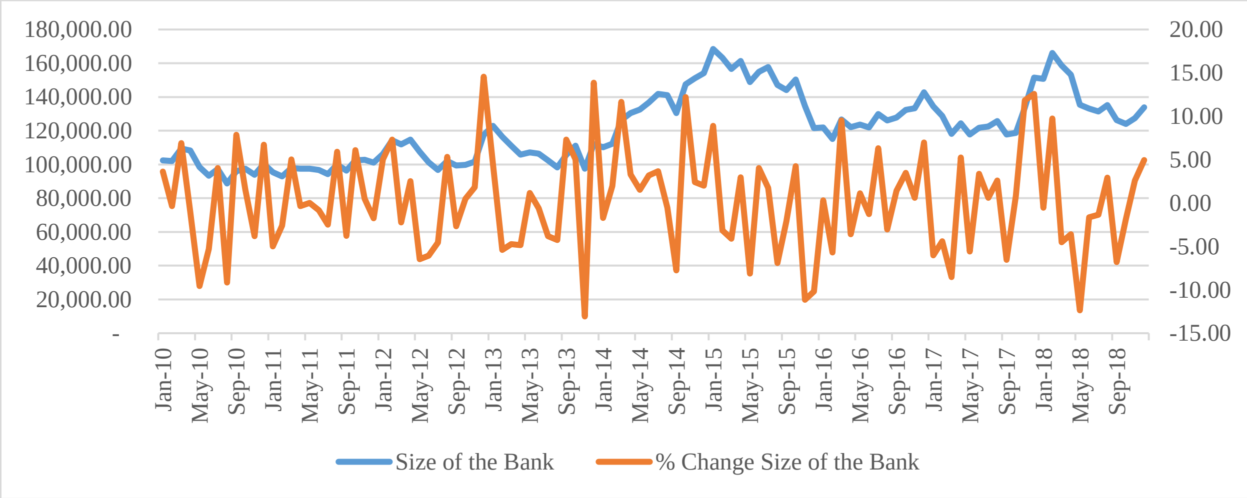


The bank’s operating efficiency ratio between 2010 and 2012 averaged 2.3% before briefly decreasing in March 2012 and in 2013, the ratio increased back to the average levels of 2.5% until 2018.

3.5.2.6. Size of the bank

Size of the bank is measured by its market capitalisation. Figure 10 below, shows that the bank's undisclosed market capital was at the highest in January 2015 and again in March 2018.

Figure 10: Size of the Bank

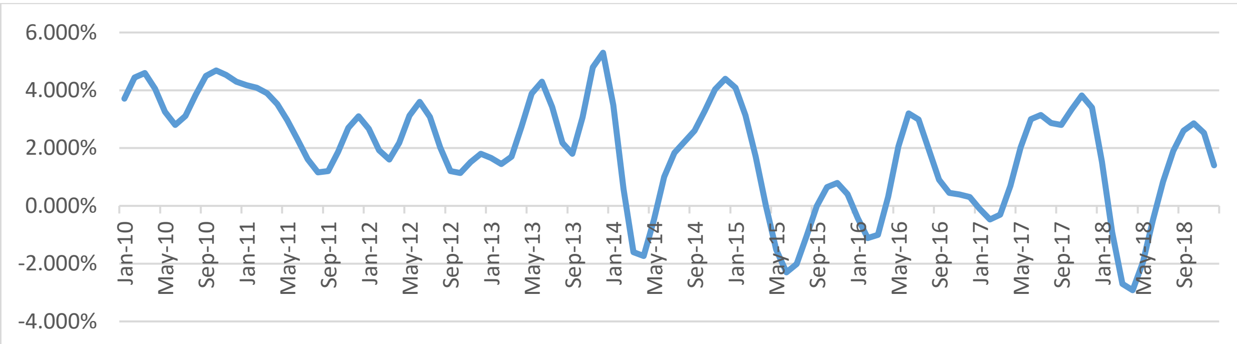


3.5.3. Macro-economic Variables

3.5.3.1. Real gross domestic product

Gross domestic product (GDP) is a measure of market value of final goods and services produced in an economy during a specified period. Real GDP is GDP that has been adjusted for price changes (inflation) and like GDP; they capture the level of economic activity. A productive economy means that businesses are active in producing goods and will to employ people in order to achieve production, thereby providing income to the households, as such a decrease in non-performing loans (Blanchard & Johnson, 2011). Figure 11 below shows real GDP growth rate in South Africa between 2010 and 2018.

Figure 11: Real GDP growth rate

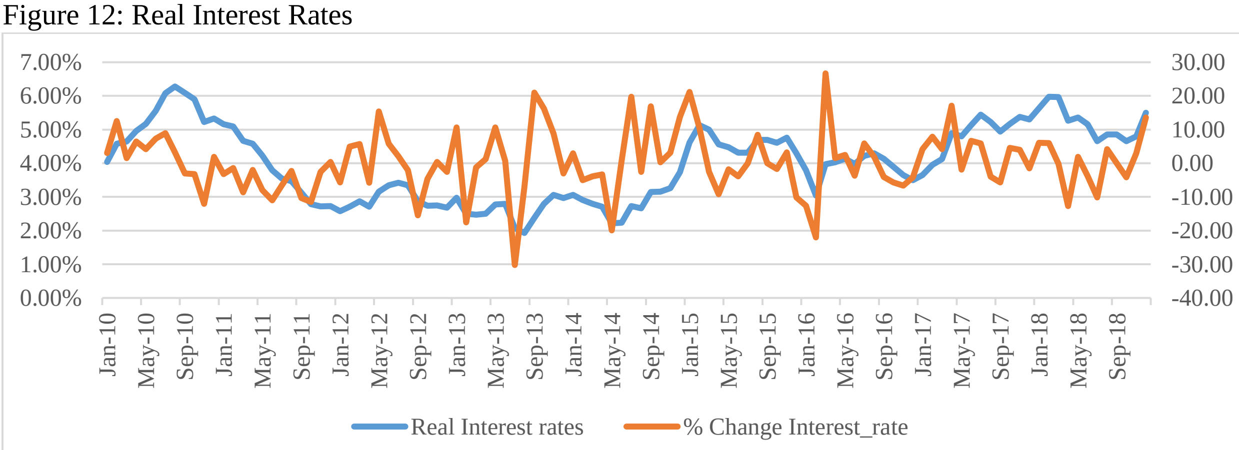


From Figure 11 above, real GDP growth rate averaged 1.9 percent and experienced contractions between 1020 and 2018 with a low of -2.9 percent in April 2013 and a high of 5.3 percent in December 2013.

3.5.3.2. Real interest rate

Interest rate is the price charged by banks for taking the risk of lending funds to customers. Interest on the loan, is a charge over and above the repayment of capital amount borrowed from the bank. Real interest rate is the interest rate adjusted for inflation. Figure 12 below, captures the real interest rates performance over the period 2010-2018.

Figure 12: Real Interest Rates



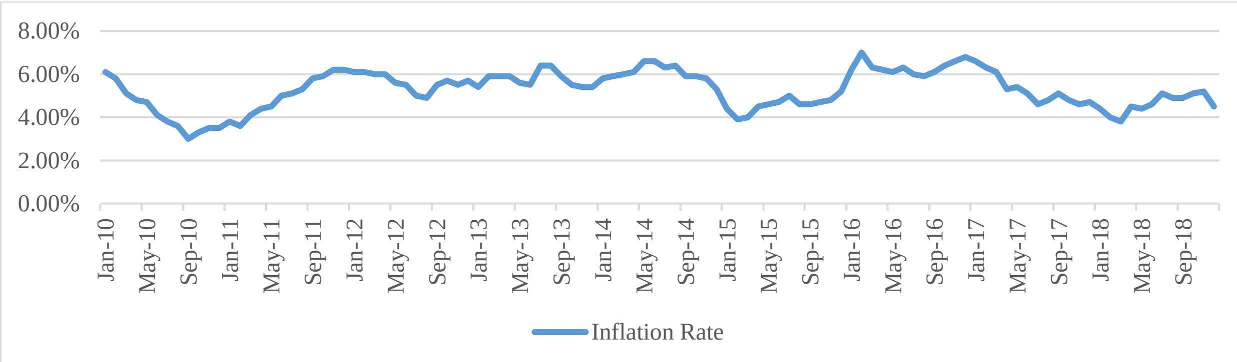
From Figure 12 above, real interest rates were at highest in August 2010 at 6.28 percent whereafter they reflect a decreasing trend until January 2012. The real interest rates for South Africa closed 2018 at 5.50 percent.

3.5.3.3. Inflation rate

Inflation rate is the rate at which the average prices for goods in the economy are increasing over time (Blanchard & Johnson, 2011) and is measured as a percentage change in consumer price index, an official measure of inflation in South Africa.

Figure 13 below, shows inflation rate measured as a rate of change in the consumer price index.

Figure 13: Inflation Rate



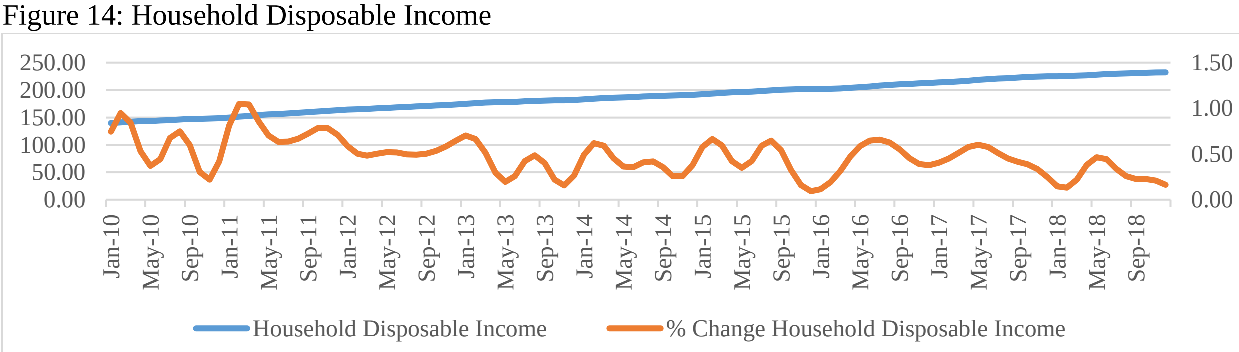
From Figure 13 above, the inflation rate in South Africa showed a decreasing trend in the last quarter of 2010 until 2011 when the average rate of inflate increased to 5.4 percent with a highest rate in the period being 2017 at 6 percent and low of 3 percent in September 2010.

3.5.3.4. Real personal income growth

Personal income represents the amount of funds households have available to meet their daily needs and obligations. Real personal income is income of a household after accounting for inflation.

Figure 14 captures the income of South African households between 2010 and 2018.

Figure 14: Household Disposable Income

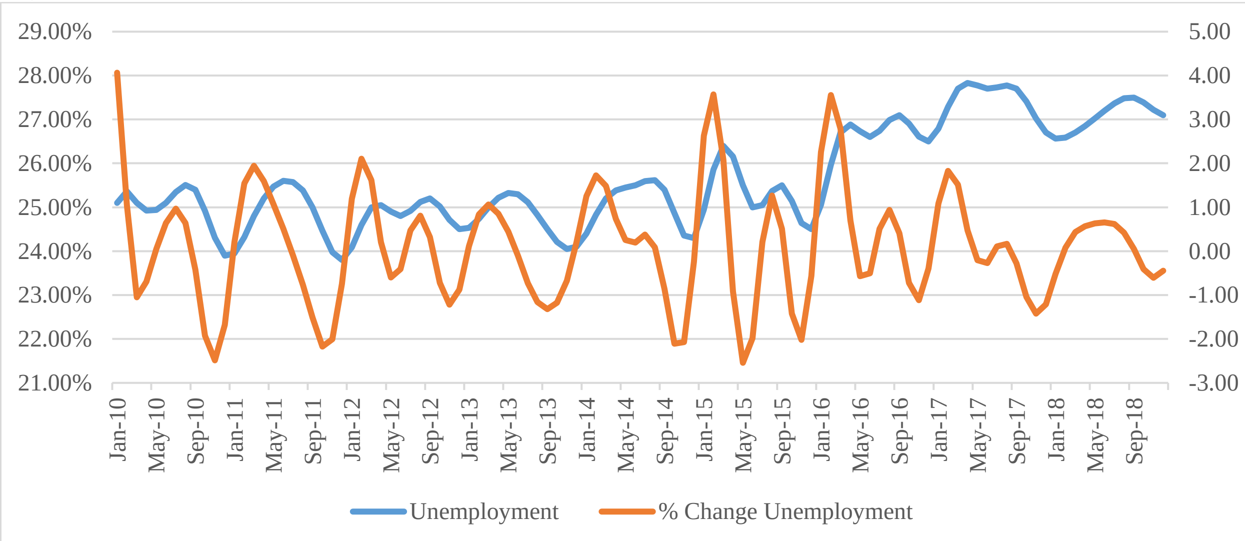


In absolute numbers, the disposable income for South African households has been showing a gradual increase throughout the period under review, 2010 to 2018. The average growth rate in the household disposable income overall averaged 0.48 percent during 2010 to 2018, with highest growth rate noted in February 2011 at 1.05 percent.

3.5.3.5. Unemployment rate

Unemployment rate is the ratio of the number of people who are unemployed to the number of people that are in the labor force. Figure 15 below, captures the trend in unemployment rate in South Africa between 2010 and 2018.

Figure 15: Unemployment



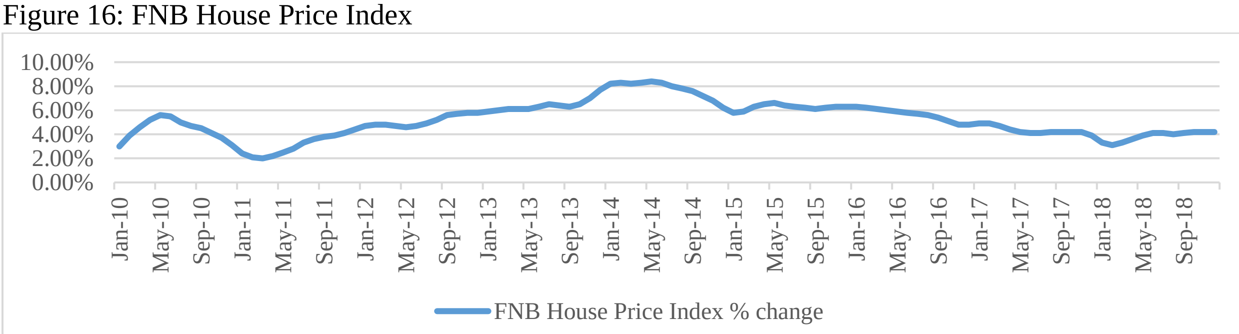
From Figure 15 above, the number of unemployed people in South Africa averaged 24 percent from 2010 and showed an increasing trend since March 2014 to a high of 27 percent in December 2018.

3.5.3.6. Housing prices

Housing prices represent the level of property prices in the region or country. The level of housing prices for this study were obtained from the FNB House Price Index, which gives a measure of the rate of change in housing prices – a price inflation rate for residential properties financed by FNB.

Figure 16 below, shows a nominal house deflation from August 2010 to June 2011. From July 2011, house prices peaked, reaching a high of 8.40 percent in July 2014. House prices slowed down again in the last half of 2014 to 2018 where they closed at 4.20 percent.

Figure 16: FNB House Price Index



3.6. Data Analysis

Analysis of data to be used in a study involves a statistical process of preparing and structuring raw data in order to extract valuable information from that data (Du Plooy, 2001). To analyse the data, this study used STATA version 13 software package. The data series was tested to confirm if it is stationary, using a unit root test. Thereafter, several diagnostic tests were conducted in order to confirm that the model did not violate the assumptions of a multiple linear regression model. The diagnostic tests conducted were as follows, tests for heteroscedasticity, multicollinearity, linearity and autocorrelation. Section 4.2 in the next chapter reports the results of diagnostic tests conducted as well as the descriptive statistics analysis conducted.

3.7. Empirical Specification

This study applied the ordinary least squares (OLS) regression model to estimate the influence of macroeconomic and bank specific factors on non-performing residential mortgage loans (NPRML). The OLS methodology was chosen because this estimation technique is linear, unbiased and has a minimum variance amongst all linear unbiased estimators of a parameter (Brooks, 2014). The investigation of nonperforming loans using econometric models is well known method in the literature, and many studies have used various econometric methods of explaining the variation on nonperforming loans across the world. For instance, Baholli, Dika and Xhabija (2015) used a simple linear regression model to explain the factors that influence nonperforming loans in Italy and Albania over the period of 2008-2014. The study used four macroeconomic variables as independent variables namely, GDP, interest rates, inflation, and credit to economy. The authors found that GDP and credit to economy contribute significantly to nonperforming loans. Nikolaidou and Vogiazas (2017) in their study investigated the drivers of credit risk in Sub Saharan banking system using an auto regressive model. This study concluded that money supply had inverse relationship with nonperforming loans for all Sub Saharan countries, while only banking factors affected South Africa and Uganda. Ghosh (2015) explained the drivers for nonperforming loans in the United States using fixed effects and GMM-dynamic estimation methods with both macroeconomic and bank specific factors as independent variables. According to this study, both state-level macroeconomic and bank specific factors influence nonperforming loans. Havrylchyk (2010) explained the factors that influence nonperforming loans in South Africa using a linear regression model. The model considered macroeconomic factors such as GDP, inflation and interest rate as independent variables. In his study, Havrylchyk, who also performed a stress test after building the model, contends that the South Africa banking sector is capable of absorbing macroeconomic shocks such that these shocks have no impact on nonperforming loans, as a result of high capitalisation levels.

This study will use a multiple linear regression model to explain factors that determine nonperforming loans in residential mortgages. In the literature review, there were many studies that used this model such as Sim (2019) who investigated the drivers of credit risk in Thailand. The study used yearly data from 2013-2017 and considered both macroeconomic and bank specific factors as independent variables. Kalluci (2018) followed the same approach for Albania between 2007-2017 but only considered macroeconomic variables. This study found GDP and unemployment to have a positive relationship on nonperforming loans. In 2016, Tsumake also employed the multiple linear regression to model the determinants of nonperforming loans in Botswana. The author found that both macroeconomic and bank specific factors play a major role in influencing nonperforming loans. It is our view that the multiple linear regression model captures well the relationship between both bank and macroeconomic factors and nonperforming loans (as a dependent variable) as modelled below:

$$NPRML_t = \beta_0 + \beta_1 \, NINT_t + \beta_2 \, RGDP_t + \beta_3 \, HPI_t + \beta_4 \, UNEMP_t + \beta_5 INFL_t + \beta_6 \, DINCO_t + \beta_7 BCAP_t + \beta_8 \, CRGTL_t + \beta_9 OPEFF_t + \beta_{10} \, PROF_t + \beta_{11} \, CRQUAL_t + \beta_{12} \, SIZE_t + \varepsilon_t$$

Where:

- Y_t represents a dependent variable,
- β_0 represents a constant,
- β_1 to β_{12} represent the slope of the coefficients at time t,
- RINT, RGDP, HPI, UNEMP, INFL, DINCO, BCAP, CRGRTL, OPEFF, PROF, CRQUAL, SIZE represent real interest rate, real GDP, housing price index. unemployment rate, inflation rate, household disposable income, bank capitalisation, credit growth for total loans, bank operating efficiency, bank profitability, bank credit quality (loan loss provisions) and bank size
- ε_t is an independently and identically distributed error term.

3.8. Check for Robustness

To check for robustness of the estimates, the regression models were run on STATA with default standard errors and the coefficients compared with the results from the robust standard errors regression. According to Lu and White (2014), a finding that the coefficients do not change much is taken to be evidence that these coefficients are ‘‘robust’’. Section 4.5 in the next chapter reports the results of robustness tests conducted to confirm the behavior of regression estimates.

3.9. Conclusion

This chapter described the methodology used to collect and process the data. The chapter also analysed the data variables used in the study and explained diagnostic tests conducted to detect if there were any violations of model assumptions. In the next chapter, we check the stationarity of the data series, conduct the diagnostic tests, run the OLS regression model, check robustness of the model and discuss the results of the estimation.

CHAPTER FOUR: EMPIRICAL RESULTS AND ANALYSIS

4.1. Introduction

This chapter begins with the analysis of data used in the regression models, followed by a presentation of descriptive statistics for the data variables used in this study. Whereafter, a discussion on the results and findings from the OLS linear regression model. The discussion commences with the results and findings noted from the model on the 0 to 89 days arrears category followed by the results from the model on the arrears category and >89 days. In interpreting the results, the aim was to identify bank and macroeconomic factors that explain default ratio rates on residential mortgage loans. Lastly, a check of the robustness of the OLS regression models used in the study is conducted results and interpreted. The last section of this chapter concludes with a discussion on the research limitations that are not addressed by this current study.

4.2. Data Analysis

Analysis of data to be used in a study involves a statistical process of preparing and structuring raw data in order to extract valuable information from that data (Du Plooy, 2001). To analyse the data, this study used STATA version 13 software package.

The data series was tested to confirm if it is stationary, using a unit root test. Thereafter, several diagnostic tests were conducted in order to confirm that the model did not violate the assumptions of a multiple linear regression model. The section below outlines diagnostic tests that were conducted, whereafter, descriptive statistics analysis was conducted.

4.2.1 Unit root testing

The Augmented Dickey-Fuller test was used to test for stationarity of the data series on all variables used in the study. Table 2 below presents the unit root results, where the null hypothesis is that the data is not stationary.

Table 2: Augmented Dickey-Fuller unit root test result summary

Variable	Coef.	Std. Err	t-Statistic	Prob.
NPRML89	-1.74	0.20	-8.54	0.00
NPRML90	-0.97	0.10	-9.71	0.00
BCAP	-1.03	0.10	-10.45	0.00
CRGTL	-1.21	0.10	-12.59	0.00
CRQUAL	-1.06	0.10	-10.80	0.00
PROF	-0.02	0.01	-2.46	0.02
HPI	-0.01	0.01	-1.41	0.16
DINCO	-0.06	0.03	-2.32	0.02
INFL	-0.78	0.10	-8.00	0.00
OPEFF	-0.64	0.12	-5.18	0.00

RGDP	-0.05	0.02	-2.64	0.01
NINT	-1.28	0.09	-13.75	0.00
SIZE	-1.09	0.10	-11.13	0.00
UNMEP	-0.61	0.07	-8.49	0.00

The results show that the majority of variables are stationary with ρ not equal to zero, with exception of the housing price index, which returned a p-vale of 0.16, a number that is greater than 0.05, meaning that the variable has unit root. In order to induce stationarity on the variable, the housing price index was first-differenced per table 2a below, whereafter; this variable returned a p-value of 0 which confirms that the variable is stationary.

Table 2a: Augmented Dickey-Fuller unit root test result summary for differenced variables

Variable	**Coef.**	**Std. Err**	**t-Statistic**	**Prob.**
HPI	1.12	-8.07	0.00	1.12

4.2.2 Model Assumptions test

The regression model aims to predict the direction and strength of the relationship between variables (Brooks, 2014). The section below shows key assumptions tested in order to preserve the validity and robustness of the regression results of the study.

4.2.2.1 Testing for Normality

One of the principal assumptions in the classical linear regression model is that the data should be normally distributed, hence a test of normality must be conducted (Brooks, 2014). Mandelbrot (1963) states that a normal distribution has a coefficient of kurtosis equal to 3 and skewness of 0.

4.2.2.1.1 Testing for Normality of residuals

To test for normality of residuals, the Jarque-Bera test was conducted using STATA. A p-value greater than 0.05 implies that the null hypothesis cannot be rejected.

Table 3: Jarque-Bera (Skewness/Kurtosis) Test for Normality of Residuals

H_0: Normality
Variables: resid
chi2(1) = 160.9
Prob > chi2 = $1.2e^{-35} \sim 0.000$

The results on Table 3 above show that the p-value is 0.000, which means that the normality assumption is violated.

4.2.2.1.2 Testing for Normal distribution in variables

To test for normality of variables, the results below were obtained from STATA. A p-value greater than 0.05 implies that the null hypothesis for normal distribution cannot be rejected, and from the table below, we note that data largely mirrors normal distribution but has more lower values than the sample mean as kurtosis is below 3. Table 3a below also shows that data for NPRML89, NPRML90, CRGTL, OPEFF, PROF, RGDP and UNEMP is not normally distributed, as the p-values are below 0.05.

Table 3a: Descriptive Statistics (Skewness/Kurtosis) Test for Normality of Variables

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Probability
NPRML89	0.00	0.00	0.00	0.00	0.00	2.59	14.72	0.00
NPRML90	0.02	0.02	0.02	0.01	0.00	0.43	1.69	0.00
BCAP	0.07	0.07	0.09	0.06	0.01	0.05	2.25	0.28
CRGTL	0.33	0.34	0.37	0.29	0.02	-0.25	1.45	0.00
CRQUAL	0.00	0.00	0.00	0.00	0.00	0.41	2.41	0.10
DINCO	0.00	0.00	0.01	0.00	0.00	0.36	3.03	0.32
HPI	0.05	0.05	0.08	0.02	0.01	0.15	2.62	0.59
INFL	0.05	0.05	0.07	0.03	0.01	-0.39	2.40	0.11
OPEFF	0.02	0.02	0.03	0.02	0.00	-0.79	2.49	0.00
PROF	0.01	0.01	0.01	0.01	0.00	-1.14	3.91	0.00
RGDP	0.02	0.02	0.05	-0.03	0.02	-0.56	2.62	0.04
RINT	0.04	0.04	0.06	0.02	0.01	0.06	1.86	0.05
SIZE	0.00	0.00	0.16	-0.12	0.06	0.31	2.86	0.40
UNEMP	0.26	0.25	0.28	0.24	0.01	0.45	1.99	0.02

When outliers are present in the data, robust regression provides much better regression coefficient estimates as this approach minimises the negative effect of outliers and learns the representation of data (Western, 1995). Robust regression efficiently estimates the parameters even in the presence of outliers, by decreasing the influence of these outliers when estimating the parameters (Pandey, 2020). Huber and Ronchetti (2009) argue that robust regression methods are more credible than other diagnostic approaches as they work without the researcher's subjective decisions on whether to reject or accept a suspicious observation. As such, the robust regression was chosen because it produces insensitive, consistent and highly efficient estimates.

In his paper titled 'Distributions of financial accounting ratios, some empirical evidence' Deakin (1976) concluded that financial data commonly follow non-normal distributions with a good number of outliers. To resolve the issue of distributions that are non-normal, many studies attempted to normalise the distributions by transforming the data through a simple algebraic function or a regression model or by removing the outliers until distributions become normal (Deakin, 1976; Bougen & Drury, 1980; Frecka &

Hopwood, 1983). Deakin (1976) suggested that a square root of the lognormal transformation would help reduce non-normality although not eliminate it. The procedure uses the square or log of the data values and is helpful in reducing right skewness. On the other hand, in 1983, Frecka and Hopwood conducted a study that removed outliers using Tests named N14 and N15 in Barnett and Lewis (1978). This procedure is based on the sample kurtosis and skewness and shows that the square root transformed distribution of ten out of eleven variables achieved normality after removing a sufficient number of outliers with Tests N14 and N15. In order to improve normality in this study, data values will be transformed through using the natural logs of the data.

4.2.2.2 Homoscedasticity of residuals

One of the principal assumptions in the classical linear regression model is that there should be Homoscedasticity of data. This means that the variances along the line of best fit remain similar as you move along the line (Brooks, 2014). In the event that error terms do not contain the same variance, the disturbances are heteroscedastic. The test on Table 4 below was conducted on STATA in order to detect heteroscedasticity. Table 4 below presents the results of the test.

Table 4: Breusch-Pagan / Cook-Weisberg test for Heteroscedasticity

H_0: Constant variance
Variables: resid
chi2(1) = 476.16
Prob > chi2 = 0.0000

The results on the afore-mentioned table show a p-value of 0.000, a number that is less than 0.005 and therefore significant. This means that the variances along the line of best fit do not remain similar as you move along the line. The assumption of homoscedasticity is violated. To correct heteroscedasticity, a robust regression is run, instead of the normal multiple linear regression.

4.2.2.3 Test of autocorrelation

There is autocorrelation when there are patterns in the residuals from the model. Autocorrelation can be caused by various factors such as omitted variables or misspecification that may be caused by ignoring non-linearities in a model. To detect degree of autocorrelation, the Durbin Watson test is widely used and a result that is closer to 2 indicates that there is no autocorrelation in the model. In this study the results presented on Table 5 below returned a Durbin Watson-statistic of 1.903820 which is not far from 2. It can therefore be concluded that there is no correlation between residuals.

Table 5: The Durbin-Watson Test for Autocorrelation

Durbin-Watson Stat	1.903820

4.2.2.4 Test for Multicollinearity

Multicollinearity refers to a condition where two or more explanatory variables in a regression model are very highly related with one another. In the event that the regression model has multicollinearity, the affected coefficients may fail to achieve statistical significance as their p-values are increased and consequently low t-statistic values are produced (Brooks, 2014). To detect multicollinearity, this study used the Pearson correlation matrix as well as the Variance inflation factor (VIF). The Pearson correlation matrix tests the relationship between the individual variables and shows the propensity of the relationship. The VIF is another test used to detect multicollinearity in a regression model also quantifies the level of inflation on the variance of the coefficient. Table 6 below depicts the Pearson correlation matrix test.

Table 6: The Pearson Correlation Matrix

	NPRML89	NPRML90	BCAP	CRGTL	CRQUAL	DINCO	INFL	HPI	OPEFF	PROF	RGDP	RINT	SIZE	UNEMP
NPRML89	1.00	-0.61***	-0.06*	-0.70***	-0.18**	-0.36***	-0.06*	-0.14*	0.39***	0.06*	-0.23***	0.42***	-0.10***	0.61***
NPRML90	-0.61***	1.00	0.26**	0.73***	0.35***	0.26***	0.17*	0.06*	-0.42***	-0.02***	0.29***	-0.65***	0.07***	-0.54***
BCAP	-0.06*	0.26*	1.00	-0.06**	0.06***	0.04***	-0.35***	-0.67***	-0.06**	-0.35**	0.21***	0.29***	0.08**	0.26***
CRGTL	-0.70***	0.73***	-0.06**	1.00	0.01***	0.41**	-0.04*	0.11**	-0.54***	-0.28***	0.42***	-0.45***	0.05***	-0.81***
CRQUAL	-0.18**	0.35***	0.06***	0.01***	1.00	-0.10*	0.37***	0.27****	0.34***	0.36***	-0.22***	-0.47***	0.02**	0.02**
DINCO	-0.36***	0.26***	0.04***	0.41**	-0.10*	1.00	-0.07***	-0.31**	-0.47*	-0.21**	0.20**	-0.02**	0.04***	-0.22*
INFL	-0.06*	0.17*	-0.35***	-0.04*	0.37***	-0.07***	1.00	0.47***	0.10***	0.40**	-0.21**	-0.79***	0.05**	-0.01*
HPI	-0.14*	0.06*	-0.67***	0.11**	0.27***	-0.31**	0.47***	1.00*	0.39***	0.45**	-0.20***	-0.54**	0.04***	-0.22**
OPEFF	0.39***	-0.42***	-0.06*	-0.54***	0.34***	-0.47*	0.10***	0.39***	1.00	0.32***	-0.35**	0.10**	0.14***	0.44***
PROF	0.06*	-0.02***	-0.35**	-0.28***	0.36***	-0.21**	0.40**	0.45**	0.32**	1.00	-0.35**	-0.35**	0.01***	0.14*
RGDP	-0.23***	0.29***	0.21***	0.42***	-0.22***	0.20**	-0.21***	-0.20***	-0.35**	-0.35**	1.00	0.04***	0.11***	-0.32***
RINT	0.42***	-0.65***	0.29***	-0.45***	-0.47***	-0.02**	-0.79***	-0.54**	0.10***	-0.35**	0.04***	1.00	-0.08**	0.45**
SIZE	-0.10***	0.07***	0.08**	0.05***	0.02**	0.04***	0.05**	0.04***	0.14***	0.01***	0.11***	-0.08**	1.00	-0.07*
UNEMP	0.61***	-0.54***	0.26***	-0.81***	0.02**	-0.22**	-0.01*	-0.22**	0.44***	0.14*	-0.32***	0.45***	-0.07***	1.00

* indicates significance at 10% level

** indicates significance at 5% level

*** indicates significance at 1% level

From Table 6 above, the pairwise correlation results show some level of multicollinearity among the explanatory variables. Therefore, further investigation in form of a VIF test is conducted on Table 7 below.

Table 7: The Variance Inflation Factor (VIF)

Variable	VIF	1/VIF
RINT	17.27	0.06
INFL	9.90	0.10
CRGTL	8.60	0.12
HPI	4.79	0.21
UNEMP	4.09	0.24
BCAP	3.27	0.31
OPEFF	3.06	0.33
PROF	2.18	0.46
CRQUAL	1.99	0.50
DINCO	1.82	0.55
RGDP	1.49	0.67
SIZE	1.12	0.89
Mean VIF	4.96	

The rule of thumb for Multicollinearity is that the VIF should be less than 10, otherwise a VIF value that exceeds 10 indicates a high multicollinearity between variables (O'brien, 2007). The results show a VIF value that is higher than 10 for real interest rate, exhibiting a presence of multicollinearity.

In order to correct multicollinearity nominal interest rate is considered, instead of real interest rate. Nominal interest rate was generated by adding the inflation rate to the real interest rate. Table 8 below exhibits the new Pearson Correlation Matrix after removing the real interest rate and adding nominal interest rate.

Table 8: New Pearson Correlation Matrix after removing Real Interest Rate

	NPRML89	NPRML90	BCAP	CRGTL	CRQUAL	DINCO	INFL	HPI	OPEFF	PROF	RGDP	SIZE	UNEMP	NINT
NPRML89	1.00	-0.61	-0.06	-0.70	-0.18	-0.36	-0.06	-0.14	0.39	0.06	-0.23	-0.10	0.61	0.62
NPRML90	-0.61	1.00	0.26	0.73	0.35	0.26	0.17	0.06	-0.42	-0.02	0.29	0.07	-0.54	-0.84
BCAP	-0.06	0.26	1.00	-0.06	0.06	0.04	-0.35	-0.67	-0.06	-0.35	0.21	0.08	0.26	0.02
CRGTL	-0.70	0.73	-0.06	1.00	0.01	0.41	-0.04	0.11	-0.54	-0.28	0.42	0.05	-0.81	-0.80
CRQUAL	-0.18	0.35	0.06	0.01	1.00	-0.10	0.37	0.27	0.34	0.36	-0.22	0.02	0.02	-0.29
DINCO	-0.36	0.26	0.04	0.41	-0.10	1.00	-0.07	-0.31	-0.47	-0.21	0.20	0.04	-0.22	-0.12
INFL	-0.06	0.17	-0.35	-0.04	0.37	-0.07	1.00	0.47	0.10	0.40	-0.21	0.05	-0.01	0.01
HPI	-0.14	0.06	-0.67	0.11	0.27	-0.31	0.47	1.00	0.39	0.45	-0.20	0.04	-0.22	-0.27
OPEFF	0.39	-0.42	-0.06	-0.54	0.34	-0.47	0.10	0.39	1.00	0.32	-0.35	0.14	0.44	0.29
PROF	0.06	-0.02	-0.35	-0.28	0.36	-0.21	0.40	0.45	0.32	1.00	-0.35	0.01	0.14	-0.06
RGDP	-0.23	0.29	0.21	0.42	-0.22	0.20	-0.21	-0.20	-0.35	-0.35	1.00	0.11	-0.32	-0.21
SIZE	-0.10	0.07	0.08	0.05	0.02	0.04	0.05	0.04	0.14	0.01	0.11	1.00	-0.07	-0.06
UNEMP	0.61	-0.54	0.26	-0.81	0.02	-0.22	-0.01	-0.22	0.44	0.14	-0.32	-0.07	1.00	0.73
NINT	0.62	-0.84	0.02	-0.80	-0.29	-0.12	0.01	-0.27	0.29	-0.06	-0.21	-0.06	0.73	1.00

The pairwise correlation results from Table 8 above show some level of multicollinearity among the explanatory variables. Therefore, further investigation in form of a VIF test is conducted on Table 9 below.

Table 9: New Variance Inflation Factor (VIF) after removing Real Interest Rate

Variable	VIF	1/VIF
NINT	6.38	0.16
INFL	1.88	0.53
CRGTL	8.60	0.12
HPI	4.79	0.21
UNEMP	4.09	0.24
BCAP	3.27	0.31
OPEFF	3.06	0.33
PROF	2.18	0.46
CRQUAL	1.99	0.50
DINCO	1.82	0.55
RGDP	1.49	0.67
SIZE	1.12	0.89
Mean VIF	3.39	

From Table 9 above, after removing the real interest rate and adding nominal interest rate, none of the explanatory variables recorded a VIF above 10. There is low correlation among the explanatory variables. The mean VIF is now 3.39, further confirming that the assumption of no Multicollinearity is not violated.

4.3. Descriptive Statistics

Table 10 below presents the descriptive statistics for the data variables used in this study. These descriptive statistics include sample mean, standard deviation, minimum and maximum values of all variables in the regression model.

Table 9: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
NPRML89	108	0.00	0.00	0.00	0.00
NPRML90	108	0.02	0.00	0.01	0.02
BCAP	108	0.07	0.01	0.06	0.09
CRGTL	108	0.33	0.02	0.29	0.37
CRQUAL	108	0.00	0.00	0.00	0.00
DINCO	108	0.00	0.00	0.00	0.01
HPI	108	0.05	0.01	0.02	0.08
INFL	108	0.05	0.01	0.03	0.07
NINT	108	0.09	0.01	0.08	0.10
OPEFF	108	0.02	0.00	0.02	0.03
PROF	108	0.01	0.00	0.01	0.01
RGDP	108	0.02	0.02	-0.03	0.05
SIZE	108	0.00	0.06	-0.12	0.16
UNEMP	108	0.256425	0.011281	0.238000	0.278316

The ratio for non-performing residential mortgage loans between 1 and 89 days ranges from 0.12 percent to 0.49 percent, with a mean value of 0.0018. Inflation rate peaked at maximum of 7 percent while the unemployment rate in South Africa continues to increase, reaching a maximum of 28.8 percent and a minimum of 23.8 percent.

4.3 Variables used in the study

Table 11 below shows the choice of explanatory variables used in the study.

Table 11: Variables used in the study

Explanatory variable	Symbol	Description	Source	Expected Sign
Macroeconomic Variables				
Real GDP growth	RGDP	Inflation Adjusted percentage change in GDP	Bloomberg	(-)
Household disposable income	DINCO	Personal Households Income in South Africa	World Bank	(-)
Unemployment rate	UNEMP	Unemployed-to-Labor Force	Bloomberg	(+)
Nominal interest rate	NINT	SA Nominal Interest Rates	South African Reserve Bank	(+)
Inflation rate	INFL	Percentage change in SA CPI	Bloomberg	(+/-)
Housing Price Index	HPI	Fnb House Price Index	FNB	(-)
Bank Specific Variables				
Bank's profitability	PROF	RoA: Net Income Before Tax (EBIT) ÷ Total Assets	Undisclosed Bank Financials	(-)
Operating efficiencies	OPEFF	Non interest Expenses ÷ Total Assets	Undisclosed Bank Financials	(+)
Credit Quality	CRQUAL	Provisions for Loan Losses ÷ Total Loans	Undisclosed Bank Financials	(+)
Size of the bank	SIZE	Market Capitalisation of the Bank	Undisclosed Bank Financials	(-)
Bank capitalisation	BCAP	Total Equity Capital ÷ Total Assets	Undisclosed Bank Financials	(+/-)
Banking Industry Variables				
Credit Growth	CRGTL	Total Loans ÷ Total Assets	South African Reserve Bank	(+)

4.4 Regression Results

Since the assumptions of homoscedasticity have been violated, a robust regression was run, instead of the normal multiple linear regression.

In interpreting the results from the OLS regression model, this study considered the size of the coefficients. This value tells us how responsive non-performing residential mortgage loan rate is to a change in an independent variable. In interpreting the overall model fit, the study considered the R^2, which tells us the degree of explanatory power that the variables, combined, have on the non-performing residential mortgage loan rates.

4.5.1 Regression Results: Model 1 with NPRML89 as dependent Variable

Table 12 presents the results of the regression analysis of non-performing residential mortgage loan rate on the 0 to 89 days category.

Table 12: Regression Results: NPRML89 as dependent variable

Linear regression					Number of Obs	108
					F(12, 95)	27.93
					Prob > F	0.00
					R-squared	0.64
					Root MSE	0.00
NPRML89	**Coef.**	**Robust Std. Err.**	**t**	**P > | t |**	**[95% conf.**	**Interval]**
NINT	-0.02	0.03	-0.73	0.47	-0.07	0.03
RGDP	0.00	0.00	1.01	0.31	0.00	0.01
HPI	-0.02	0.01	-3.38	0.00	-0.03	-0.01
UNEMP	0.02	0.01	2.15	0.03	0.00	0.03
INFL	0.01	0.01	0.83	0.41	-0.01	0.02
DINCO	-0.05	0.02	-3.08	0.00	-0.09	-0.02
BCAP	-0.05	0.01	-3.38	0.00	-0.07	-0.02
CRGTL	-0.01	0.01	-1.59	0.11	-0.02	0.00
OPEFF	0.08	0.02	3.33	0.00	0.03	0.12
PROF	-0.08	0.09	-0.94	0.35	-0.25	0.09
CRQUAL	-78.18	46.64	-1.68	0.10	-170.77	14.41
SIZE	0.00	0.00	-1.08	0.28	0.00	0.00
_cons	0.01	0.00	1.37	0.17	0.00	0.02

Based on table 12 above, the estimated regression model 0 to 89 days non-performing residential mortgage loan rate is as follows, rounded off to two decimals:

NPRML89 = 0.01 – 0.02(NINT) + 0.00(RGDP) – 0.02(HPI) + 0.02(UNEMP) + 0.01(INFL) – 0.05(DINCO) – 0.05(BCAP) – 0.01(CRGTL) + 0.08(OPEFF) – 0.08(PROF) – 78.18(CRQUAL) – 0.00(SIZE) + ε

The study considers statistical significance at 5 percent (95 percent confidence level) and makes an assessment on whether the coefficients are statistically significant or not, by considering the p-value. The R-squared value of 0.64 shows that the independent variables altogether explain about 64 percent of variations in less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). The F-statistic also has a significant p-value of 0.00, which means that the variables fit the model.

The results show that nominal interest rate (NINT) recorded a coefficient of -0.02 with a p-value of 0.45 (greater than 5 percent or 0.05 or 0.05). This implies an insignificant negative effect of NINT on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is a low probability that changes in NPRML89 are associated with changes in NINT. This finding is in contrast with literature as most previous studies have found interest rate to have a significant positive relationship with non-performing loans. Lagged by three periods, an explanation for this result could be that the impact of changes in interest rates is not visible in the short run (less than 89 days) as borrowers are still able to delay default as much as possible and that the interest rates on the majority of mortgage loans are fixed and not affected by changes in interest rates. This rationale is supported by the result noted in the 90 day default rate in the model below, where interest rate shows a significant relationship.

Real GDP (RGDP) recorded a coefficient of 0.00 with a p-value of 0.31 (greater than 5 percent or 0.05). This implies an insignificant positive effect of RGDP on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is a low probability that changes in NPRML89 are associated with changes in RGDP. This result is in contrast with the literature (Louzis, Vouldis and Metaxas, 2012; Castro, 2013 7 Ghosh, 2015) but agrees with a finding by Kalluci (2018) in Albania. The result does not seem reasonable, a growth in the state of a nation's economic environment should improve the borrower's financial capacity to service their debt obligations and reduce chances of going into arrears. Although insignificant, the reasons behind this could be that the improvements in South Africa's real economy during the period under review were not substantial to result in a reduction in non-performing loans or that as economic environment improved, borrowers increased their spending to a point where they were unable to service all their consumption spending over time.

Housing Price Index (HPI) recorded a coefficient of 0.018 with a p-value of 0.00 (less than 5 percent or 0.05). This implies a significant positive effect of HPI on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is high probability that changes in NPRML89 are associated with changes in HPI. Increase in HPI by 1 percent leads to decrease in NPRML89 by 2 percent. This negative relationship is consistent with the work of Tam, Hui and Zheng (2009) and Castro (2013), as house prices increase, borrowers are more motivated to repay their debts in order to benefit from increased value of the property asset.

Unemployment rate (UNEMP) recorded a coefficient of 0.02 with a p-value of 0.03 (less than 5 percent or 0.05). This implies a significant positive effect of UNEMP on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is high probability that changes in NPRML89 are associated with changes in UNEMP. Increase in UNEMP by 1 percent leads to increase in NPRML89 by 2 percent. This result supports by findings numerous studies that have investigated this variable's influence on non-performing loans in various countries (Castro, 2013; Messai & Jouini, 2013; Skarica, 2014; Ghosh, 2015; Szarowska, 2018).

Inflation rate (INFL) recorded a coefficient of 0.01 with a p-value of 0.41 (greater than 5 percent or 0.05). This implies an insignificant positive effect of INFL on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is low probability that changes in NPRML89 are associated with changes in INFL. Although we expected the result to be significant, the author did consider the possibility of the result going either way, as warned by Klein (2013), the level of relationship between inflation on the non-performing loans ratio can be vague, due to the fact that the relationship can take any of the negative or positive impact. Our result supports Castro, 2013; Alexandri & Santoso, 2015 and Asfaw, Bogale & Teame, 2016, who attributed this result to the concept of the net off that occurs between real loan values and on customer's real income, stating that inflation erodes both values

Household Disposable Income (DINCO) recorded a coefficient of -0.05 with a p-value of 0.00 (less than 5 percent or 0.05). This implies a significant negative effect of DINCO on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is high probability that changes in NPRML89 are associated with changes in DINCO. Increase in DINCO by 1 percent leads to decrease in NPRML89 by 5 percent. As also found by Rinaldi and Sanchis-Arellano (2006), Dash and Kabra (2010) and Ghosh (2015) this result is sensible because as household receive more income, they are able to fulfil serviceability requirements on their residential mortgages.

Bank Capitalisation (BCAP) measured by Equity to Total Assets ratio recorded a coefficient of -0.05 with a p-value of 0.00 (less than 5 percent or 0.05). This implies a significant negative effect of BCAP on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is high probability that changes in NPRML89 are associated with changes in BCAP. Increase in BCAP by 1 percent leads to decrease in NPRML89 by 5 percent. This finding contrast the positive relationship found by Rajan (1994) and Ghosh (2015), but it supports the finding by Keeton & Morris (1987).

Bank Credit Growth for Mortgage Loans (CRGTL) measured by Residential Mortgage Loans to Assets Ratio recorded a coefficient of -0.01 with a p-value of 0.11 (greater than 5 percent or 0.05). This implies an insignificant negative effect of CRGTL on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is low probability that changes in NPRML89 are associated with changes in CRGTL, a result that is in contrast with findings from Klein (2013), Chaibi and Ftiti (2015), Ghosh (2015) and Nikolaidou & Vogiazas (2017) and signifies that banks do take note of customer affordability when approving new loans, thus even if borrowers acquire new credit facilities such as credit cards or overdrafts, this will not affect non-performing loans.

Bank Operating Efficiency (OPEFF) measured by Non-Interest Expense to Assets ratio recorded a coefficient of 0.08 with a p-value of 0.00 (less than 5 percent or 0.05). This implies a significant positive effect of OPEFF on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is high probability that changes in NPRML89 are associated with changes in OPEFF. Increase in OPEFF by 1 percent leads to increase in NPRML89 by 8 percent. This result is consistent with Abid (2014) and Ghosh (2015).

Bank Profitability (PROF) measured by Return on Assets Ratio recorded a coefficient of -0.08 with a p-value of 0.35 (greater than 5 percent or 0.05). This implies an insignificant negative effect of PROF on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is low probability that changes in NPRML89 are associated with changes in PROF. However the NPRML89 rates decrease by 8 percent as PROF increase by 1 percent, this seems reasonable as highly profitable banks have less incentive to issue riskier loans as supported by Ghosh (2015), Ramlall (2009) and Gavila & Santabarbara (2006).

Bank Credit Quality (CRQUAL) measured by Loan loss provisions to Total Loans ratio recorded a coefficient of -78.18 with a p-value of 0.10 (greater than 5 percent or 0.05). This implies an insignificant negative effect of CRQUAL on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is low probability that changes in NPRML89 are associated with changes in CRQUAL. This result is not consistent with Ghosh (2015) and does not seem reasonable, increased provisions for loan losses as a ratio to total loans indicate a deterioration of a quality of the bank's loan book. A rise in the ratio is by definition, expected to increase non-performing loans. What could explain this result is that banks spend more time managing and recovering loans once provisions have been made to ensure that loans do not get into arrears.

Bank Size (SIZE) measured by bank's market capital recorded a coefficient of -0.00 with a p-value of 0.28 (greater than 5 percent or 0.05). This implies an insignificant negative effect of SIZE on less than 89 days Non-Performing Residential Mortgage Loans (NPRML89). There is low probability that changes in NPRML89 are associated with changes in SIZE. Although insignificant, the impact is consistent with Salas and Saurina (2002), Abid et al (2014) and Ghosh (2015), larger banks have opportunity and resources to adopt better risk management strategies than smaller banks.

4.5.2 Regression Results: Model 2 with NPRML90 as dependent Variable

Table 13 below exhibits results of the regression analysis of non-performing residential mortgage loan rate on the 90 days category.

Table 13: Regression Analysis Results: NPRML90 as dependent variable

Linear regression					Number of Obs	108
					F(12, 95)	178.43
					Prob > F	0.00
					R-squared	0.92
					Root MSE	0.00
NPRML90	**Coef.**	**Robust Std. Err.**	**t**	**P > | t |**	**[95% conf.**	**Interval]**
NINT	-0.37	0.04	-10.51	0.00	-0.44	-0.30
RGDP	0.01	0.01	1.78	0.08	0.00	0.03
HPI	0.02	0.02	1.61	0.11	-0.01	0.06
UNEMP	0.04	0.02	2.23	0.03	0.00	0.07
INFL	0.10	0.02	6.27	0.00	0.07	0.13
DINCO	0.15	0.07	2.27	0.03	0.02	0.28
BCAP	0.21	0.03	8.13	0.00	0.16	0.26
CRGTL	0.01	0.01	0.77	0.44	-0.01	0.03
OPEFF	-0.44	0.08	-5.43	0.00	-0.60	-0.28
PROF	-0.01	0.17	-0.08	0.94	-0.35	0.33
CRQUAL	-285.18	107.29	2.66	0.01	72.18	498.19
SIZE	0.00	0.00	0.00	1.00	0.00	0.00
_cons	0.03	0.01	3.44	0.00	0.01	0.04

Based on table 13 above, the estimated regression model for 90 day non-performing residential mortgage loan rate is as follows, rounded off to two decimals:

NPRML89 = 0.03 – 0.37(NINT) + 0.01(RGDP) + 0.02(HPI) + 0.04(UNEMP) + 0.10(INFL) + 0.15(DINCO) + 0.21(BCAP) + 0.01(CRGTL) - 0.44(OPEFF) – 0.01(PROF) + 285.19(CRQUAL) – -0.00(SIZE) + ε

The study considers statistical significance at 5 percent (95 percent confidence level) and makes an assessment on whether the coefficients are statistically significant or not, by considering the p-value. The R-squared value of 0.9193 shows that the independent variables altogether explain about 92 percent of variations in more than 90 days Non-Performing Residential Mortgage Loans (NPRML90). The F-statistic also has a significant p-value of 0.000, which means that the variables fit the model.

The results show that nominal interest rate (NINT) recorded a coefficient of -0.37 with a p-value of 0.00 (less than 5 percent or 0.05). This implies a significant negative effect of NINT on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is high probability that changes in

NPRML90 are associated with changes in NINT. An increase in NINT by 1 percent leads to decrease in NPRML90 by 37 percent. The regression results seem unreasonable, higher interest rates should increase the chances of a borrower struggling to repay the debt and should increase the level of non-performing residential mortgage loans.

Real GDP (RGDP) recorded a coefficient of 0.012 with a p-value of 0.08 (greater than 5 percent or 0.05). This implies an insignificant positive effect of RGDP on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is a low probability that changes in NPRML90 are associated with changes in RGDP. This result is in contrast with the literature (Louzis, Vouldis and Metaxas, 2012; Castro, 2013 7 Ghosh, 2015) in both strength and direction and does not seem reasonable, a growth in the state of a nation's economic environment should improve the borrower's financial capacity to service their debt obligations and reduce chances of going into arrears. Although insignificant, the reasons behind this could be that the improvements in South Africa's real economy during the period under review were not substantial to result in a reduction in non-performing loans or that as economic environment improved, borrowers increased their spending to a point where they were unable to service all their consumption spending over time.

Housing Price Index (HPI) recorded a coefficient of 0.02 with a p-value of 0.11 (greater than 5 percent or 0.05). This implies an insignificant positive effect of HPI on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is low probability that changes in NPRML90 are associated with changes in HPI. This finding is inconsistent with Castro (2013) and Ghosh (2015) both in strength and in direction, as the authors found evidence of significant negative relationship between HPI and non-performing loans. A reason behind this could be that higher housing prices increase the collateral values required when getting a loan and improve the borrower's capacity to attain more debt in the market. This increased capacity could lead to over borrowing which consequently increases to magnitude and scale of defaults.

Unemployment rate (UNEMP) recorded a coefficient of 0.04 with a p-value of 0.03 (less than 5 percent or 0.05). This implies a significant positive effect of UNEMP on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is high probability that changes in NPRML90 are associated with changes in UNEMP. Increase in UNEMP by 1 percent leads to increase in NPRML90 by 3.6 percent. This result supports by findings numerous studies that have investigated this variable's influence on non-performing loans in various countries (Castro, 2013; Messai & Jouini, 2013; Skarica, 2014; Ghosh, 2015; Szarowska, 2018).

Inflation rate (INFL) recorded a coefficient of 0.10 with a p-value of 0.00 (less than 5 percent or 0.05). This implies a significant positive effect of INFL on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90), thereby supporting findings by Klein, 2013; Washington, 2014; Abid et al, 2014; Kjosevski & Petkovski, 2017; Mpofu and Nikolaidou, 2018 and Vaicondam, Hishan and Shan (2019). There is high probability that changes in NPRML90 are associated with changes in INFL. A 1 percent increase in INFL leads to a 10 percent increase in NPRML90.

Household Disposable Income (DINCO) recorded a coefficient of 0.15 with a p-value of 0.02 (less than 5 percent or 0.05). This implies a significant positive effect of DINCO on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is high probability that changes in NPRML90 are associated with changes in DINCO. Increase in DINCO by 1 percent leads to increase in NPRML90 by 2.5 percent. The relationship is negative for NPRML89, which signifies that borrowers acquire more credit as income increases in the short term, but over time, excessive borrowing will lead to over indebtedness and thus default. This rationale is also supported by the positive relationship noted under credit growth (although insignificant).

Bank Capitalisation (BCAP) measured by Equity to Total Assets Ratio recorded a coefficient of 0.21 with a p-value of 0.00 (less than 5 percent or 0.05). This implies a significant positive effect of BCAP on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is high probability that changes in NPRML90 are associated with changes in BCAP. Increase in BCAP by 1 percent leads to decrease in NPRML90 by 21 percent. Consistent with Louzis, Vouldis and Metaxas (2011) and Ghosh (2015), this results supports the notion of the too-big-to fail opportunity enabled by having high equity capital levels (Rajan, 1994) and as confirmed by the similar positive relationship noted under loan loss provisions (CRQUAL) in the paragraph below, the result indicates that banks with high equity capital tend to employ poor credit policies under the presumption of “too-big-to-fail”.

Bank Credit Quality (CRQUAL) measured by Loan loss provisions to Total Loans ratio recorded a coefficient of 285.18 with a p-value of 0.01 (less than 5 percent or 0.05). This implies a significant positive effect of CRQUAL on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is high probability that changes in NPRML90 are associated with changes in CRQUAL. A result that is consistent with Ghosh (2015). This result is consistent with findings by Ghosh (2015), a growth in provisions for losses indicates poor credit quality of the bank’s loan book which in turn solidifies the moral hazard hypothesis indicated by Keeton and Morris (1987) which argues that banks engage riskier loans in effort to achieve higher profits.

Bank Credit Growth for Mortgage Loans (CRGTL) measured by Residential Mortgage Loans to Assets Ratio recorded a coefficient of 0.01 with a p-value of 0.4 (greater than 5 percent or 0.05). This implies an insignificant positive effect of CRGTL on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is low probability that changes in NPRML90 are associated with changes in CRGTL. In direction, this finding is consistent with Klein (2013), Chaibi and Ftiti (2015), Ghosh (2015) and Nikolaidou & Vogiazas (2017) and signifies that when customer situations are tough, borrowers tend to acquire new credit facilities such as overdrafts or personal loans in order to reduce their mortgage debt and keep their account status satisfactory. Although customers may benefit from this strategy in short term, over time the excessive borrowing will lead to over indebtedness and therefore default.

Bank Operating Efficiency (OPEFF) measured by Non-Interest Expense to Assets ratio recorded a coefficient of -0.44 with a p-value of 0.00 (less than 5 percent or 0.05). This implies a significant negative effect of OPEFF on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90), leading to support Abid et al (2014). There is high probability that changes in NPRML90 are associated with changes in OPEFF. Increase in OPEFF by 1 percent leads to decrease in NPRML90 by 44 percent. This result is consistent with Hughes, Lang, Mester & Moon (1995) and supports the explanation by Berger and DeYoung (1997) of the bad management hypothesis that attributes a decrease in non-performing loans to increased efficiency.

Bank Profitability (PROF) measured by Return on Assets Ratio recorded a coefficient of -0.01 with a p-value of 0.93 (greater than 5 percent or 0.05). This implies an insignificant negative effect of PROF on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is low probability that changes in NPRML90 are associated with changes in PROF. In direction, this result is consistent with Gavila & Santabarbara (2006), Ramlall (2009) and Ghosh (2015), and differs in strength. This signifies that profitability of banks is not a key factor that influences non-performing loans in South Africa.

Bank Size (SIZE) measured by bank's market capital recorded a coefficient of -2.83 with a p-value of 1.00 (greater than 5 percent or 0.05). This implies an insignificant negative effect of SIZE on greater than 90 days Non-Performing Residential Mortgage Loans (NPRML90). There is low probability that changes in NPRML90 are associated with changes in SIZE. This result is consistent with Louzis, Vouldis and Metaxas (2012).

4.7. Check for Robustness of Estimates

To check for robustness of the estimates, the regression models are run with default standard errors and the coefficients compared with the results from the robust standard errors regression. According to Lu and White (2014), a finding that the coefficients do not change much is taken to be evidence that these coefficients are ‘‘robust’’. If the signs and magnitudes of the estimated regression coefficients are also plausible, this is commonly taken as evidence that the estimated regression coefficients can be reliably interpreted as the true causal effects of the associated regressors.

Table 14 below shows the comparison of coefficients from the regression with default standard errors (OLS) and that with robust standard errors. See original STATA results in appendices.

Table 14: Check for Robustness

	Model 1 (NPRML89 as dependent variable)		Model 2 (NPRML90 as dependent variable)	
	OLS Estimates	Robust Estimates	OLS Estimates	Robust Estimates
NINT	-0.02	-0.02	-0.37	-0.37
RGDP	0.00	0.00	0.01	0.01
HPI	-0.02	-0.02	0.02	0.02
UNEMP	0.02	0.02	0.04	0.04
INFL	0.01	0.01	0.10	0.10
DINCO	-0.05	-0.05	0.15	0.15
BCAP	-0.05	-0.05	0.21	0.21
CRGTL	-0.01	-0.01	0.01	0.01
OPEFF	0.08	0.08	-0.44	-0.44
PROF	-0.08	-0.08	-0.01	-0.01
CRQUAL	-78.18	-78.18	285.18	285.18
SIZE	0.00	0.00	0.00	0.00
CONSTANT	0.01	0.01	0.03	0.03

The results clearly show insignificant differences in the estimates for both models. This means that the coefficients resulting from both models are robust. The signs and magnitudes of the estimated regression coefficients are also plausible and can be reliably interpreted as the true causal effects of the associated regressors.

In summary, the results from the two regression models in presented on Table 15 below.

Table 15: Regression Results: Summary

Dependent Variables	NPRML89				NPRML90			
Independent Variables	**Coefficient**	**P-value**	**Implication**		**Coefficient**	**P-value**	**Implication**	
NINT	-0.02	0.47	Negative	Insignificant	-0.37	0.00	Negative	Significant
RGDP	0.00	0.31	Positive	Insignificant	0.01	0.08	Positive	Insignificant
HPI	-0.02	0.00	Negative	Significant	0.02	0.11	Positive	Insignificant
UNEMP	**0.02**	**0.03**	**Positive**	**Significant**	**0.04**	**0.03**	**Positive**	**Significant**
INFL	0.01	0.41	Positive	Insignificant	0.10	0.00	Positive	Significant
DINCO	**-0.05**	**0.00**	**Negative**	**Significant**	**0.15**	**0.03**	**Positive**	**Significant**
BCAP	**-0.05**	**0.00**	**Negative**	**Significant**	**0.21**	**0.00**	**Positive**	**Significant**
CRGTL	-0.01	0.11	Negative	Insignificant	0.01	0.44	Positive	Insignificant
OPEFF	**0.08**	**0.00**	**Positive**	**Significant**	**-0.44**	**0.00**	**Negative**	**Significant**
PROF	-0.08	0.35	Negative	Insignificant	-0.01	0.94	Negative	Insignificant
CRQUAL	-78.18	0.10	Negative	Insignificant	285.18	0.01	Positive	Significant
SIZE	0.00	0.28	Negative	Insignificant	0.00	1.00	Negligible	Insignificant

The summary table 15 shows that for macroeconomic factors Unemployment (UNEMP) and Household Disposable Income (DINCO) are significant determinants of Non-Performing Residential Mortgage Loans; while for the bank specific factors, Bank Capitalization (BCAP) and Operational Efficiency (OPEFF) are significant determinants.

Housing Price Index (HPI) is a significant determinant of less than 89 days Non-Performing Residential Mortgage Loans, but not a significant influencer for greater than 90 days Non-Performing Residential Mortgage Loans.

Nominal Interest Rate (NINT), Inflation (INFL) and Credit Quality (CRQUAL) are also significant determinants of greater than 90 days Non-Performing Residential Mortgage Loans but not significant for less than 89 days Non-Performing Residential Mortgage Loans.

4.8. Limitations of the Study

The study used monthly data, while data such as macroeconomic and bank variables are published on a quarterly or bi-annual basis. Interpolating quarterly data to create monthly series is very likely to create an estimation bias. Furthermore, a select list of variables was used in the analysis, as we were not able to include all potential key variables such as return on equity, levels of public debt as a percentage of GDP and many other variables. Lastly, an investigation of non-performing loans across all loan-types at household and corporate levels can also be conducted.

4.9. Summary of the Chapter

This chapter analysed data used in the OLS regression models and presented the descriptive statistics for the data variables used in this study. Whereafter, a discussion on the results and findings from the OLS linear regression model was done through a presentation of the actual results and interpretation of the meaning behind each result. A check of the robustness of the regression models used in the study was conducted and interpreted as that the coefficients resulting from both models were robust. Lastly, the limitations of the current study were discussed and potential opportunities for further research was highlighted. The next chapter, provides conclusion and recommendations on the factors found to significantly influence credit risk on non-residential mortgage loans.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The objective of this study was to investigate factors that influence credit risk on residential mortgage loans in South Africa. This study covered the period 2010 to 2018. Increasing rates of default affect profitability of banks and the wider economy. To manage this exposure, banks require robust methodologies that quantify bank's exposures to adverse scenarios. Credit Risk Managers can use the results of this study to model specific scenarios to ascertain what effect a change in a variable would have on the residential mortgage loan book. Such information would be helpful in adapting risk management strategies and policies that will minimise losses and direct portfolio shape. An example of such response strategy would be the issuing of loans with high loan-to-value levels.

The study revealed that arrears rates less than 89 days rates and default rates greater than 90 days are affected by different macroeconomic and bank specific variables. Housing Price Index (HPI), Unemployment (UNEMP) and Household Disposable Income (DINCO) were found to be the main macroeconomic determinants for non-performing residential mortgage loans that are less than 89 days. While Bank's Capitalization (BCAP) and Operational Efficiency (OPEFF) were the main bank specific determinants for non-performing residential mortgage loans that are less than 89 days.

The model for non-performing residential mortgage loans that are more than 90 days showed that Inflation (INFL), Unemployment (UNEMP) and Household Disposable Income (DINCO) are statistically significant macroeconomic determinants for non-performing residential mortgage loans. Whilst for bank specific factors, the study showed that the Bank's Capitalization (BCAP), Operational Efficiency (OPEFF) and Credit Quality (CRQUAL) are the main variables to influence non-performing residential mortgage loans that are more than 90 days. Although it was expected that the Household Disposable Income would have a statistically significant impact on non-performing loans, it was not entirely expected that this relationship would be positive. The reasons behind this have not been investigated further as this would require a separate study on its own. It could be that borrowers acquire more credit as income increases in the short term, but over time, excessive borrowing leads to over indebtedness and thus a default on loan repayments. This rationale is also supported by the positive relationship noted under credit growth (although insignificant).

The study concludes that for both models on non-performing residential mortgage loans less than 89 days and greater than 90 days; Unemployment (UNEMP) and Household Disposable Income (DINCO) are significant macroeconomic factors that determine Non-Performing Residential Mortgage Loans; while for

Bank Capitalization (BCAP) and Operational Efficiency (OPEFF) are significant bank specific determinants. These results have important implications for the managing of credit risk of the bank, which is influenced directly by the well-being of levels of borrower defaults on loans. The first of these is that any factor that has a significant impact on Household Disposable Income will have a significant impact on well-being of a bank's loan book. The direction of the relationship on the two models is in two folds, for Household Disposable Income (DINCO), negative for non-performing residential mortgage loans less than 89 days which is consistent with Rinaldi and Sanchis-Arellano (2006), Dash and Kabra (2010) and Ghosh (2015) this result is sensible because as household receive more income, they are able to fulfil serviceability requirements on their residential mortgages. However the direction of the relationship is positive for non-performing residential mortgage loans less than 90 days. Which signifies that borrowers acquire more credit as income increases in the short term, but over time, excessive borrowing will lead to over indebtedness and thus default. This rationale is also supported by the positive relationship noted under credit growth, although insignificant, this relationship implies that as borrowers acquire additional credit in form of overdrafts and credit cards, the probability of default also increases. Credit Risk Managers can use the results to understand and model what changes in global economic conditions that affect household income specifically could have on a loan book.
The positive relationship result for Unemployment (UNEMP) is consistent with expectations and also with results from numerous studies that have investigated this variable's influence on non-performing loans internationally (Castro, 2013; Messai & Jouini, 2013; Skarica, 2014; Ghosh, 2015; Szarowska, 2018). An increase in unemployment will by definition lead to a decrease in income available to the affected borrowers. Whilst the banks would have considered and priced in the expectations of an increases in unemployment, any upward unexpected change in unemployment during the lifecycle of a loan could lead to a substantial increase in borrower's inability to service the loan. Given these results, Credit Risk Managers can conduct stress testing on the residential loan book to isolate and examine the level of magnitude a change in this variable a bank can withstand before unemployment pose a risk to well-being of a bank's loan book.

Lastly, Credit Risk Managers can use levels of bank capitalisation and operational efficiencies as key inputs when crafting credit risk management strategies and targets for the banks; these metrics can also be used as key risk and performance indicators to understand and monitor changes in the credit risk environment.

Overall, the results outlined above suggest that an improvement in South Africa's economic health is vital in relieving households to reduce non-performing residential mortgage loans. Additionally, the lending behavior of South African banks is important for the reduction of non-performing residential mortgage loans.

5.2 Recommendations

The study recommends that banks consider the behavior of macroeconomic factors when issuing loans and adopt dynamic measures tailored to respond solidly to both the current and expected state of the economy. Prudent measures must be adapted in periods when economic growth is declining. Banks should prioritise robust credit risk management strategies with the same enthusiasm and desire as achieving sustainable profits. This balanced strategy if maintained from origination and throughout the lifecycle of the loans, will yield sustainable performance and good quality loan book. Banks should also ensure continuous monitoring of the determinants of non- performing residential mortgage loans to ensure that they are able to identify early potential credit risk exposures and implement dynamic response strategies.

Regulators of the South African banking industry should continue ensuring that banks are continuously financially healthy by having efficiency and capitalisation ratios that are driven by sound and sustainable credit risk management strategies. By doing so, any effect from changes in these two determinants of credit risk will be supported sound credit risk management processes. In closing,

Lastly, the South African government could also assist in reducing the levels of non-performing residential loans through economic stimulation strategies such as infrastructure improvement, foreign direct investments and economic growth, in order to minimise unemployment.

5.3 Possible Future Research

The study used a select list of variables was used in the analysis, as we were not able to include all potential variables. Future studies may be interested in testing additional variables such as return on equity, levels of public debt as a percentage of GDP and many other variables to supplement the results of this study. Lastly, an investigation of non-performing loans across all loan types at both household and corporate levels can also be conducted in order to the preciseness and validate the consistency of the results of this study. The question of why household disposable income has a positive relationship with non-performing loans older than 90 days is something that can potentially be explored further as this result was unexpected.

REFERENCES

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

Absa. 2019. Home loan debt management. [Online]. Available: https://www.absa.co.za/personal/loans/for-a-home/home-loan-debt-management/ (Accessed: 25 January 2020).

Ahmad, F. & Bashir, T. 2013. Explanatory power of macroeconomic variables as determinants of nonperforming loans: Evidence from Pakistan. *World Applied Science Journal*, 22:243-255.

Al-Bahrani, A. & Su, Q. 2015. Determinants of mortgage pricing: A Quantile Regression Analysis. *Journal of Housing Economics*, 30: 77-85.

Allen, F., Jackowicz, K., Kowalewski, O. & Kozłowski, L. 2017. Bank lending, crises, and changing ownership structure in Central and Eastern European countries. *Journal of Corporate Finance*, 42:494-515.

Alexandri, M.B & Santoso, T.I. 2015. Non Performing Loan: Impact of Internal and External Factor (Evidence in Indonesia). *International Journal of Humanities and Social Science Invention*, 4(1):87-91.

Amuakwa-Mensah, F. & Boakye-Adjei, A. 2015. Determinants of non-performing loans in Ghana banking industry. *International Journal of Computational Economics and Econometrics*, 5(1):35-54.

Angklomkliew, S., George, J. & Packer, F. 2009. Issues and developments in loan loss provisioning: the case of Asia. *BIS Quarterly Review*,69-83

Apergis, N. 2014. The long-term role of non-traditional banking in profitability and risk profiles: Evidence from a panel of U.S. banking institutions. *Journal of International Money and Finance*, 45:61-73.

Asfaw, A.S., Bogale, H.N. & Teame, T.T. 2016. Factors Affecting Non-Performing Loans: Case Study on Development Bank of Ethiopia Central Region. *International Journal of Scientific and Research Publications*, 6(5):656-670.

Baholli. D.,F., Dika., I. & Xhabija., G. 2015. Analysis of Factors that Influence Non-Performing Loans with Econometric Model. *Mediterranean Journal of Social Sciences, 6(1):391-398.*

Banks Act. 2012. Regulations Relating to Banks. [Online]. Available: https://www.gov.za/sites/default/files/gcis_document/201409/35950rg9872gon1029.pdf (Accessed: 20 January 2020).

Barnett, V. & Lewis, T. 1978. *Outliers in Statistical Data*. 3rd edition. John Wiley & Sons.

Bashir, A.M. 2000. Determinants of profitability in Islamic banks: Some evidence from the Middle East. *Islamic Economic Studies*, 11(1).

Basten, C. & Koch, C. 2015. The causal effect of house prices on mortgage demand and mortgage supply: Evidence from Switzerland. *Journal of Housing Economics* 30:1-22.

Bah, E.M., Faye, I. & Geh, Z.F. 2018. *Housing Finance in Africa. In: Housing Market Dynamics in Africa*. 57-108. Palgrave Macmillan, London.

Beck, R., Jakubik, P. & Piloiu, A. 2013. Non-Performing Loans: What Matters in Addition to the Economic Cycle?. European Central Bank Working Paper.

Berger, A. & DeYoung, R. 1997. Problem loans and cost efficiency in commercial banks. *Journal of Banking and Finance*, 21(6): 849-870.

Blanchard, O.J. & Johnson, D.R. 2011. *Macroeconomics*. 6th ed. New York Pearson.

Bosman, P. 2009. Employee assistance and the new National Credit Act. *Professional Accountant*, 9(1): 34-36.

Becker, B. & Ivashina, V. 2014. Cyclicality of credit supply: Firm level evidence. *Journal of Monetary Economics*, 62: 76-93.

Bougen, P.D & Drury, J.C. 1980. UK Statistical Distributions of Financial Ratios. *Journal of Business Finance & Accounting,* 7(1):39 – 47.

Brits. 2012. Mortgage Foreclosure under the Constitution: Property, Housing and the National Credit Act. Doctoral thesis, Stellenbosch University, Stellenbosch.

Brooks. C. 2014. *Introductory Econometrics for Finance*. 3rd ed. New York. Cambridge University Press

Case, K.E., Quigleyt, J.M. & Shiller, R.J. 2005. Comparing wealth effects: the stock market versus the housing market. *Advances in Macroeconomics,* 5(1):1-34

Castro, V. 2013. Macroeconomic determinants of the credit risk in the banking system: the case of the GIPS. *Economic Modelling*, 31: 672-683.

Chaibi, H. & Ftiti, Z. 2015. Credit risk determinants: Evidence from a cross-country study. *Research in International Business and Finance,* 33:1-16.

Collis, J., & Hussey, R. 2014. *Business Research: a practical guide for undergraduate and postgraduate students*. 4th Edition. United Kingdom: Palgrave.

Crowley, J. 2008. Credit Growth in the Middle East, North Africa, and Central Asia Region. *International Monetary Fund Working Paper*:8-184.

Ćurak, M., Pepur, S. & Poposki, K. 2013. Determinants of nonperforming loans – evidence from Southeastern European banking systems. *Banks and Bank Systems,* 8(1)

Daglish, T. 2009. What motivates a subprime borrower to default? *The Journal of Banking and Finance,* 33(4):681-693.

Deakin, E.B. 1976. Distributions of Financial Accounting Ratios: Some Empirical Evidence. *The Accounting Review,* 51:90-96

Di Lollo, A. & Drummond, M. 2019. 2019 Housing Finance Yearbook: South Africa profile. [Online]. Available: http://housingfinanceafrica.org/documents/2019-housing-finance-yearbook-south-africa-profile/ (Accessed: 17 November 2019).

Dietrich, A. & Wanzenried, G. 2011. Determinants of bank profitability before and during the crisis: Evidence from Switzerland. *Journal of International Financial Markets, Institutions and Money*, 21:307-327.

Du Plooy, G.M. 2001. *Communication Research - Techniques, Methods and Applications*. 2nd edition. Lansdowne: Juta.

Engelhardt, G.V. 1996. Consumption, Down Payments, and Liquidity Constraints. *Journal of Money, Credit and Banking*, 28(2): 255-271.

Espinoza, R & Prasad, A. 2010. Nonperforming Loans in the GCC Banking System and their Macroeconomic Effects. International Monetary Fund Working Paper 10/24

EY.2017. IFRS 9 expected credit loss – Making sense of the transition impact. [Online]. Available: https://www.ey.com/Publication/vwLUAssets/ey-ifrs-9-expected-credit-loss/$File/ey-ifrs-9-expected-credit-loss.pdf (Accessed: 25 January 2020).

Flavin, M. & Yamashita, T. 2002. Owner-occupied housing and the composition of the household portfolio. *American Economic Review*. 92(1):345-362.

FNB. 2019. Variable interest rate. [Online]. Available: https://www.fnb.co.za/home-loans/change-your-payment-options.html (Accessed: 25 January 2020).

FNB. 2019. Change your payment options. [Online]. Available: https://www.fnb.co.za/home-loans/change-your-payment-options.html (Accessed: 25 January 2020).

Fofack, H., 2005. Nonperforming loans in Sub-Saharan Africa: Causal Analysis and Macroeconomic Implication, World Bank Policy Research Working Paper, 3769.

Frecka, T.J. & Hopwood, W.S. 1983. The Effects of Outliers on the Cross-Sectional Distributional Properties of Financial Ratios. *The Accounting Review*, 58: 115-128

Garcia-Herrero, A., Gavila, S. & Santabarbara, D. 2006. What Explains Low Profitability of Chinese Banks?, *Journal of Banking & Finance*, 33(11):2080-2092.

Ghosh, A. 2015. Banking Industry Specific and Regional Economic Determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20 (2015): 93-104.

Havrylchyk, O. 2010. A macroeconomic credit risk model for stress testing the South African banking sector. South African Reserve Bank Working Paper, 10/02.

Huber, P.J. & Ronchetti, E.M. 2009. *Robust Statistics*. 2nd Edition. New Jersey: John Wiley & Sons.

Hughes, J.P., Lang, W., Mester, L.J. & Moon, C.G. 1995. "Recovering Technologies that Account for Generalized Managerial Preferences: An Application to Non-Risk-Neutral Banks," Federal Reserve Bank of Philadelphia Working Paper. In Espinoza, R & Prasad, A. 2010. *Nonperforming Loans in the GCC Banking System and their Macroeconomic Effects*. International Monetary Fund Working Paper 10/24.

Human Settlements. 2003. National Housing Policy. [Online]. Available: http://www.dhs.gov.za/sites/default/files/documents/national_housing_2009/6_Social_Rental_Interventions/3%20Vol%206%20Social%20Housing%20Policy.pdf (Accessed: 25 January 2020)

Hwarire, C. 2012. Loan Repayment and Credit Management of Small Businesses: A Case Study of a South African Commercial Bank. The African Development Finance Workshop Proceedings, Cape Town, South Africa, 7-8 August 2012.

Gimeno, R. & Martinez-Carrascal, C. 2010. The relationship between house prices and house purchase loans: the Spanish case. *The Journal of Banking and Finance,* 34 (8):1849-1855.

González-Aguado, C. & Suarez, J. 2015. Interest rates and credit risk. *Journal of Money, Credit and Banking*, 47(2-3): 445-480.

Ifeacho, C. & Ngalawa, H. 2014. Performance of The South African Banking Sector since 1994. *The Journal of Applied Business Research*, 30(4).

Kalluci., I. 2018. The Explanatory Variables of Non-Performing Loans in Albania, During and After the Financial Crisis. *European Journal of Business and Management*, 10(35):73:81.

Jiménez, G. & Saurina, J. 2006. Credit Cycles, Credit Risk, and Prudential Regulation. *International Journal of Central Banking,* 2:65–98.

Keeton, W. & C. Morris. 1987. "Why Do Banks' Loan Losses Differ?" Federal Reserve Bank of Kansas City. *Economic Review*, 3-21.

Kelly, A. 2002. "Skin in the Game": Zero Down payment Mortgage Default. *Journal of Housing Research*, 17 (2): 75-100.

Khemraj, T. & Pasha S. 2009. The determinants of non-performing loans: an econometric case study of Guyana.

Khemraj, T. & Pasha, S. 2013. Determinants of non-performing loans in licensed commercial banks: Evidence from Sri Lanka. *Asian Economic and Financial Review*, *5*(6):868-882.

Kjosevski, J. & Petkovski, M. 2017. Non-performing loans in Baltic States: determinants and macroeconomic effects. *Baltic Journal of Economics,* 17(1):25-44.

Klein, N. 2013. Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance. International Monetary Fund Working Paper 13/72.

Kondo, I.; Perri, F. & Hur, S. 2013. Inflation Risk and Sovereign Spreads. 2013 Meeting Papers 855, *Society for Economic Dynamics*.

Lu, X. & White, H. 2014. Robustness checks and robustness tests in applied economics. *Journal of Econometrics*, 178:194-206.

Louzis D. P., Vouldis A. T. & Metaxas V. L. 2012. Macroeconomic and Bank-Specific Determinants of Non-performing Loans in Greece: A Comparative Study of Mortgage, Business and Consumer Loan Portfolios. *Journal of Banking & Finance,* 36(4): 1012-1027.

Maddaloni, A. & Peydró, J. -L. 2011. Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the Euro-area and the U.S. lending standards. *Review of Financial Studies,* 24:2121-2165.

Mandelbrot, B. 1963. The Variation of Certain Speculative Prices. *Journal of Business*, 36:394 - 419.

Marais, L., Botes, L., Pelser, A. & Venter, A. 2005. "The non-payment of mortgage bonds in South Africa: the voice of defaulters". *Acta Structilia*, 12(2):1-24.

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

Mian, A. & Sufi, A. 2009. The consequences of mortgage credit expansion: evidence from the U.S. mortgage default crisis. *The Quarterly Journal of Economics*, 124 (4):1449-1496.

Mileris, R. 2015. The impact of macroeconomic environment on credit risk in commercial banks. *Ekonomika*, 91(3)

Moss, V. 2013. Mortgage Default Behavior in South Africa's Low Income Homeowners Relates to Banks Borrower Education Programmes. *International Journal of Finance & Banking Studies*, 2 (2): 66-75

Mpofu, T. & Nikolaidou, E. 2018. Determinants of credit risk in the banking system in Sub-Saharan Africa. *Review of Development Finance*, 8:141-153.

Mpofu, T. & Nikolaidou, E. 2019. Macroeconomic and bank-specific determinants of non-performing loans in sub-Saharan Africa. School of Economics Macroeconomic Discussion Paper Series 2019-02, School of Economics, University of Cape Town.

National Credit Regulator. 2006. *National Credit Regulations*. 489:118-124 Cape Town.

National Housing Finance Corporation. 2003. Reasons for Non Payment of Mortgage Loans and Municipal Services. Discussion paper. Houghton, South Africa. In Kohn, D. & Pischke, J., D. 2011. *Housing Finance in Emerging Markets: Connecting Low-Income Groups to Markets*. Springer. New York.

Nedbank. 2019. Payment Problems. [Online]. Available: https://www.nedbank.co.za/content/nedbank/desktop/gt/en/personal/loans/home-loans/Payment-Problems.html (Accessed: 25 January 2020).

Nikolaidou, E. & Vogiazas, S. 2017. Credit risk determinants in Sub-Saharan banking systems: Evidence from five countries and lessons learnt from Central East and South East European countries. *Review of Development Finance*, 7:52-63.

Njoki, A.K. 2014. The Relationship between Interest Rates and Mortgage Default Rate Among Financial Institutions in Kenya. Unpublished Masters dissertation, University of Nairobi, Kenya.

Nkusu, M. 2011. Nonperforming Loans and Macrofinancial Vulnerabilities in Advanced Economies. *International Monetary Fund Working Papers*, 11(161):1.

Ofori-Abebrese, G., Pickson, R. & Opare, E. 2016. The Effect of Bank Specific Factors on Loan Performance of HFC Bank in Ghana. *International Journal of Economics and Finance*, 8 (7): 185-192.

O'brien, R.M. 2007. A caution regarding rules of thumb for Variance Inflation Factors. *Quality and Quantity*, 41:673-690.

Pandey, N. 2020. Robust Techniques to Estimate Parameters of Linear Models. [Online]. Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3694906 (Accessed: 12 February 2021).

Pesola, J. 2011. Joint effect of financial fragility and macroeconomic shocks on bank loan losses: evidence from Europe. *The Journal of Banking and Finance,* 35 (11): 3134-3144.

Peric, P.S & Konjusak, N. 2017. how did rapid credit growth cause non-performing loans in the CEE countries?. *South East European Journal of Economics and Business*, 2:73-84.

Podpiera, J. & Weill, L. 2008. Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability*, 4:135-148.

Rajha, K.S. 2017. Determinants of Non-Performing Loans: Evidence from the Jordanian Banking Sector. *Journal of Finance and Bank Management*, 5(1):54-65.

Ramlall, I. 2009. Bank-Specific, Industry-Specific and Macroeconomic Determinants of Profitability in Taiwanese Banking System: Under Panel Data Estimation. *International Research Journal of Finance and Economics*, 34:160-167.

Rajan, R., 1994. Why Bank Credit Policies Fluctuate: A Theory and Some Evidence. The Quarterly Journal of Economics, 109: 399-441. In Ghosh, A. 2015. Banking Industry Specific and Regional Economic Determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20: 93–104.

Reinhart, Carmen M. & Kenneth S. Rogoff. 2011. "From Financial Crash to Debt Crisis." *American Economic Review*, 101(5):1676-1706.

Rinaldi, L. & Sanchis-Arellano, A. 2006. Household Debt Sustainability: What Explains Household Non-performing Loans? An Empirical Analysis. European Central Bank Working Paper.

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

SARB. 2019. Quarterly Bulletin – March 2019. [Online]. Available: https://www.resbank.co.za/Lists/News%20and%20Publications/Attachments/9148/01Full%20Quarterly%20Bulletin%20%E2%80%93%20March%202019.pdf (Accessed: 12 May 2019).

SARB. 2019. Current Market Rates. [Online]. Available: https://www.resbank.co.za/Research/Rates/Pages/CurrentMarketRates.aspx (Accessed: 17 November 2019).

SARB. 2019. Monthly release of selected data. BA900. [Online]. Available: https://www.resbank.co.za/Research/Statistics/Pages/Banks-BA900-Economic-Returns.aspx (Accessed: 22 October 2019).

SARB, 2008. South Africa's implementation of Basel II and Basel III. [Online]. Available: https://www.resbank.co.za/PrudentialAuthority/Deposit-takers/Banks/Supervision/Pages/South-Africa%27s-implementation-of-Basel-II-and-Basel-III.aspx (Accessed: 12 November 2019).

SARB. 2016. Bank's Act: 23(6)(c). [Online]. Available: https://www.resbank.co.za/Lists/News%20and%20Publications/Attachments/7306/Amended%20Regulations%20effective%201Jul2016.pdf (Accessed: 12 November 2019).

Shehzad, C. T., de Haan, J., & Scholtens, B. 2010. The impact of bank ownership concentration on impaired loans and capital adequacy. *Journal of Banking & Finance*, 34:399–408.

Sim, S.P. 2019. Bank's Credit Risk and Its Determinants: A Study on Bank of Ayudhya in Thailand. [Online]. Available: https://ssrn.com/abstract=3310689 or http://dx.doi.org/10.2139/ssrn.3310689 (Accessed: 28 February 2020).

Stansell, S.R., Millar, J.A. (1976). An empirical study of mortgage payment to income ratios in a variable rate mortgage program. *Journal of Finance*, 31(2), 415-425.

Skarica, B. 2014. Determinants of non-performing loans in Central and Eastern European countries. *Financial Theory and Practice*, 38(1):37-59.

Stern, G. & Feldman, R. 2004. Too Big to Fail: The Hazards of Banks Bailouts. The Brookings Institution, Washington DC. In Ghosh, A. 2015. Banking Industry Specific and Regional Economic Determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, 20:93–104.

Szarowska, I. 2018. Effect of macroeconomic determinants on non-performing loans in Central and Eastern European countries. *International Journal of Monetary Economics and Finance*, 11(1).

Tajik, M., Aliakbari, S., Ghalia, T. & Kaffash, S. 2015. House prices and credit risk: Evidence from the United States. *Economic Modelling* 51:123-135

Tam, W.M., Hui, E. & Zheng, X. 2009. Residential Mortgage Default Behaviour in Hong Kong. *Housing Studies*, 25(5):647-669.

Taylor, T. 2017. *Principles of macroeconomics: Economics and the Economy*. 4th ed. Minneapolis

The Banking Association of South Africa. 2019. Background of National Credit Act. [Online]. Available: https://www.banking.org.za/consumer-information/consumer-information-legislation/national-credit-act/ (Accessed: 12 November 2019).

The National Credit Regulator. 2019. Annual Report 2018 - 2019. [Online]. Available: http://pmg-assets.s3-website-eu-west-1.amazonaws.com/NCR_AR_2018.2019_CD_Singles.pdf (Accessed: 12 November 2019).

Tsumake, G.K. 2016. What are the determinants of non-performing loans in Botswana?. Unpublished masters dissertation, University of Cape Town, Cape Town.

Touny, M.A. & Shehab, M.A. 2015. Macroeconomic determinants of non-performing loans: An empirical study of some Arab countries. *American Journal of Economics and Business Administration*, 7(1): 11.22.

Vithessonthi, C. 2016. Deflation, bank credit growth, and non-performing loans: Evidence from Japan. *International Review of Financial Analysis,* 45: 295-305

Viswanadham, N. 2015. Determinants of non-performing loans in commercial banks: A study of NBC bank Dodoma Tanzania. *International Journal of Finance and Banking Studies*, 4(1): 2147-4486.

Vaicondam, Y., Hishan, S.S. & Shan, P.S. 2019. The Study on Factors That Influencing Banks' Non-Performing Loans in Malaysia. *International Journal of Engineering and Advanced Technology*, 8 (5C).

Von Furstenberg, G.M. 1969, Default risk on FHA-insured home mortgages as a function of the terms of financing: A quantitative analysis. *Journal of Finance*, 24: 459-477.

Wambui, N.S. 2013. The effect of interest rate volatility on mortgage default rate in Kenya. *International Journal of Business, Humanities and Technology*, *3*(1).

Washington, G.K., 2014. Effects of macroeconomic variables on credit risk in the Kenyan banking system. *International Journal of Business and Commerce*, 3 (9):1-26.

Western, B. 1995. Concepts and Suggestions for Robust Regression Analysis. *American Journal of Political Science*, 39 (3):786-817

Wu, W., Li, J. & Hong, C. 2017. Verifying the Determinants of the Mortgage Defaults on Home Mortgage. Interna*tional Journal of Economics and Financial Issues*, 7(5):266-273.

Wilkinson, N. 2005. *Managerial Economics: A problem solving approach*. Cambridge University Press, New York.