Top-down stress testing of the largest full service South African banks

by

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Submitted in partial fulfilment of the requirements for the degree

MSc Actuarial Science

In the Faculty of Natural and Agricultural Sciences

University of Pretoria

Pretoria

November 2020

Declaration

I, Dirk Cornelis Uys Conradie, declare that the dissertation which I hereby submit for the degree MSc Actuarial Science at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other institution.

Signature: ____________________________________

Date: ____________________________________

Acknowledgments

I would like to acknowledge and thank my supervisor, Prof. Beyers. His guidance and various contacts in the banking industry provided a valuable sounding board to ensure the most important elements were covered in a practical manner. I also want to thank my wife, Melissa, who encouraged me and provided the support I needed to complete the study.

Abstract

Banks are key to a well-functioning economy. Periods of economic stress could put banks and therefore the financial system at risk so regulators such as the Prudential Authority in South Africa need to know if banks are resilient to economic stress. A model that forecasts the impact of severe economic stress is developed using publicly available information. The model forecasts the credit losses, deposit volumes and other general equity movements of the biggest five full-service South African banks to assess capital and liquidity strain for any defined macroeconomic stress scenario over the next 3 years. The full-service banks being considered account for more than 90% of all bank lending in deposits in the market and therefore covers the vast majority of banking systemic risk in South Africa. It is shown that different macroeconomic factors affect these banks in different ways due to differences in the type of customers with deposits with each institution and differences in credit risk associated with various loan products. From an overall market perspective economic growth, lending levels, household debt levels and equity markets are the key drivers of deposit volumes. Credit risk in turn is primarily driven by interest rates, inflation and household debt to disposable income.

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Chapter 1

1. Introduction

1.1 Stress testing background

A robust and well-regulated banking system is required to have a well-functioning economy [1]-[4]. The default of listed banks increases systemic risk that can cause cascading bank failures and spill over into other sectors of the economy [4]. This could also include the failure of other non-bank commercial entities [5][6]. A bank default also reduces confidence in the financial system which further increases systemic risk [7]. The lending activities of banks support wider economic growth [1][6][8]. It has also been shown that bank failures can exacerbate negative economic consequences over a prolonged period [5]. The fortunes of banks, growth in the economy and systemic risk is therefore interrelated [9][10].

Common risk factors faced by banks increases bank systemic risk relative to other sectors [1][11]. The level of systemic risk can be measured in several ways including the exposure of banks to under-capitalisation in the financial markets, a bank's contribution to fragility of the financial system and bank equity volatility and leverage [12]. Deposits with banks can often be called on at short notice while loans are repaid over a much longer period [8]. Banks also rely on other short-term funding that creates liquidity risk if this funding is no longer available [6][9]. Due to this function banks face significant liquidity risk if deposits withdraw and credit risk if borrowers default [1][2][9][13][32][33]. Confidence in the financial system and economy guards against vast depositor withdrawals [2][5] while stringent regulation and capital requirements mitigate the risk of credit losses and day to day movements in liquidity [10]. Banks are also subject to market risk through their trading book activities such as creating savings and investment vehicles, acting as intermediaries in over the counter derivative transactions, directly taking market positions (proprietary trading) and investing in businesses (private equity).

The implementation of regulation needs to balance many factors such as the need to maintain stability and confidence in the financial system with moral hazard of putting a safety net in place. The required level of capital also needs to balance increased resilience that result from more capital with the potential increase in risk as banks attempt to generate a sufficient return on capital [10],[12]. Balancing these factors, however, requires an accurate assessment of bank risk using a range of tools [7].

Stress testing at a bank level has been applied by banks operating across multiple jurisdictions since the early 1990's. The use of stress testing as a macro-prudential followed later in the 1990's [14]. Stress testing is one macroprudential tool that banking regulators such as the Prudential Regulatory Authority (PRA) in the United Kingdom (UK), the United States of America Federal Reserve (FED) and the Prudential Authority (PA) within the administration of the South African Reserve Bank (SARB) to exercise regulatory oversight [15],[16],[17]. Stress testing relies on a combination of assessments performed by each bank (bottom-up modelling) and assessment at an aggregate level (top-down modelling) [18]. Bottom-up modelling requires detailed data on the exposure and structure of each bank and therefore also relies on modelling that captures the specific risk of each entity. This modelling has the advantage of incorporating the specific features of each bank in detail. It, however, needs a lot more data and requires more complex modelling. Top-down modelling can be performed on less data and capture market level trends and risks better than bottom-up modelling. It may, however, not fully reflect the unique features of each bank [18].

Stress testing conducted by the PA can be refined based on best practice examples set by the Bank of England (BoE) and FED [15]-[17][19]. The current stress testing conducted by the PA is based on the Internal Capital Adequacy Process (ICAAP) requirements outlined in Basel [15]. The PA also conduct a common scenario stress test on systemically important banks every two years where bottom-up bank stress tests are compared to a top-down PA assessment. This stress testing framework can be refined to provide more detailed guidance and clearer standards that banks should comply with when doing detailed bottom-up stress testing. The PA can also benefit from a top-down stress testing model similar to the BoE and FED models to investigate wider market impacts and to provide a cross-check for the bottom-up results submitted by banks [16][17][19].

The purpose of stress testing is to warn regulators of bank vulnerability that could lead to a financial or credit cycle downturn [18]. This is important since regulatory intervention is more likely to be needed during a severe macroeconomic stress [7]. Over the past 208 years 268 banking crises have occurred and the economic fallout following the COVID-19 pandemic may cause another banking crisis [1]. The length of the financial cycle is uncertain and longer than the typical business cycle driven by economic activity [20]. Recent history that includes the Asian financial crisis of 1998 and the global financial crisis of 2008 shows that multiple uncertain contributors can cause a downturn and highlights the importance of macro-prudential tools that can strengthen bank resilience or highlight specific vulnerabilities that can be proactively addressed [15], [21]. A top-down stress testing model that evaluates systemic risk (risk of failure of a large proportion of financial institutions) can help regulators make informed decisions around discretionary capital add-ons, direct interventions, bailouts and crisis resolution [22]. Stress testing models can be used to investigate the risk of contagion between banks in a period of crisis and guide remedial actions once a crisis hits [23]. It is therefore a useful tool even if a crisis might not be averted or pre-empted by stress testing [23].

This research proposes a top-down modelling approach that uses publicly available information to forecast the key balance sheet elements of the biggest South African banks under a stressed macroeconomic scenario. The key risks include credit risk, liquidity risk and general movement in equity to account for the remaining risks. Literature around stress testing frameworks, methods and key drivers of bank risk is first investigated. A prototype model is then developed by considering historic bank and market data. Each model component includes the investigation of the extent to which macroeconomic factors drive that component and a practical way to forecast the risk for a defined macroeconomic stress scenario. Finally, all components are combined into a forecast of bank equity and capital requirements and liquidity shocks to assess the resilience of the banks under consideration to a severe economic stress scenario.

1.2 Banking System Risks and the South African Market

Banking systems are complex networks with multiple links such as interbank lending, correlation between asset values, feedback loops where a crisis reduced economic growth which further exacerbates bank losses and common funding sources [1][20][24]-[26]. The level of interconnectedness increases systemic risk [12]. A feedback loop that constrains funding can be particularly severe as illustrated by the Lehman Brothers failure during the global financial crisis in 2008 [1][23][27][28]. Sectoral shock such as drops in prices may lead strain in local economies which in turn may lead to the failure of banks that service those sectors [29]. Economic conditions also drive the need for bank funding and therefore liquidity risk [9]. Illiquid banks with low quality assets or little capital would be more prone to failure [29]. These links can lead to cascading bank failures if one bank fails [11][20]. A market wide shock can also reduce asset values which in turn could lead to a single bank or cascading bank failure [20],

[23]. Considering the resilience of banks under macroeconomic stress is therefore important [1][30][31].

Activities related to the broader financial market also creates risk. Investment banking activities can increase the risk of a bank since these activities are subject to multiple risks which include market risk and credit risk [32]. Banks are also subject to various idiosyncratic risk drivers that would often be reflected in the share price of the bank [3][11][20]. The global financial crisis demonstrated how securitisations fuelled an asset bubble in the housing market and allowed a vast amount of risk to accumulate [32]. Banks made losses due to the crash in the property market and general level of increased defaults even though they were not directly exposed to the losses on loans that they securitised.

The economic stress currently being experienced due to the COVID-19 pandemic shows that the nature of stress can vary considerably from crisis to crisis. The COVID-19 related stress is different compared to the 2008 global financial crisis. The 2008 crisis was concentrated in the financial sector and was characterised by high interest rates and inflation with prime rates that peaked at 15.5% from June to November 2008 and inflation that peaked at 8.7% in May 2009. The South African equity market (as represented by the JSE All Share Index) dropped by 34% between June and October 2008 and only recovered to levels seen in June 2007 by the end of 2009. Over 2009 the South African GDP dropped by 1.5%. In contrast the stress caused by COVID-19 is much more widespread with nearly all sectors experiencing strain. Energy, construction, hospitality, transport and financial sectors are expected to be severely impacted. The underlying macroeconomic conditions are also very different. The prime rate is a level last seen in 1973 and inflation is within the South African Reserve Bank target range. The JSE All Share Index showed a similar drop of 33% between the end of December 2019 and 23 March 2020. The impact on GDP and subsequent job losses are however, expected to far exceed the levels seen during the 2008 crisis. Initial estimates indicate a record GDP drop and a large increase in unemployment.

Different risk factors affect banks in different ways. Banks with high leverage, low earnings, low liquidity and risky assets would be more prone to failure [29]. These risk factors can affect the risk of failure and time to failure. A bank with a large volume of retail deposits may be more profitable due to reduced funding costs when compared to wholesale funding such as bonds. Increased risk also leads to increased funding costs [13]. Such a bank can however, face liquidity constraints very quickly if the retail depositors believe that they are at risk of not being able to access their deposits. The volume of bank liabilities also affects the severity a bank failure and the consequential reduction in economic growth [5]. A large mortgage portfolio can increase the risk of failure due to the sensitivity to property prices and the large size of these portfolios. A drop in real estate prices was a key driver of the 2008 financial crisis [33]. It can, however, also increase the time to failure if it is not the initial cause of strain in the bank. Higher profit margins could provide a buffer in times of strain and increase the time to default if retained earnings are built up. It can also point towards a portfolio with more risk which would increase the risk of failure [34].

A stress test model that directly or indirectly accounts for a wide variety of risks will allow regulators and banks to better understand and manage their risks.

The South African banking market is concentrated in five big banks that include FirstRand, Absa, Nedbank, Standard Bank and Investec when the total bank lending and bank deposits in the market is considered [35]. The economic impact of a bank failure is positively correlated with its size so considering the largest banks would therefore also consider the majority of the systemic and economic risk [3][5][10]. The development of a top-down model is therefore limited to these five banks that offer a complete set of products to the retail and wholesale market.

Figure 1: Contribution of key elements to the assets and liabilities of the biggest five South African banks

The majority of assets for these banks are loans and advances, investments that include trading portfolio assets and bills while the majority of liabilities are deposits [35]. From Figure 1 it can be seen that loans and advances (net of credit impairments) and investments and bills, including trading portfolio assets, make up 80% (between 77% and 87% for individual banks) of the bank's assets as at April 2019. Deposits account for 78% (between 72% and 85% for individual banks) of the bank's liabilities as at April 2019. The structure of the bank balance sheets further reinforces the need to focus on credit and deposit liquidity risk.

Although the scale of these banks makes them more resilient to stress than smaller banks, it does introduce a significant amount of concentration risk if one of these banks were to fail [20].

1.2.1 Deposits in the South African market

Deposits are used to fund the lending activities of the banks and represent a much cheaper source of funding than capital market funding in the form of bonds and loans [9]. Changes in the mix and volume of deposits can therefore adversely affect the profitability of banks since a reduction in deposits will require more capital market funding [9][36].

Banks borrow short through call deposits that should be immediately available or term deposits that could have a term from a few months to several years. Banks then lend long by issuing loans with typical terms from 1 month in the case of unsecured term loans to 30 years for loans related to property. This timing mismatch and illiquidity of loan assets is the primary driver of bank liquidity risk [2].

The main deposit customer types are retail clients (households and foreign non-residents), corporates (private non-financial corporates, unincorporated business enterprises and non-profit organisations), financial institutions ("FI") (insurers, pension funds, money market unit trusts, other unit trusts, fund managers, medical schemes, financial intermediaries and special purpose entities), banks (interbank funding including negotiable certificates of deposit, promissory notes, other interbank deposits and foreign bank funding) and governments and state owned entities (central government tax and other accounts, provincial government, social security, the SARB, Landbank, Corporation for Public deposits and the Post Bank, local government, the public financial sector including the Industrial Development Corporation ("IDC") and Development Bank of South Africa, Public Investment Corporation and state owned enterprises). Note that this classification is based on categories prescribed by the SARB in the Government Gazette for monthly BA900 regulatory reporting purposes.

As at April 2019 there is a total of R 4,036 trillion in deposits with banks in South Africa. Figure 2 shows that these deposits are concentrated in five entities with 91.7% or R 3,699 trillion that has been deposited in FirstRand, Absa, Nedbank, Standard Bank and Investec [35].

The majority (80%) of these deposits have a term of less than six months. The loans of these banks are however, concentrated at longer terms with 43% of loans being mortgage loans, another 13% instalment sales and leases with overdrafts and credit cards making up the remaining 44% [35]. There is therefore a clear mismatch in the terms of assets and liabilities which creates liquidity risk [13].

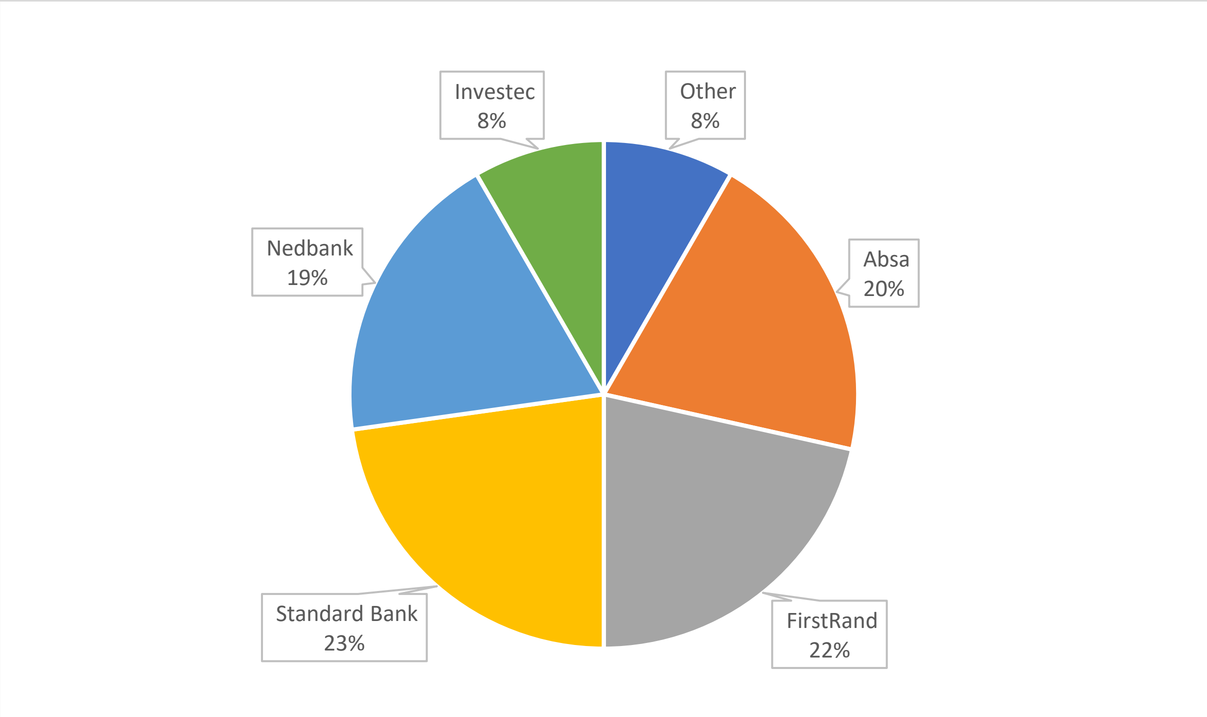

Figure 2: Proportion of deposits per entity for banks in South Africa

The mix of deposit types and funding sources of the banks also need to be considered since each deposit type has different behaviour and different sources of funding have different costs. Based on the SARB BA900 data the deposits and balance sheet liabilities of the five biggest banks in South Africa can be summarised as follows:

Figure 3 shows that the biggest South African banks are well diversified in terms of deposits from a wide variety of sources such as individuals, financial institutions, the public sector, companies and even other banks. Figure 4 however, shows that the banks are predominantly (77.7% of all liabilities) dependent on deposit funding with funding liabilities such as bonds only making up 15.1% of the total balance sheet liabilities. Replacing lost deposits with funding liabilities may therefore be challenging over the short to medium term.

Forecasting the volume and mix of bank deposits is therefore a critical part of forecasting the overall resilience of the bank to stressed macroeconomic conditions.

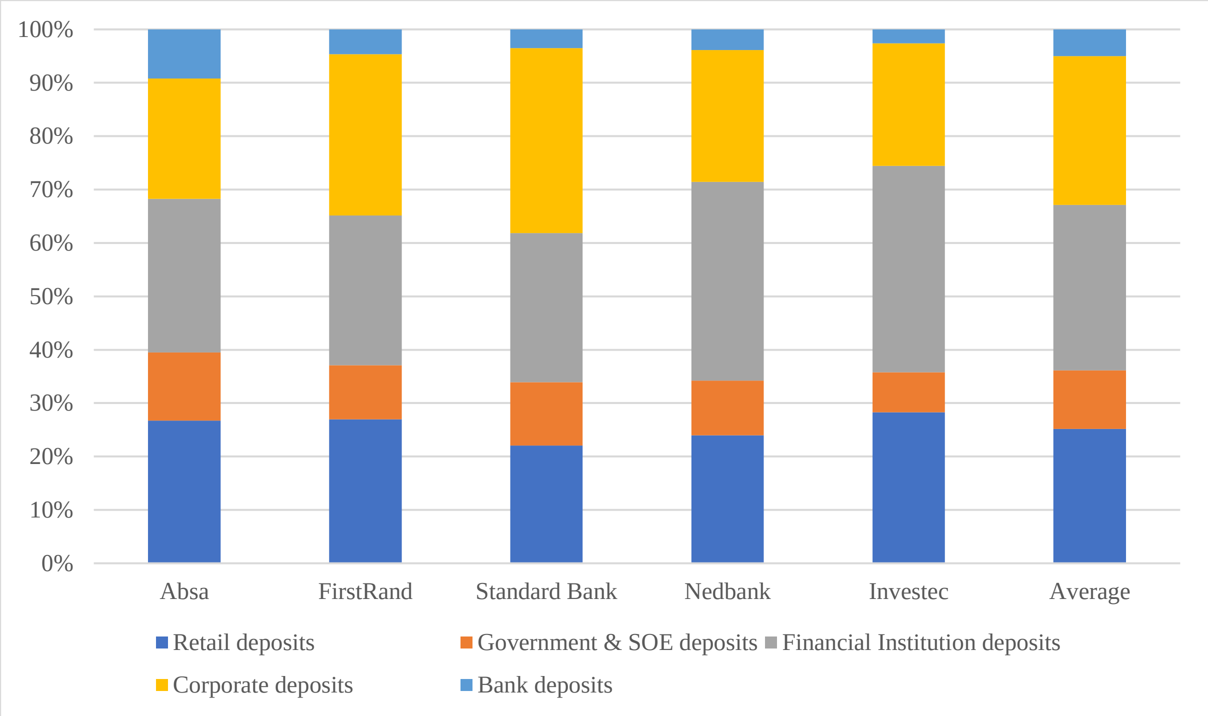

Figure 3: Distribution between depositor types of the biggest South African banks

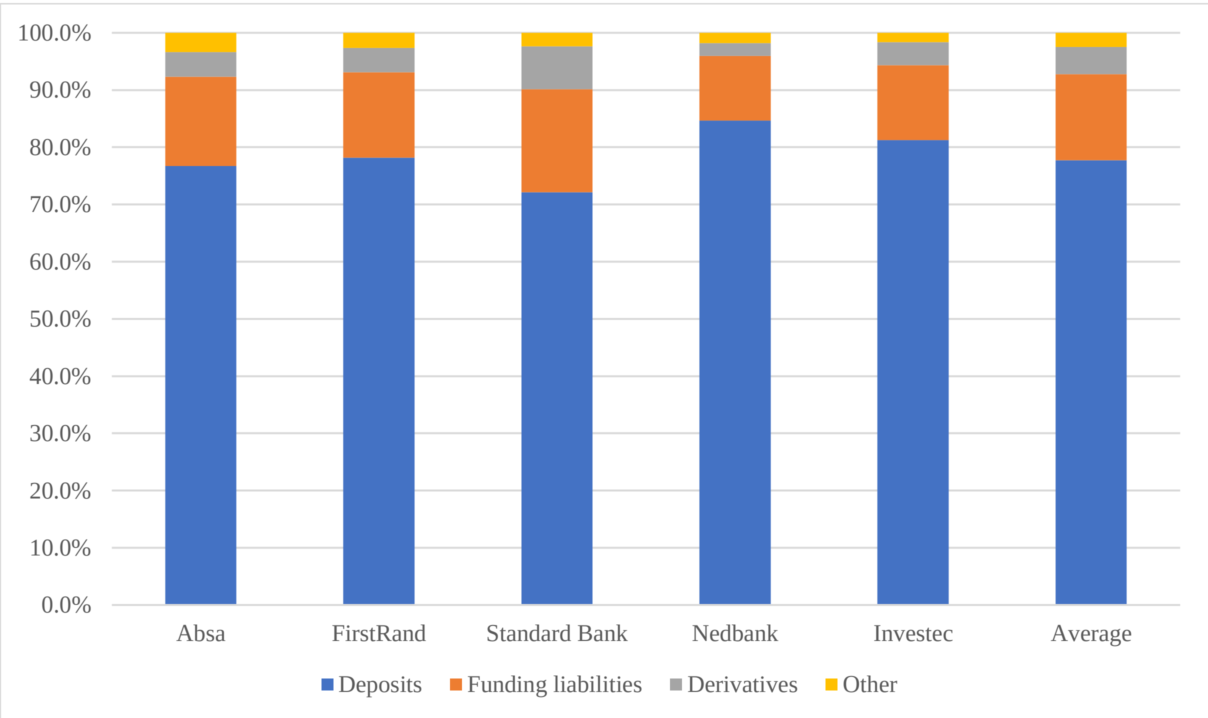

Figure 4: Liability balance sheet split of the biggest South African banks

1.2.2 Lending in the South African market

One of the primary functions of banks is to provide funding and liquidity to the markets in the form of loans. The main risk related to loans is credit risk [18]. The level of credit risk of a bank has also been shown to drive its contribution to systemic risk as it relates to the risk-taking activities of banks [12]. Loans make up the majority of assets for banks in South Africa and therefore credit risk is also one of the primary risks faced by banks in South Africa.

Loans can be categorised based on the counterparty to the loan which includes individuals, companies and the public sector. Loans and advances can also be segmented on the basis of the type of loan that includes mortgages, secured loans, unsecured loans, credit cards, overdrafts and short-term credit. The various publicly available datasets however, segment lending data in a different way. For example, credit cards and overdrafts can be combined as credit facilities while secured loans, unsecured loans and short-term credit can be combined into instalment debtors.

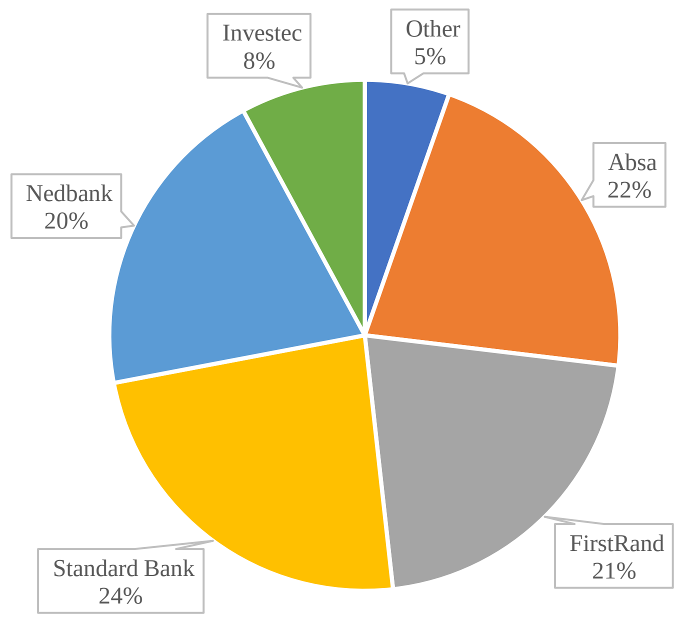

Figure 5: Proportion of loans per entity for banks in South Africa

As at April 2019 there is a total of R 3,424 trillion in loans granted by banks in South Africa. Figure 5 shows that these loans are mainly granted by five entities with 94.6% or R 3,240 trillion that has been granted by FirstRand, Absa, Nedbank, Standard Bank and Investec [35].

The type of loans needs to be considered since different loans will have a different repayment periods and levels of risk. The credit risk of secured loans will also be directly affected by the market value of the security. Based on the SARB BA900 data the loans and balance sheet assets of the five biggest banks in South Africa can be summarised as follows:

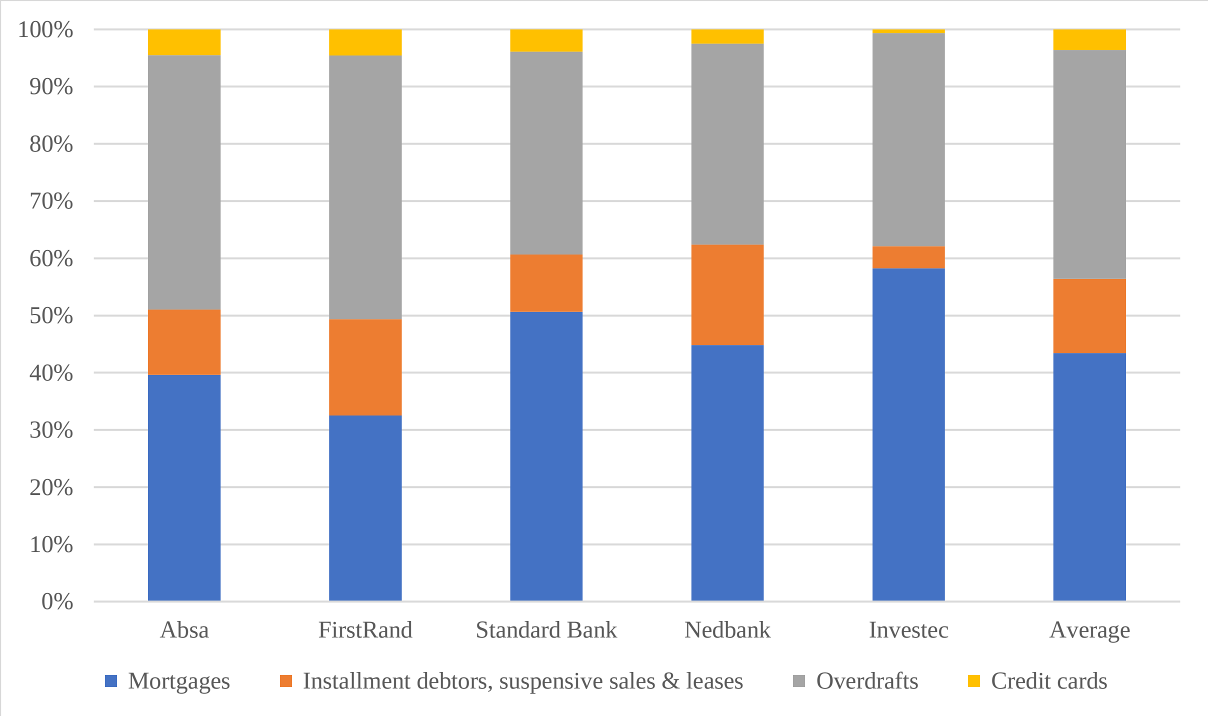

Figure 6: Distribution between lending categories of the biggest South African banks

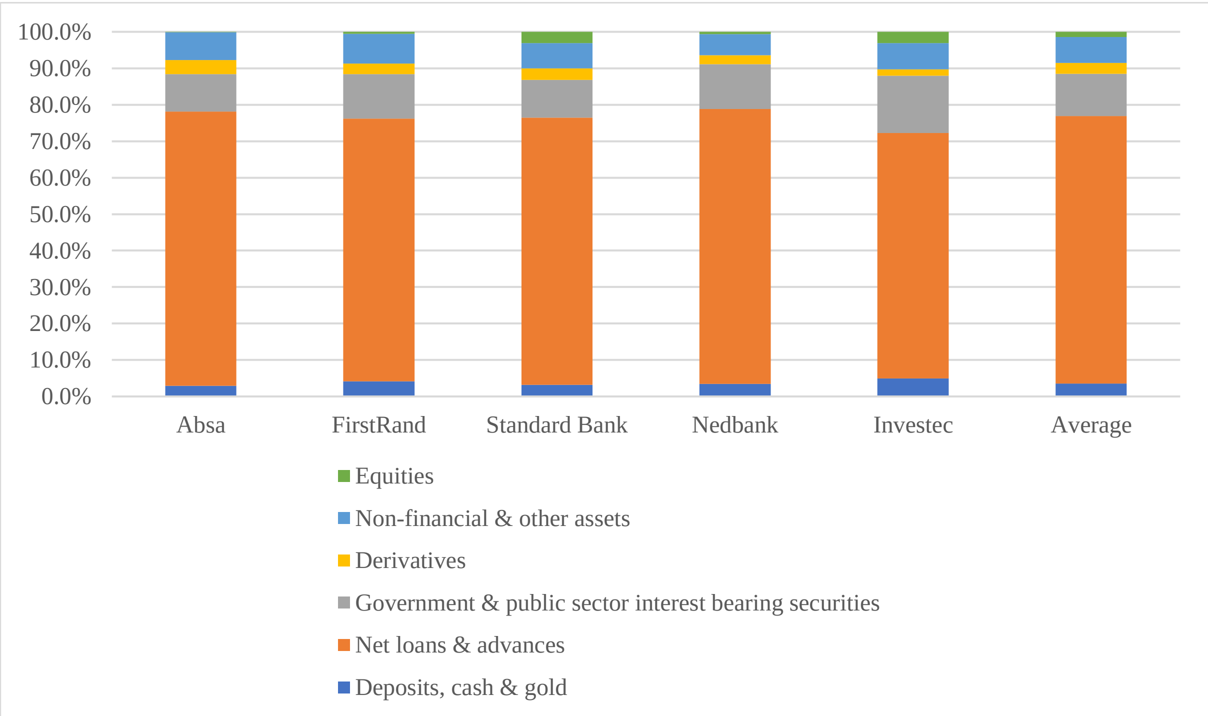

Figure 7: Asset balance sheet split of the biggest South African banks

Figure 6 above shows that the lending activities of the biggest South African banks are fairly concentrated which highlight some of the key systemic risks. There is a large volume of mortgage lending (R 1,424 trillion or 41.6% of total lending) in the South African market [35]. Mortgage lending credit losses can vary greatly since default rates show a high degree of variability [37] which combines with large variances in the severity of losses as the underlying collateral values change. Overdraft and credit cards exposures can also rapidly change if bank customers use their available credit facilities. Figure 7 shows that the large South African banks also have a large exposure to the government with R595 billion in government and public sector interest bearing securities ("PSIBS"). This exceeds the total equity of R377 billion that these banks have available [35]. The exposure to equity investments are more limited at R71 billion.

Forecasting the credit risk associated with bank loans is therefore a critical part of forecasting the overall resilience of the bank to stressed macroeconomic conditions [1].

1.3 Stress Test Frameworks

The Basel accord defines five main components of stress testing [21], [23]:

1. Definition of the risk exposures subject to the stress;
2. A scenario that defines the stress being applied;
3. A model that calculates the impact on the risk exposures when the scenario plays out;
4. A measure of the outcome; and
5. Accounting for potential feedback effects within the financial system.

The stress scenario is defined as a single scenario that is applied to all banks in the market. The different structures of banks mean that the scenario is not equally severe for all banks in the market. Regulators therefore require banks to perform reverse stress tests to define severe scenarios relevant to their own structure. This information is often used to inform future stress tests [15][38].

The way that Basel stress testing is applied in different jurisdictions differs in terms of the guidelines provided and the tools that regulators use to aggregate, test and analyse stress testing submissions by banks. In the USA and the UK, regulators specify detailed modelling guidelines. These modelling guidelines provide guidance around the methods, assumptions of level of sophistication of the stress testing models developed by banks. These regulators also maintain centralised top-down stress testing models to validate the submissions on banks and to consider system wide effects such as cascading failures. In South Africa the Basel regulations are implemented through the Banks Act with regulations published through the Government Gazette. Various guidance notes are also issued to provide clarity on the regulations. In line with the regulations the PA specifies a series of qualitative modelling requirements that banks should adhere to when submitting their stress testing results. To date there is no readily available public information describing a centralised top-down model that may exist within the PA [15][21][23].

Assessing capital adequacy during a period of stress is the primary focus of stress testing models. This includes setting counter cyclicality buffers and discretionary Pillar 2 capital add-ons. Bank failures such as Bear Steans, Lehman Brothers, Northern Rock and Washington Mutual shows that capital in isolation cannot prevent failures and that a tool such as stress testing is needed to investigate events that may deplete capital and cause a bank failure [38]. Systemic and idiosyncratic risk was mitigated by stress testing. Bank disclosures show that capital levels increased before the global financial crisis and that it doubled between 2008 and 2016 [16]. Stress testing that was performed by banks and regulators was also a very effective crisis management and resolution tool since it considered explicit management actions during stressed periods [20][23]. Stress testing also forces banks and regulators to understand the interactions between components of the bank and the wider banking system. This strengthens risk management procedures and allows a more informed risk appetite and strategy to be set [23]. It is, however, difficult to measure the exact effectiveness of stress testing models since bank failures will still occur while there is no simple way to measure bank failures that have been prevented by stress testing [20][23]. Research also shows that stress testing in its current form is a poor early warning system for the failures that did occur [4][20][23]. Regulators and the banking system can therefore benefit from further improvements in stress testing.

1.4 Stress Testing in the USA, UK and South Africa

Some of the earliest stress testing involved sensitivity testing that showed the impact of changing an isolated input into a single risk model. Analysis of past stress events also provide a backward-looking view of risk by considering losses under range of actual past outcomes or losses that followed a specific historic stress. Since then models have evolved to account for the interactions between risks while multiple inputs are stressed [13][21].

A variety of risks that includes credit, market, operational and liquidity risk needs to be considered [15]. A top-down stress test model is therefore important to model banks without sophisticated in-house modelling capabilities and to acts as a cross check of the bottom-up stress testing results of more sophisticated banks [23][39].

Literature on stress testing models indicate that credit risk and market risk modelling tend to be more sophisticated than liquidity and macroeconomic feedback models that are not as well developed [21][23][26]. Modelling is typically done over a two to three year horizon with the assumption that lending continues over the stress period. This assumption is made since lending supports the economy. An assumption that lending is cut would in itself lead to even more adverse outcomes [17][21].

The current Comprehensive Capital Analysis and Review (CCAR) stress testing in the USA started in 2010 after the global economic crisis [38]. The aim of CCAR is to assess if banks have [16]:

- Effective capital planning processes;
- Sufficient capital to absorb losses during stressed conditions, while meeting obligations to creditors and counterparties;
- Capacity to continue to serve as credit intermediaries.

CCAR is based on detailed data submissions by the banks and a range of models developed and maintained by the FED [19]. Data submission include account level payment histories, collateral and borrower information, undrawn facilities, historic revenue and expense numbers, trading balances and transactions. A projection of risk weighted assets ("RWA") and the sensitivity of the trading book to various factors also need to be modelled and submitted by the banks [19]. Three macroeconomic stress scenarios are specified in addition to two additional scenarios that banks determine based on their own risk profile. The aim is not to arrive at a likely scenario but rather to illustrate the impact of severe stress [19]. Banks need a forward-looking capital planning processes that includes quantitative and qualitative requirements that needs to be met and a detailed capital plan. Compliance with CCAR requirements is needed to allow the payment of dividends and avoid additional capital requirements [16].

CCAR stress testing projections outline net income and capital ratios on a quarterly basis. Net income is projected by projecting components such as revenue, expenses, losses and impairments flowing into pre-tax income such as loan and investment security losses, operational risk losses, losses on trading and counterparty positions and mortgage portfolio specific losses [19]. Loans are projected at a product level (for example mortgage loans, personal loans, large corporate loans) over the 3-year projection horizon. Market risk losses are modelled by considering an instantaneous shock that is not directly related to the 3-year macroeconomic stress scenario. [19].

The suite of models used by the FED aims to accurately represent the overall market impact rather than the exact impact for each individual bank. This allows the resilience of the banking system as a whole to be evaluated [19].

The BoE also sets a stress scenario that is intended to be broad enough and severe enough to determine capital adequacy when tail risk events occur [17]. Stress testing by the BoE is different from the FED stress testing in the sense that there are no detailed account level data submissions. Banks perform a detailed bottom-up stress testing projection of their balance sheet and income statement based on detailed requirements set by the BoE. These submissions are then aggregated and assessed. The BoE also has a top-down model called the Risk Assessment Model of Systemic Institutions (RAMSI). This model predominantly uses aggregated bank information that can be found in the public domain [8][24][25].

The BoE stress testing specifies a 5-year macroeconomic scenario. Banks then need to project the banking book and trading book profitability and assess capital adequacy under the scenario. A misconduct cost stress has also been added. The macroeconomic stress is defined as an absolute point which means that the relative stress will become smaller as the current macroeconomic conditions deteriorate [17]. The BoE stress testing is focussed on the biggest banks that account for 80% of the market. The resilience of these banks and their ability to maintain the supply of credit can therefore be assessed. The BoE uses results to set bank specific capital buffers, market wide counter cyclicality buffers, sectoral capital requirements, the PRA buffer and a buffer for Global Systemically Important Banks (GSIBs) [17]. It should also be noted that the BoE stress testing is done over and above the ICAAP submission and European Banking Authority (EBA) stress tests [17].

The macroeconomic scenario set by the BoE is explained by using historic values of macroeconomic variables and by outlining the narrative that corresponds to the forecasted stress. An example includes a slowdown in the Chinese economy that puts pressure on commodity prices. The macroeconomic variables that are forecast includes [17]:

- asset and collateral values;
- local and global GDP growth;
- volatility in financial markets;
- interest rates;
- commodity prices such as the oil price;

- property markets;
- global growth and forex rates;
- consumer and company resilience factors such as household debt to disposable income.

Similar to the FED stress test market risk is stressed as an instantaneous shock that is only broadly related to the overarching macroeconomic scenario. Operational risk losses and expected losses for known misconduct issues are also projected [17].

In South Africa the SARB conducts stress testing in line with the ICAAP requirements outlined in the publications by the Basel Committee for Banking Supervision (BCBS) that forms part of the Bank of International Settlements (BIS). This has been put into law through the Banks' Act regulation 39 section 16 b [15]. Under the ICAAP process banks set scenarios including a base and stress scenario that is approved by the board of the bank. The ICAAP needs to outline impacts on revenue (such as interest income, fee income, non-interest income and impairments), balance sheet exposure measures and RWA and capital ratios under the defined scenarios [15].

Based on the annual ICAAP submissions the SARB could take several actions including increasing capital buffers, requesting specific remedial action or directly intervening through actions such as preventing the payment of dividends [15].

1.5 Tehniques used to model bank stress

The main focus areas of modelling bank distress are the consideration of bank balance sheets and the impact of macroeconomic conditions [14][13][31]. The models can either focus on individual measures such as the proportion of defaulted loans or capital ratios or aggregate measures such as combined loss distributions [14]. Various techniques to model bank stress has been proposed. This includes multivariate discriminant analysis, logit analysis, probit analysis, principal component analysis, nonparametric methods and artificial intelligence techniques such as neural networks that use between 1 and 48 factors [32][33][40]. The modelling of general corporate failure has also evolved from univariate analysis to complex multivariate techniques such as neural networks that aim to capture nonlinear relationships [41]. The more complex techniques such a neural networks require large amounts of data that may not always be available.

Modelling of bank risk includes the use of statistical models such as the Cox proportional hazards model based on metrics such as the ratio of commercial and industrial loans to total loans, ratio of loans to deposits, ratio of loans to total assets, ratio of municipal securities to total assets, capital versus total assets, ratio of expenses to income and ratio of net income to capital. These metrics focus on the composition of the loan book, bank liquidity, bank capitalisation and profitability [42]. Other proportional hazard models focus on bank efficiency, use of deposit insurance, bank assets, ratio of equity to assets, ratio of bond holdings to assets, ratio of loans to total assets, ratio of cash assets to deposits and the ratio of borrowed funds to assets [36]. Such modelling is however, backward looking as the financial ratios are not forecasted in line with expected economic conditions.

Other techniques such as multivariate discriminant analysis use recent bank information to distinguish healthy banks from those with a high probability of failure. This and other modelling highlighted bank capital levels, loan quality and bank profitability as the key variables [30]. Although these variables can be forecasted for a quarter it is more suited to monitoring and identifying banks in distress rather than forecasting economic conditions that may lead to bank distress [33].

Other approaches attempt to forecast bank balance sheet and income statement movements instead of an overall outcome such as failure. Such modelling, however, relies on some simplifying assumptions such as mean reversion, strictly increasing credit risk impairment and static balance sheets which mean that loan and deposit volumes cannot increase or decrease during the stressed period. Specific information such as stage transition rates, cure rates, write-off rates, average default rates and loss given default values for the bank needs to be known [43]. These values are not publicly disclosed. There is also no functionality to run macroeconomic scenarios that are not already built into the default and loss rate estimates. Models that consider early warning signals and then estimate probability of failure has also been developed. These models combine bank specific capital adequacy, asset quality, management, earnings, liquidity and sensitivity to market risk with country macroeconomic and banking sector information [44].

Early warning models have also used artificial intelligence techniques such as random forests. Data over 28 years for 18,381 banks was gathered. The key variables were interest charged on loans and interest paid on deposits [40]. The use of such data intensive techniques which would not be challenging for markets such as South Africa where fewer larger banks operate.

Bank stress testing performed from a market perspective without the use of granular bank specific data is therefore not integrated across they key risk drivers and incorporates bank specific balance sheet information to varying degrees. There is therefore room for an approach that combines many of the stress test modelling that tends to be done in isolation with bank specific balance sheet information.

1.6 Need for a South African Top-Down Stress Test Methodology

Banks are complex entities that are exposed to many interrelated risks. The continued occurrence of crises over time highlight the need for further improvements in the macro-prudential tools used by regulators. Even though stress testing has been around since the early 1990's, it only became more sophisticated and widely used after the 2008 global financial crisis. Stress testing is increasingly being used as a risk management tool at the market level by regulators or by the banks themselves [13]. A top-down stress testing model that can evaluate systemic risk (risk of failure of a large proportion of financial institutions) can help regulators make informed decisions around discretionary capital add-ons, direct interventions, bailouts and crisis resolution [28]. Each crisis reinforces the need to effectively evaluate the resilience of banks to allow effective regulation [7][33]. In South Africa the concentration of deposits and lending in five full-service banks that are listed also means that the failure of one of these banks would have severe consequences and therefore systemic risk is elevated [10][11][35].

A search through published papers and SARB publications have not revealed a clearly documented top-down modelling methodology that is used for macro-prudential regulation. Stress test modelling in general also tends to focus on specific elements such as credit, liquidity or market risk or bank financial ratios without considering the specific features that would drive the credit and liquidity risk of a bank. There is therefore scope for the development of a centralised top-down methodology based on the USA and UK systems. It can be used by the SARB in the South African market to inform macro-prudential decision making or to assess the accuracy of bank specific ICAAP macroeconomic stress test submissions. More stringent bottom-up modelling requirements based on detailed modelling guidance would also drive improvements in these models developed and maintained by the individual South African banks. Although this may not prevent the next banking crisis, it will allow led to more equitable and accurate discretionary capital requirements through an improved assessment of vulnerabilities in the system. A top-down stress testing methodology based on publicly available information provides a cross check to more detailed bottom-up stress testing performed by the banks themselves. A top-down approach using public information is also easier to maintain and will produce results quicker than a full bottom-up stress testing exercise. The structure of such a model also lends itself to refinement based on bank specific data and risk estimates.

Chapter 2

2. Design of a South African Top-Down Stress Test Model

2.1 Model design overview

The biggest South African bank balance sheets are concentrated in loan assets subject to credit risk, deposits subject to liquidity risk and market risk exposures subject to market risk. Credit, liquidity and market risk have also been shown to be some of the key risks faced by banks [31][42][44]. This study investigates the key macroeconomic drivers of credit and liquidity risk and adds the impact of market risk through a simulation that considers past empirical market risk losses. Bank risk is driven by common factors so the aim is to identify macroeconomic factors that explain credit and liquidity risks that would be common to the whole banking industry [11][31]. The focus is also on a limited number of factors since adding more complexity and variables doesn't necessarily add more predictive power and increases model risk [41]. This is also aligned to other models that include macroeconomic factors such as GDP, inflation, equity prices, house prices, government bond yields, international investment to GDP, debt to GDP and private sector credit flow to GDP [44]. Credit risk is represented by changes in accounting credit loss impairments. Liquidity risk is modelled by predicting the change in the volume of total deposits in the market and changes in the market share of each bank. Market risk considers past market risk losses suffered by the banks. This approach is needed since the instrument positions held by banks are dynamically adjusted based on current market conditions and client demand. A top-down stress test model is therefore not practical since it would require modelling the exact instrument composition of a bank and the effectiveness of bank hedging under various stressed conditions. This prototype top-down stress test model forecasts movements in loan credit losses, deposit volumes and market risk losses for the biggest five South African banks over a 3-year horizon. This allows bank specific information to be combined with macroeconomic forecasts which enhances the predictive power of the model [31].

This model is a working prototype that will provide a base for the PA to develop their own top-down stress test methodology. It also highlights risks in the South African banking system that is not apparent in publicly available information that analyse risks in isolation. The model balances accuracy with complexity and only uses publicly available information to make the model available to a wider range of stakeholders. Other stress testing models have to balance similar factors to get to an accurate model that can be developed, maintained and run in an efficient manner [14]. The modular nature of the model means that the complexity of individual components can be increased over time.

2.2 Data Collection

Data to perform modelling is collected from a number of sources. The main data sources include the following:

- SARB
    - BA900 returns that contain detailed monthly data at a bank level. This includes information on assets and liabilities such as loans and deposits per sector and client type [35]. The BA900 data was preferred to bank annual financial statements since it is available in a consistent electronic format over a long period without the need for onerous manual data aggregation.
    - Historic macroeconomic variables including the prime rate, total credit extended to the private sector, government bonds (0 to 3, 3 to 5, 5 to 10 and above 10 year term groups), disposable income of households, national government deficit/surplus as a percentage of GDP, ratio of gross savings to GDP and household debt to disposable income [45].
- National Credit Regulator (NCR)
    - Retail consumer data reports such as the number of customers in good standing.
    - Loan product arrears ageing analysis per quarter [37].
- Statistics South Africa
    - Historic macroeconomic variables including CPI and GDP [46].
- JSE
    - Historic macroeconomic variables including the JSE ALSI index [47]
- Bureau for economic research
    - Historic macroeconomic variables including the consumer confidence, business confidence indices [48],[49]
- Standard & Poors
    - Historic South African sovereign credit rating
    - Historic default rates per sovereign credit rating [50]
- Bank specific capital information

- Pillar 3 reports highlighting RWA and available core equity tier 1 (“CET1”) capital [51]-[55]

Depending on the availability of data and delays in values being published, the values for the macroeconomic variables are sourced from a starting point between January 1996 and June 2003 up to an end point between February 2017 and May 2017. Monthly values are also not available for all variables. Where monthly values are not available, the quarterly growth rate is transformed into a monthly growth rate using the following formula:

$$rate_{monthly} = (1 + rate_{quarterly})^{\frac{1}{3}} - 1 \tag{1}$$

It is assumed that the rate remains constant throughout the period. Similarly, quarterly and half-yearly growth rates could then be derived from these monthly rates using the following formulas:

$$rate_{quarterly} = (1 + rate_{monthly})^{3} - 1 \tag{2}$$

$$rate_{half-yearly} = (1 + rate_{monthly})^{6} - 1 \tag{3}$$

The final set of monthly rates are depicted in Figure 8 to Figure 11 below. The aim of the stress testing model is to find relationships between macroeconomic factors and the key risks being modelled. To achieve that there needs to be a clear change during a period of stress.

Figure 8 shows a clear relationship between interest rates and periods of global economic strain. Interest rates increased in 1998, 2002 and 2008 when the world GDP suddenly dropped [56].

Figure 9 shows that other economic indicators also react to periods of stress. South African real GDP growth reduced around 1998, 2001 and 2009 while inflation spiked around 2002 and 2009. Consumer and business confidence also tend to decrease during crisis periods. Credit extension to the private sector also reduced during or after stressed periods and in some cases increased before the crisis occurred.

Figure 10 shows that the relationship between crisis conditions and gross savings to GDP is less clear cut. That is due to the potential increase in the ratio due to reductions in GDP. In a similar manner household debt to disposable income needs careful consideration. Banks tend to reduce lending during a crisis period which may lead to reduced debt levels in the market. Increased debt levels can also lead to a build-up of risk as observed during the build-up to the 2008 crisis.

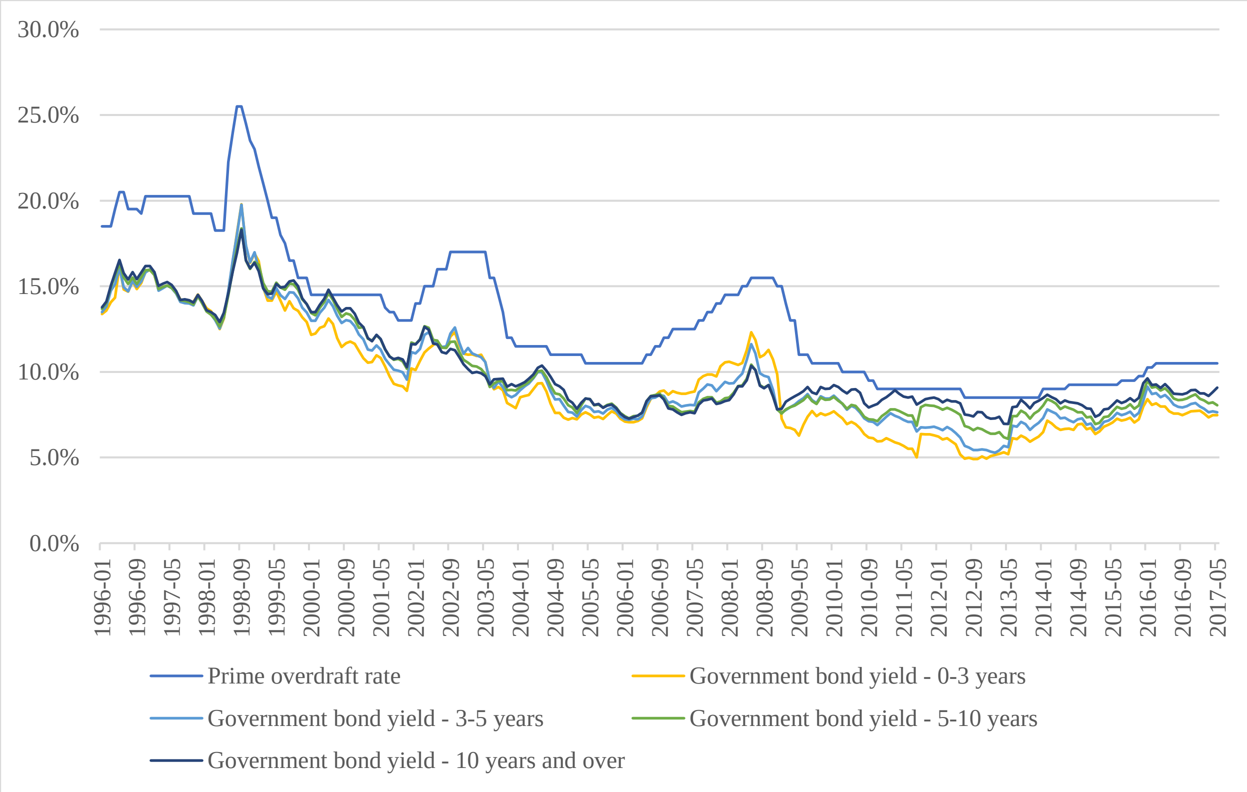

Figure 8: Prime rate and government bond yields

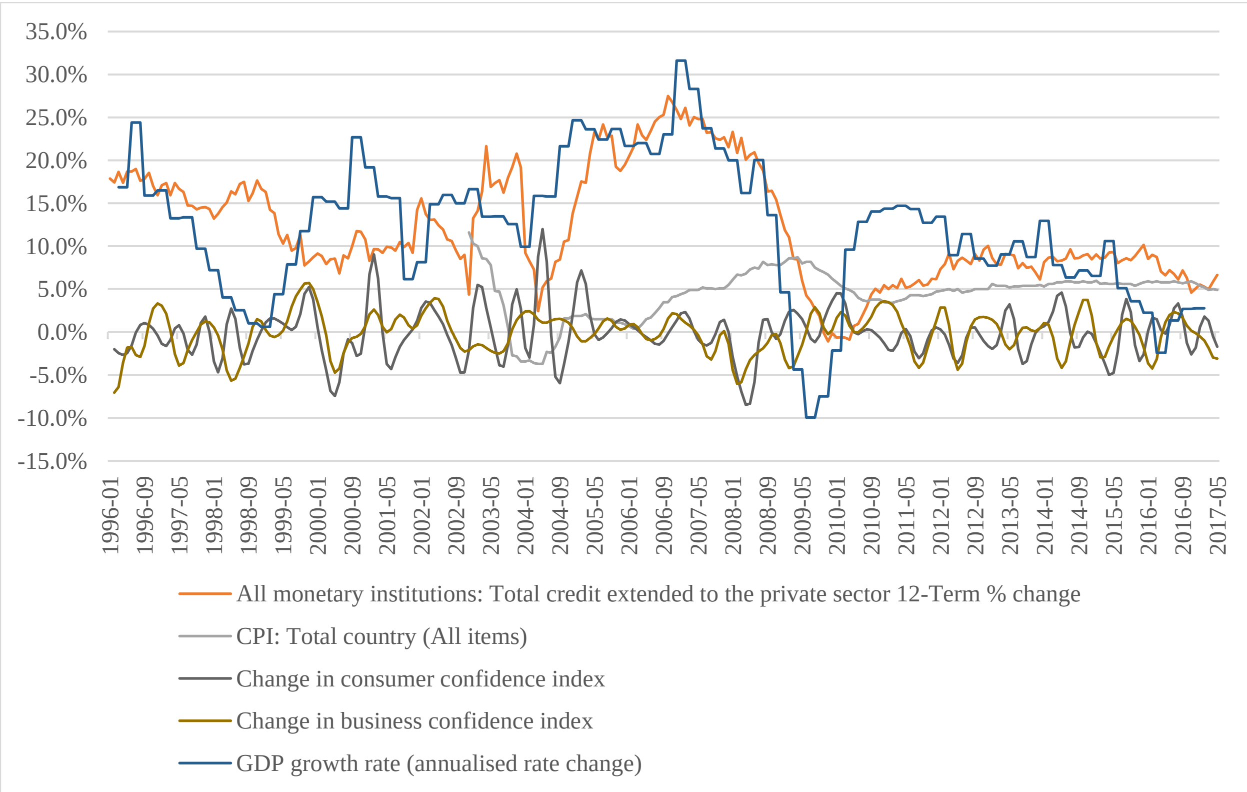

Figure 9: Credit extension, CPI, GDP, consumer and business confidence

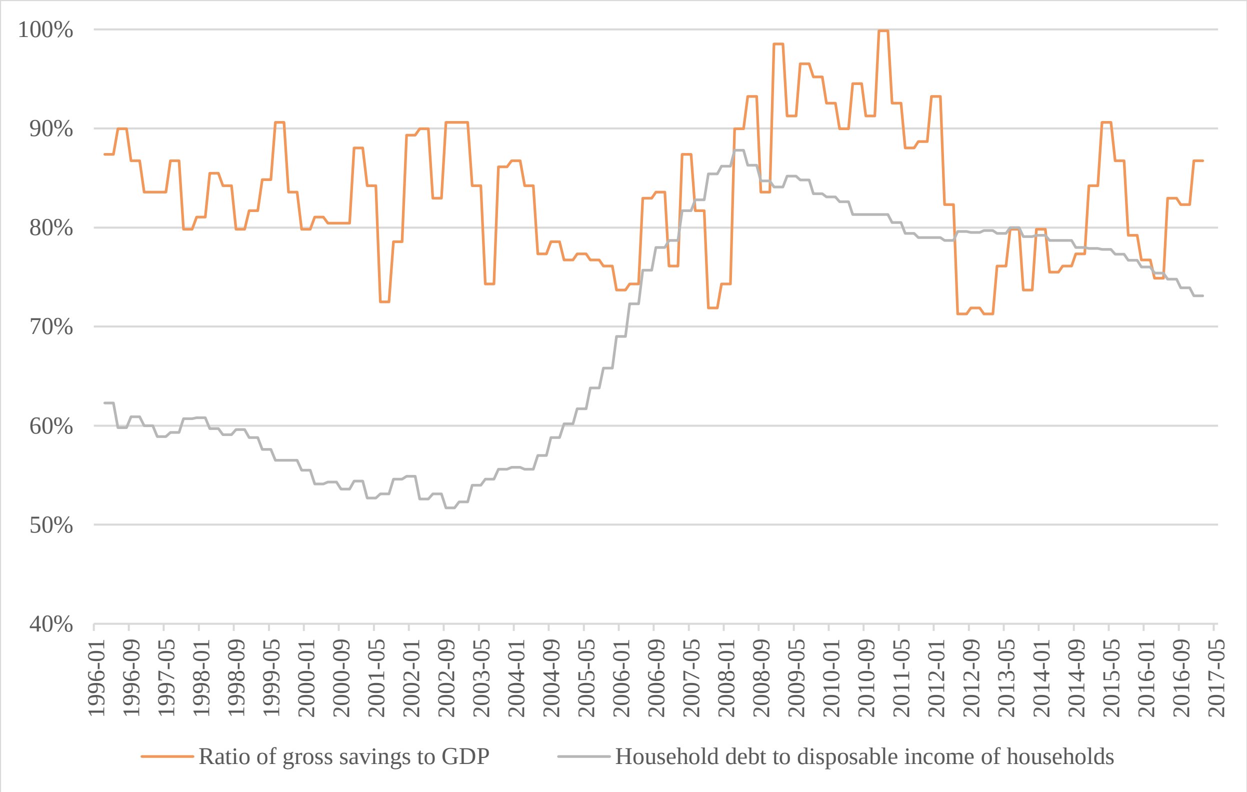

Figure 10: Gross saving to GDP and household debt to disposable income

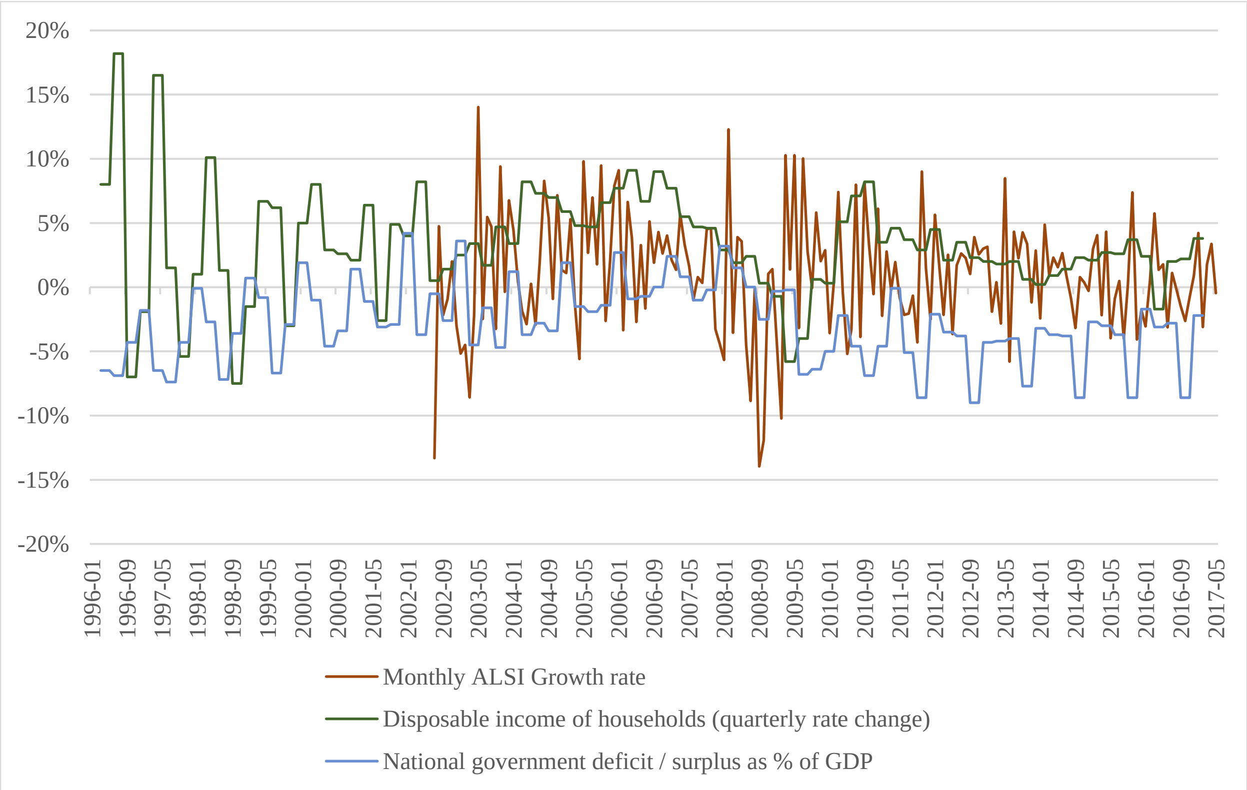

Figure 11: All share index growth, household disposable income and national government surplus/(deficit)

Figure 11 shows that the stock markets react rapidly to economic stress. The use of the stock market levels does however, come with risk since the markets often overreact and then rebound sharply. Stock markets are also affected by factors such as dividend payments although the key focus of the modelling is periods of stress when dividend payments would not have a large impact relative to stressed market movements. Bank credit and liquidity risk on the other hand won't deteriorate as sharply or recover as quickly. Household disposable income should be a good indicator of the resilience of households to stress and therefore their expected level of credit losses. Reductions in disposable income also seem to occur during periods of stress. The national government surplus or deficit is also a challenging metric to interpret. Government spending that leads to a deficit may support consumers and reduce credit losses. It is, however, also indicative of economic strain as manifested through reduced taxes that leads to or increases a deficit. The range of historic economic data therefore needs to be carefully evaluated to arrive at a robust stress testing methodology.

2.3 Balance sheet & income statement modelling elements

The balance sheets of the five biggest South African banks are used to determine the key elements that need to be covered in detail by this top-down model. The absolute size and potential variability are considered. For example, loans and advances subject to credit risk are the biggest asset while trading assets in turn exhibits a high level of volatility due to market risk. The following balance sheet components are modelled in detail:

- Assets
    - Loans and advances
    - Public sector interest bearing securities
- Liabilities
    - Deposits

All other elements are modelled through the direct simulation of equity movements not related to changes in credit risk impairments. These balance sheet elements that could change and lead to such equity movements include:

- Assets
    - Central bank money and gold
    - Deposits with South African banks
    - Deposits with and loans and advances to foreign banks, denominated in rand

    - Loans granted under resale agreements
    - Foreign currency loans and advances
    - Redeemable preference shares
    - Derivative & trading assets
    - Non-financial assets
    - Other assets
- Liabilities
    - Other borrowed funds
    - Foreign currency funding
    - Other liabilities to the public
    - Other liabilities

Future enhancements to the top-down model can model some of these other elements in more detail.

2.4 *Top-down model blueprint*

The model forecasts strain caused by macroeconomic conditions by modelling reductions in asset values caused by credit losses, reduction in deposit volumes that would lead to liquidity strain and other movements in the level of equity that can lead to minimum capital requirements being breached. The level of sophistication is determined by the amount of publicly available historic data, the strength of statistical relationships and the need for a practical prototype that can be developed within a reasonable amount of time. The model is designed to be modular so that specific elements can be enhanced and included in the overall model structure. The main elements that need to be modelled in detail are [24][25]:

- Projection of credit losses on loans and advances which is the biggest bank asset. Credit impairments on public sector interest bearing securities also rely on the modelling of credit losses.
- Projection of bank deposit volumes which is the biggest liability on a bank's balance sheet that drives funding cost and liquidity risk.
- Projection of other events that lead to changes in equity levels. This would include trading book gains and losses.

It should be noted that there is no comprehensive forecast of the bank income statement and forecasted capital adequacy ratios. Low capital equity and liquidity constrains are closely associated with bank failures and is therefore investigated to draw conclusions from the forecasts [1][30][31]. Strain is instead indicated through the projection of credit and other equity losses that can then be compared to minimum CET1 capital requirements. Similarly drops in deposit volumes will be simulated to determine the extent to which liquid assets can cover simulated drops in deposit volumes. There is no single comprehensive measure of liquidity risk [2] although various measures such as the ratio of liquid assets to total assets, ratio of loans to total assets, ratio of liquid assets to deposits or customer and short term funding, the ratio of loans to customer and short term funding and difference between average loans and average core deposits or funding gap have been proposed [9]. Based on the nature of the modelling liquidity risk is measured by considering the availability of more liquid assets on the bank balance sheet to cover reduction in deposit liabilities.

2.5 Forecast framework

The proposed top-down model references some of the features of the BoE RAMSI model while also using new techniques that suit the publicly available information. In the BoE RAMSI model the following steps are followed [24][25]:

1. Project income statement and balance sheet for a single quarter.
2. Incorporate feedback and contagion such as interbank lending, closing of funding markets including increased market funding costs and asset fire sale effects.
3. Determine final retained earnings, asset growth and dividends by considering leverage ratios, capital coverage ratios and current asset mix.
4. Calculate opening balance sheet for the next period

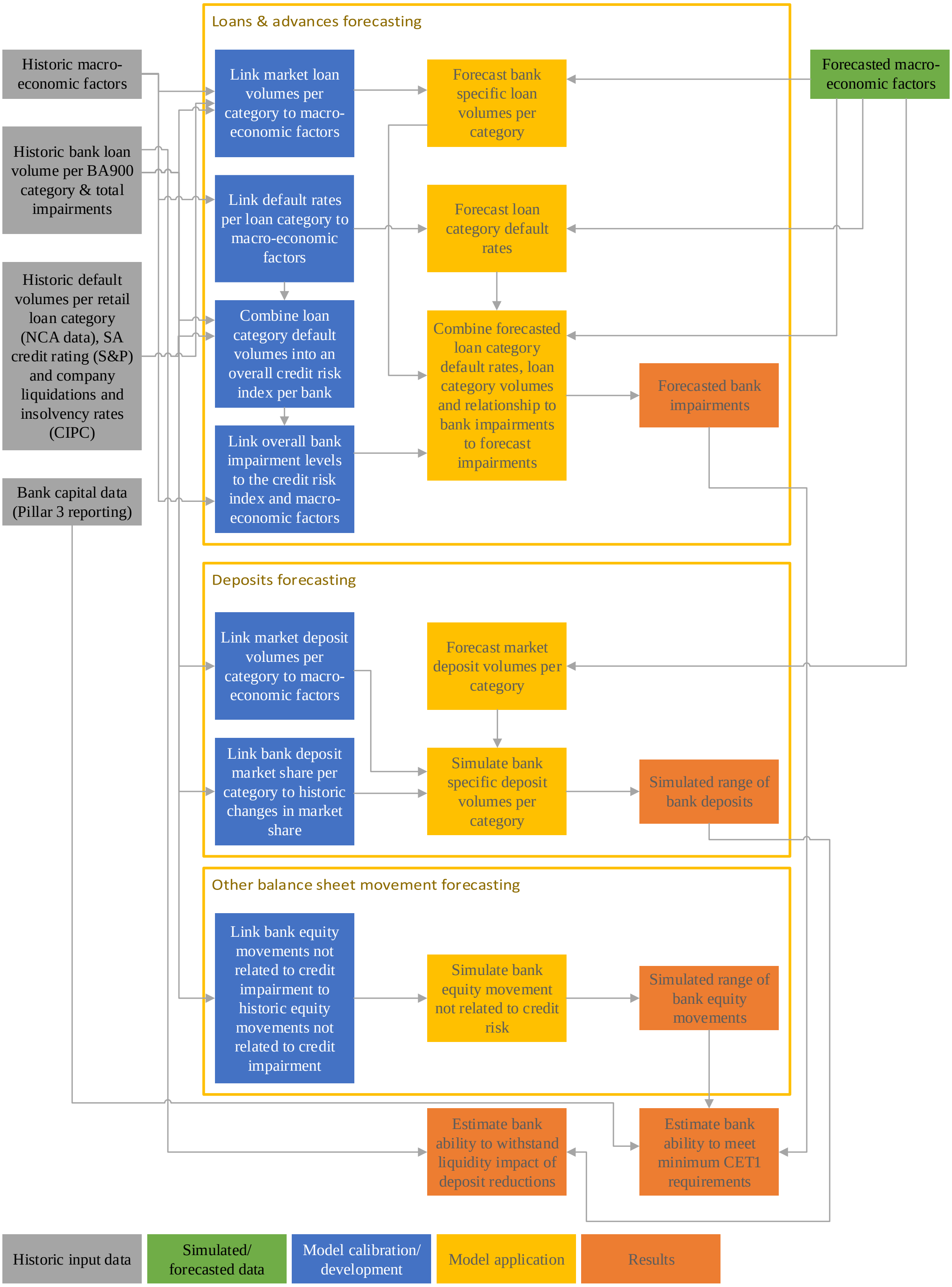

Figure 12: Top-down model outline

The proposed model structure follows the following steps

1. Estimate expected credit losses, change in market loan volumes and change in market deposit volumes based on predicted macroeconomic conditions
2. Simulate a monthly bank balance sheet by forecasting and simulating the following elements:
    - Loan volumes
    - Credit loss impairments
    - Bank deposit market share
    - Other movements in equity levels
3. Compare movements in equity levels to minimum CET1 capital requirements
4. Compare movements in deposit volumes to liquid asset levels

The direct simulation of other equity movements is aligned to models that predict the severity of stress without linking it to specific scenarios such as value at risk models (VaR) [18].

The component parts are covered in more detail in the following sections. Loans and advances forecasting is covered in section 3. while deposit forecasting is covered in section 4. The other balance sheet movement is covered in section 5. while setting of the macroeconomic forecasting, the combination of the loans and advances, deposit, other equity movement and the consequential effect on CET1 and liquidity is covered in section 6.

The projection horizon will be three years which is in line with the BoE and FED projection horizons [16][17].

Model performance will be tested by doing out-of-sample testing and considering the realism of outcomes associated with stressed macroeconomic scenarios.

Chapter 3

3. Loans and advances credit impairments

The main risk that loans and advances is subject to is credit risk. Credit risk in turn will be driven by macroeconomic factors. Credit risk is also driven by the availability of credit. Too much credit could lead to defaults if an unaffordable level of credit is granted (a credit bubble) while too little credit can also cause defaults if companies or individuals are unable fund large costs that exceed their available cash.

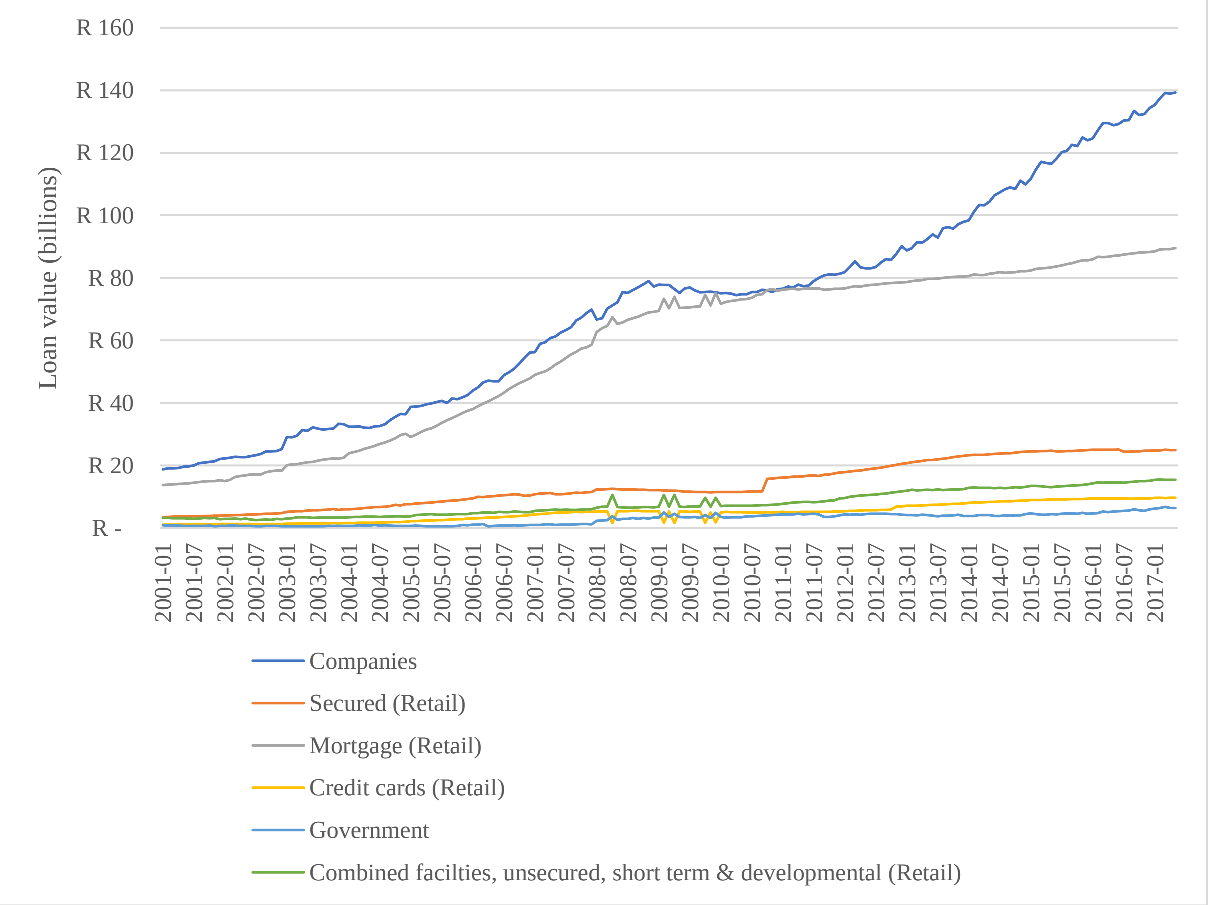

Figure 13: Total volume of loans per category for the biggest five South African banks

Historic BA900 data from the SARB is grouped to create a summary of lending for the biggest five South African banks over time [35]. All lending to companies is combined into a single category since company profitability and performance is a better indicator of credit risk rather than the type of loans that a company has. The same reasoning is applied to lending to the government. Loans to retail clients is however, split into mortgage, secured, credit cards and all other loans that includes overdrafts, unsecured loans, short term credit and developmental credit based on data published by the South African National Credit Regulator (NCR) [37]. Information around the number of registered companies and company insolvencies and liquidations is sourced from the Companies and Intellectual Property Commission (CIPC) [57]. The data from the NCR and CIPC is a good public source that represents the general level of credit risk in the retail and wholesale lending markets since default data at the same level of granularity as the BA900 lending data is not publicly available. The ability of the government to service their debt is inferred by the Standard and Poor's foreign currency credit rating [58].

It should be noted that the lending to the government in Figure 13 above, does not include the purchase of government securities such as treasury bills that also effectively represent lending to the government. Figure 13 also shows that there was steep growth in retail mortgage lending and lending to companies up to the 2008 global financial crisis. Around 2011 lending to companies once again accelerated while retail mortgage lending did not.

3.1 Method

The biggest five banks in South Africa have vast exposures to mortgages and companies. This creates a vulnerability to severe macroeconomic stresses that tend to increase company failures and distress and the state of the property market that directly affects the severity of losses when mortgages default. A top-down model component that forecasts credit impairments, which represents the losses due to credit default events, under stressed macroeconomic conditions for the biggest five banks (by lending volumes) is therefore proposed.

The components in the structure outlined in Figure 14 is covered in more detail in the subsequent sub-sections. The development of a credit risk index per loan category is outlined in section 3.2 . The combination of the credit risk index per loan category into an impairment per bank is outlined in section 3.3 .

Modelling credit risk requires reasonable and intuitive relationships between macroeconomic factors and default risk. The first step is therefore to define the directional impact that each macroeconomic factor should have on default rates. An increase in the prime rate, total credit extended to the private sector, government bonds (0 to 3, 3 to 5, 5 to 10 and above 10 year term groups), CPI, household debt to disposable income and the national government deficit as a percentage of GDP should lead to an increased number of defaults. Conversely an increase in the disposable income of households, the ratio of gross savings to GDP, GDP, the JSE ALSI index, consumer confidence and business confidence indices should lead to a decrease in default rates.

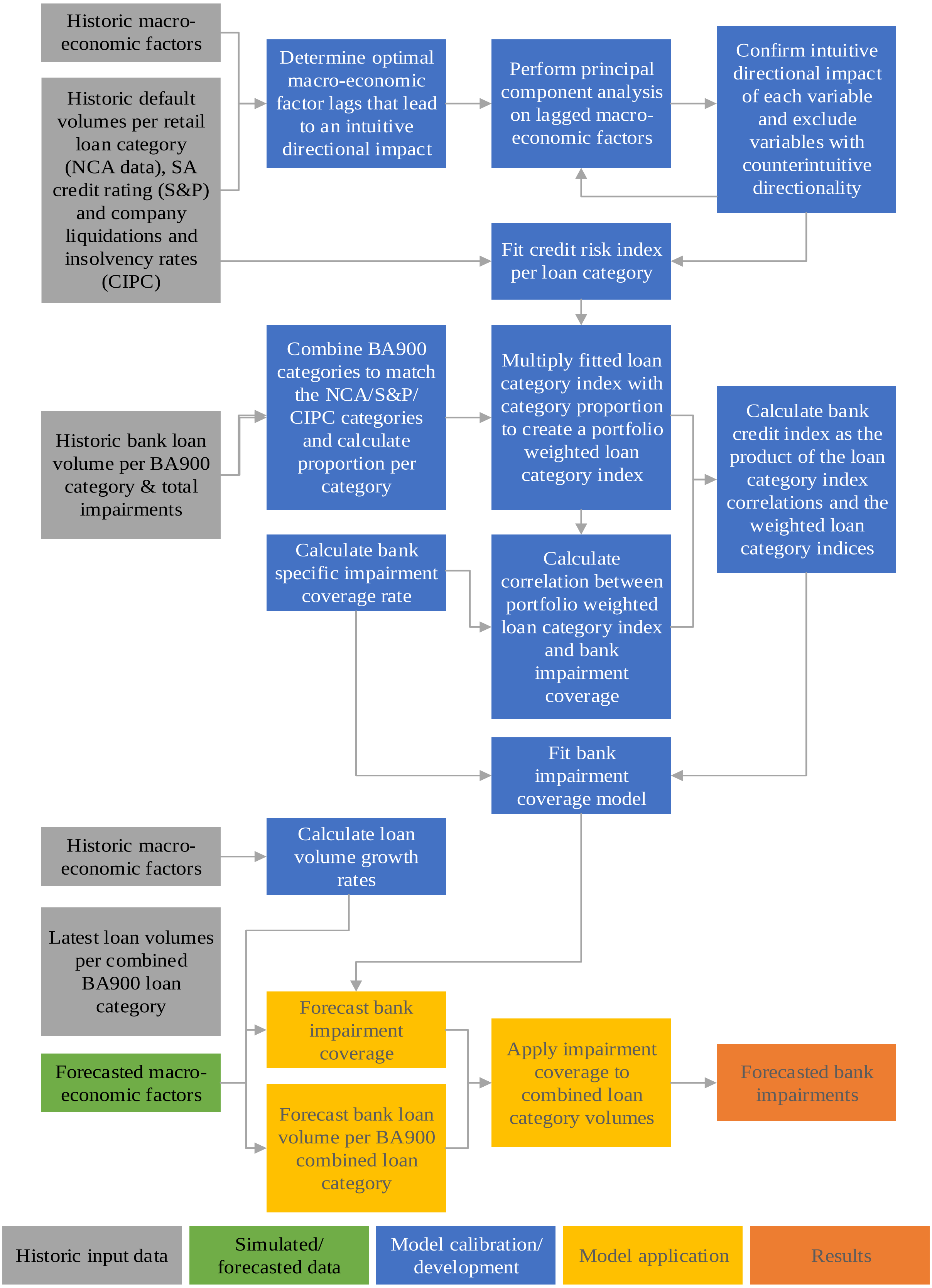

Figure 14: Top-down credit risk stress test model structure

3.2 *Modelling a default risk measure index*

The use of a credit risk index is a technique that has been employed in a number of studies [33][59]. The data from the NCR, CIPC and S&P is first transformed to a percentage (default risk measure) that reflects the level of credit risk for a given product or client type at a given point in time. The NCR data on retail customers were converted to defaulted loan proportions using the following formula:

$$def_{x,t} = \frac{Value\ 90{+}days\ arrears_{x,t}}{Total\ value_{x,t}} \tag{1}$$

Where:

$def_{x,t}$ is the proportion of loans that are defaulted for loan category x at time t

$Value\ 90 + days\ arrears_{x,t}$ is the value of loans that are 90 or more days in arrears or defaulted for loan category x at time t

$Total\ value_{x,t}$ is the total value of loans for loan category x at time t

Note that the categories in the NCR data include mortgages, secured credit, credit facilities, unsecured credit, short term credit and developmental credit.

The CIPC data on companies are converted to default rates using the following formula:

$$def_{company,t} = \frac{Insolvencies_t + Liquidations_t}{Companies_t} \tag{2}$$

$$def_{company\ quarterly\ MA,t} = 1 - \left[(1 - def_{company,t}) \times (1 - def_{company,t-1}) \times (1 - def_{company,t-2})\right]^4 \tag{3}$$

Where:

$def_{company,t}$ is the proportion of companies that default (as evidenced by liquidation or insolvency) in month t

$def_{company\ quarterly\ MA,t}$ is the annualised proportion of companies that default, averaged over a three month period up to month t

The S&P rating of the South African government foreign currency debt is mapped to an empirical probability of default by considering the long run average default rate of similarly rated countries. This is then used to produce $def_{Sovereign,t}$ which is the expected default probability of the South African government at time t.

Modelling changes in these measures of credit risk will allow the bank impairment levels to be modelled.

Figure 15 shows a clear increase in the volume of defaulted accounts around the 2009 global financial crisis. It should be noted that short term credit is only 0.2% of the total loans reported on by the NCR while developmental credit is 2.5% as at the end of 2016 [37].

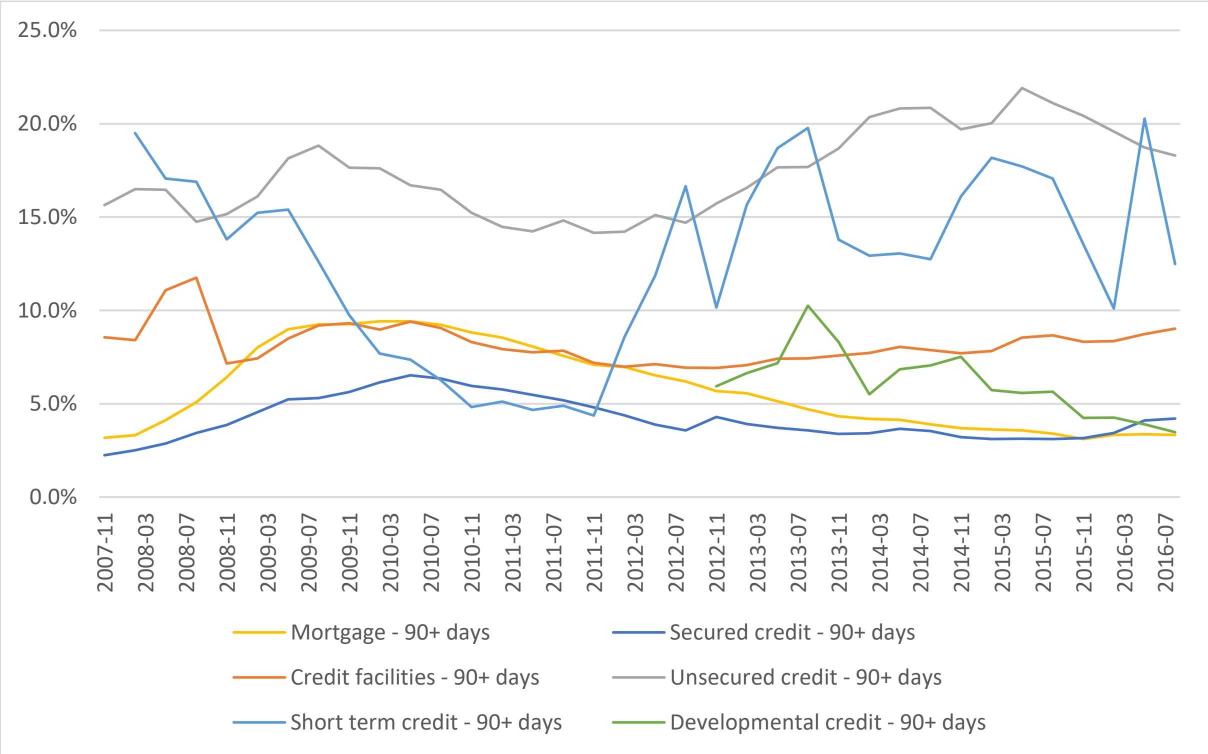

Figure 15: Proportion of loans that are more than 90 days past due per product category

The steep increase in default rates in 2014 can be partly attributed to African Bank being placed under curatorship in August 2014. At that point in time African Bank accounted for 28.4% of the personal loans market share as represented by other loans and advances to households in the SARB BA900 data [35].

Figure 16 highlights the dramatic increase in company liquidations and insolvencies during a period of stress. The peak level of 5.47% in September 2009 is 4.8 times bigger than the level of 1.41% in February 2006.

Figure 15 to Figure 17 illustrates the level of credit risk for a given product grouping. Figure 15 and Figure 16 also clearly shows the increase in loans that are more than 90 days past due (defaulted) and company insolvencies after the 2008 global financial crisis.

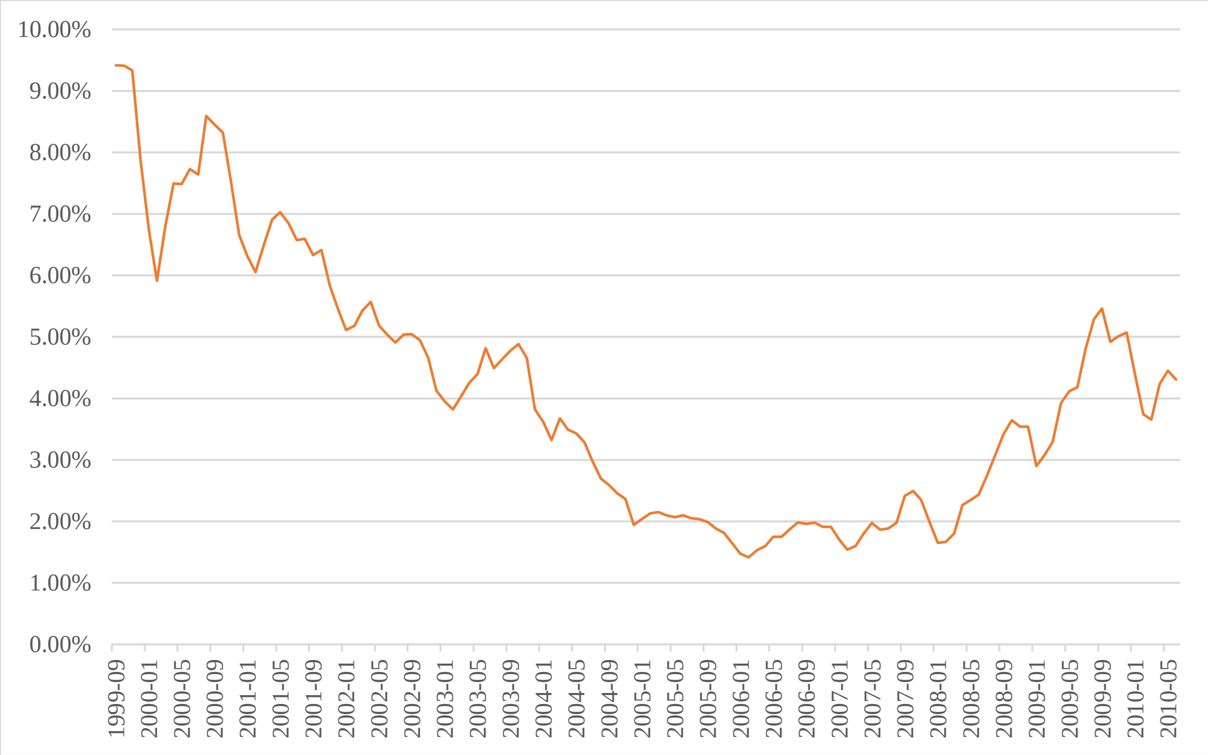

Figure 16: Annualised quarterly moving average rate of company liquidations and insolvencies

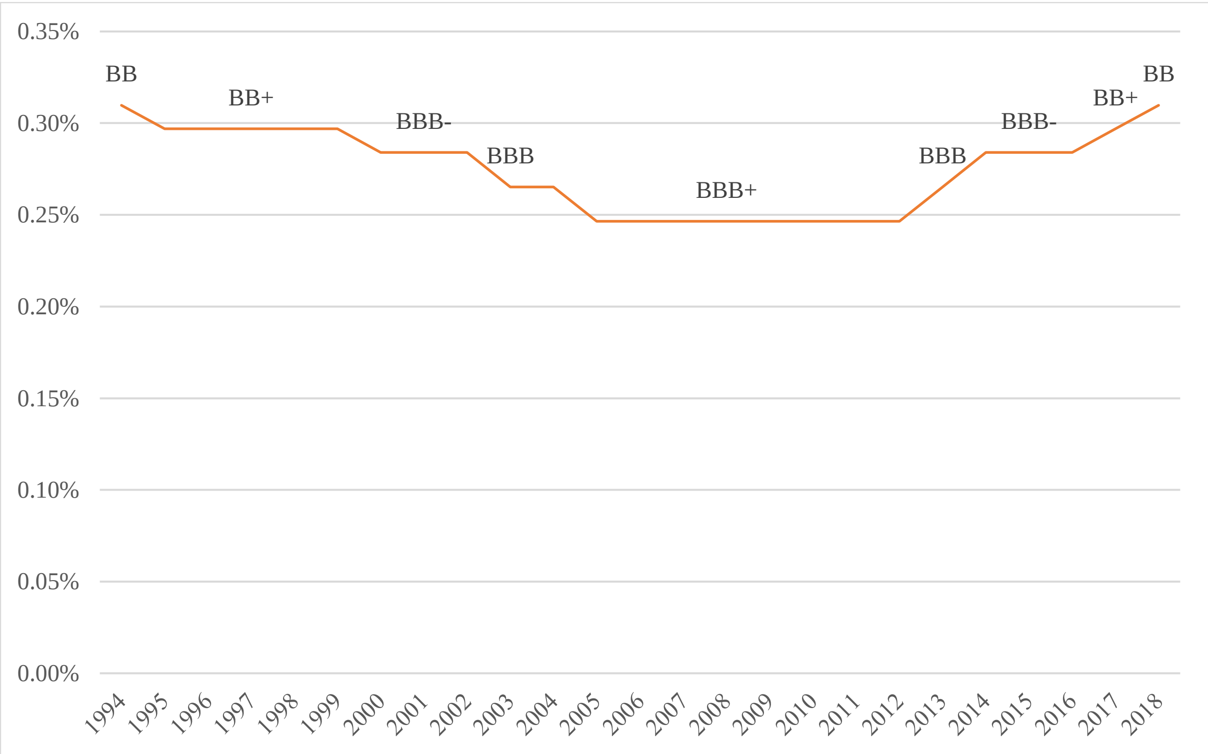

Figure 17: History of South African sovereign S&P credit rating and average annual local currency default rate corresponding to each rating

The default rate associated with each credit rating in Figure 17 is based on the historic default rates of countries with a similar credit rating as sourced from S&P data [50]. The limited number of local currency sovereign default means that the relative risk of foreign currency sovereign default is used to interpolate the local currency sovereign default risk [60].

The lag between the crisis and an increase in the volume of defaulted loans vary by product category. It can also be seen that the level of mortgage defaults have been reducing ever since 2008 which is partly due to more stringent lending requirements enforced by the banks that can also be seen in the reduced growth in mortgage advances from Figure 13. Figure 16 also shows the effect of the 1998 Asian financial crisis. Figure 17 shows that the credit rating of the South African government improved steadily from BB in 2008 to BBB+ in 2005 before deteriorating back to BB by 2018.

The correlation between quarterly macroeconomic factors and these default risk measures ($def_{x,t}$) is assessed. The effect of macroeconomic factors could also take a while to have an effect on the default risk measure. For example, individuals may have savings or other emergency funds that could delay the default on a mortgage or vehicle loan. The time between a macroeconomic factor changing and the default risk changing can therefore be incorporated by lagging the macroeconomic factors. The following process is followed to arrive at the final default risk macroeconomic factor lags:

1. Calculate the Pearson correlation between the macroeconomic factors and default risk measure. This is done using the quarterly macroeconomic figures.
2. Determine the lag period (in months) that leads to the maximum absolute level of correlation between the macroeconomic factor and the default risk measure. The lag period is limited to a maximum of 24 months to reduce the risk of finding a spurious link between variables.

Using this analysis, the following lags are chosen:

	Mortgage	**Secured credit**	**Credit facilities**	**Unsecured credit**	**Short term credit**	**Developmental credit**	**Corporate credit**	**Sovereign credit**
Prime rate	8	8	6	4	0	8	4	0
Total credit extended to the private sector	8	8	8	6	1	0	8	0
CPI: Total country (All items)	8	6	4	2	0	1	7	0

Government bond yield - 0-3 years	8	8	6	0	0	6	5	0
Government bond yield - 3-5 years	8	8	0	0	0	8	4	0
Government bond yield - 5-10 years	8	8	0	0	0	5	3	0
Government bond yield - 10 years and over	4	7	0	0	0	8	0	0
Monthly ALSI Growth rate	8	7	7	4	3	8	4	0
Change in consumer confidence index	8	8	8	7	4	8	5	5
Change in business confidence index	7	8	8	5	4	5	5	1
GDP growth rate (annualised rate change)	1	3	4	0	0	5	2	0
Disposable income of households (quarterly rate change)	3	7	4	2	0	2	2	0
National government deficit / surplus as % of GDP	8	8	8	5	0	5	7	0
Ratio of gross savings to GDP	8	8	8	6	3	2	0	6
Household debt to disposable income	6	7	1	4	0	3	7	2

Table 1: Lag in months applied to macroeconomic variables for each default risk category

Using the specified lagged macroeconomic variable directly to predict the default risk measure per category could lead to volatile results due to multicollinearity. Indices used in the modelling of bank stress also use principle component analysis and a variety of weighting techniques [61]. The risk of multicollinearity is therefore addressed by applying principle component analysis to the final lagged macroeconomic variables. The Eigen values resulting from the principle component analysis is used to choose the number of principle components to use. An Eigen value level of one is used as a benchmark. Table 4 below shows the number of principal components that is selected per loan category.

Next the directional reasonability of each variable is assessed. Any macroeconomic variable with a counterintuitive directional impact is discarded. The table below highlights the intuitive directional impact for each macroeconomic factor.

	Impact on credit risk if increased
Prime rate	Increase
Total credit extended to the private sector	Increase
CPI: Total country (All items)	Increase
Government bond yield - 0-3 years	Increase
Government bond yield - 3-5 years	Increase
Government bond yield - 5-10 years	Increase
Government bond yield - 10 years and over	Increase
Monthly ALSI Growth rate	Decrease
Change in consumer confidence index	Decrease
Change in business confidence index	Decrease
GDP growth rate (annualised rate change)	Decrease
Disposable income of households (quarterly rate change)	Decrease
National government surplus as % of GDP	Increase
Ratio of gross savings to GDP	Decrease
Household debt to disposable income	Increase

Table 2: Intuitive directional impact of each macroeconomic factor on credit risk

The final selected variables per category is as follows:

	Mortgage	Secured credit	Credit facilities	Unsecured credit	Short term credit	Developmental credit	Corporate credit	Sovereign credit
Prime rate	✓	✓	✓	×	×	×	✓	×
Total credit extended to the private sector	✓	✓	✓	✓	✓	✓	×	✓
CPI: Total country (All items)	✓	✓	✓	✓	✓	✓	×	✓
Government bond yield - 0-3 years	✓	✓	✓	✓	×	×	✓	✓
Government bond yield - 3-5 years	✓	✓	✓	✓	×	×	✓	✓
Government bond yield - 5-10 years	✓	✓	✓	✓	×	×	✓	✓

Government bond yield - 10 years and over	✓	✓	✓	×	×	×	✓	×
Monthly ALSI Growth rate	×	×	✓	×	×	×	✓	✓
Change in consumer confidence index	×	×	✓	✓	✓	✓	×	×
Change in business confidence index	×	✓	✓	✓	✓	✓	×	✓
GDP growth rate (annualised rate change)	×	✓	✓	✓	✓	×	×	✓
Disposable income of households (quarterly rate change)	×	✓	✓	✓	✓	✓	×	✓
National government deficit / surplus as % of GDP	✓	✓	✓	×	✓	×	×	✓
Ratio of gross savings to GDP	×	×	✓	✓	✓	✓	×	✓
Household debt to disposable income	✓	✓	×	×	×	×	×	×

Table 3: Final selected macroeconomic variables per default risk category

The number of principle components per default risk category for the final set of variables from Table 3 above is as follows:

	Number of principle components used
Mortgage	2
Secured credit	3
Credit facilities	4
Unsecured credit	2
Short term credit	3
Developmental credit	2
Corporate credit	1
Sovereign credit	3

Table 4: Averaging period for macroeconomic and default rates per loan category based on the Eigen value of each principal component

To forecast default risk and impairments the principle components need to be linked to the default risk measure. Three potential methods are considered:

3.2.1 *Method 1 - Index based on correlation transformed with Vasicek approach*

An index is first constructed by calculating the Pearson correlation between each principle component and the default risk measure. This correlation is then used to calculate an index using the following formula:

$$I_{x,t}^{credit} = \sum_{y=1}^{5} \sigma_{x,y} PC_{y,t}^{credit} \tag{4}$$

Where

$I_{x,t}^{credit}$ is the credit risk index for the category x default risk measure at time t

$\sigma_{x,y}$ is the correlation between principal component y and the default risk measure x

$PC_{y,t}^{credit}$ is the value of the principal component y of default risk measure x at time t

The index is then standardised using the following formula:

$$SI_{x,t}^{credit} = \frac{I_{x,t}^{credit} - \mu_x^{credit}}{\sigma_x^{credit}} \tag{5}$$

Where

$SI_{x,t}^{credit}$ is the standardised default risk measure index for category x at time t;

μ_x^{credit} is the average index value of category x;

σ_x^{credit} is the standard deviation of the index of category x.

The standardised index is the single factor that represents an increase or decrease in the credit risk for a given set of macroeconomic factors. This standardised index needs to be transformed into a prediction of default rates. This can be done using the Vasicek adjustment [62]:

$$VMA_{x,t}^{credit} = \phi\left(\frac{\sqrt{1-\rho_x^{credit}}\,\phi^{-1}\left(g_{x,t}^{TTCdef}\right) + \sqrt{\rho_x^{credit}}\,\phi^{-1}\left(SI_{x,t}^{credit}\right)}{\sqrt{1-\rho_x^{credit}}}\right) \tag{6}$$

Where:

$VMA_{x,t}^{credit}$ is the Vasicek macroeconomic adjusted default risk measure for category x at time t

$g_{x,t}^{TTCdef}$ is the long run average (through the cycle) default rate measure for category x

ϕ is the standard normal density function

ϕ^{-1} is the inverse of the standard normal density function

ρ_x^{credit} is the correlation between $g_{x,t}^{TTCdef}$ and $SI_{x,t}^{credit}$

The fit has two main objectives:

1. Provide a good fit to the actual historic default risk measure
2. Account for large increases in the default risk measure

The second criteria is important since the aim of stress testing is to evaluate the impact of extreme events rather than accurately predicting long term trends.

In equation (6) the only unknown variable is ρ_x^{credit} which is the correlation between the index and the default risk measure. The correlation is set so that the following value is minimised:

$$\left| g\ max_x^{Act\ def} - g\ max_x^{Fit\ def} \right| \quad (7)$$

Where:

$g\ max_x^{Act\ def}$ is the maximum observed default rate for loan category x

$g\ max_x^{Fit\ def}$ is the maximum default rate for loan category x as predicted by equation (6)

3.2.2 Method 2 - Index based on correlation transformed with scaling

The standardised index $SI_{x,t}^{credit}$ can also be scaled to align to the average and standard deviation of the default risk measure. The forecasted default risk measure is therefore calculated using the following formula:

$$SMA_{x,t}^{credit} = SI_{x,t}^{credit} \times \sigma_x^{dr} + \mu_x^{dr} \quad (8)$$

Where:

$SMA_{x,t}^{credit}$ is the scaled index macroeconomic adjusted deposit growth rate for deposit category x at time t.

σ_x^{dr} is the standard deviation of default risk measure x

μ_x^{dr} is the average of default risk measure x

3.2.3 Method 3 - Regression performed on principle components

The growth rates can also be estimated through linear regression applied to the principle components. The forecasted default risk measure is therefore calculated using the following formula:

$$RMA_{x,t}^{credit} = \omega_{x,0}^{credit} + \sum_{y=1}^{5} \omega_{x,y}^{credit} PC_{y,t}^{credit} \qquad (9)$$

Where:

$\omega_{x,0}^{credit}$ is the constant estimated through the regression for default risk measure x;

$\omega_{x,y}^{credit}$ is the regression weight of principal component y of default risk measure x;

$RMA_{x,t}^{credit}$ is the linear regression macroeconomic adjusted default risk measure for category x at time t.

3.2.4 Choice of default risk measure index method

The methods are evaluated by considering:

1. goodness of fit to full time series of the default risk measure
2. extent to which short periods of stress is represented by the method
3. goodness of fit when method is applied as a forecast
4. reasonability of macroeconomic variable directions

It should be noted that a balance between the criteria is needed. While overall goodness of fit would normally be a key criterion, goodness of fit under stress is added due to the focus of stress test modelling where forecasts of stressed scenarios are often not severe enough [26]. Based on the above criteria the regression approach is discarded since it could reverse the variable directions and therefore require the entire index construction process to be repeated in an iterative manner. A choice between the Vasicek and scaled index approach is therefore needed. By considering the two methods the scaled index approach is selected as the preferred approach. The scaled index approach is selected since the fit to the historic default data is better while maintaining the ability to reflect periods of severe stress. The fit on retail mortgage and company credit below illustrates this.

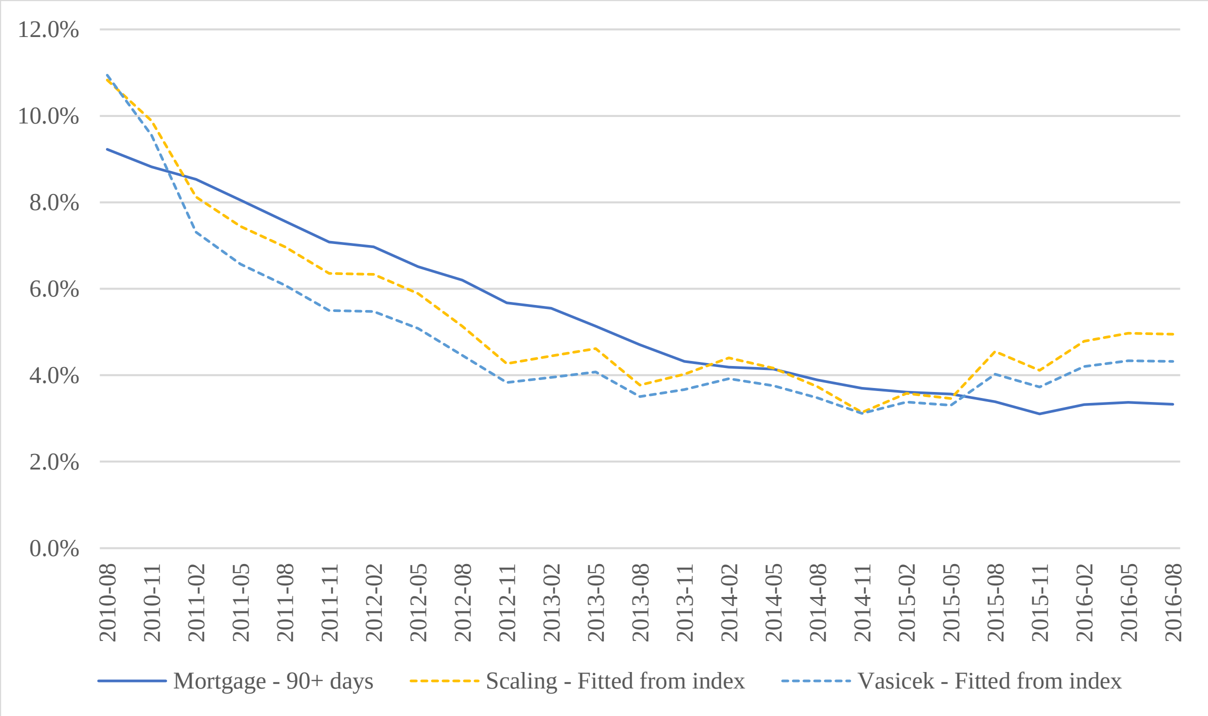

Figure 18: Comparison of Vasicek and scaled index approaches to modelling retail mortgage credit risk

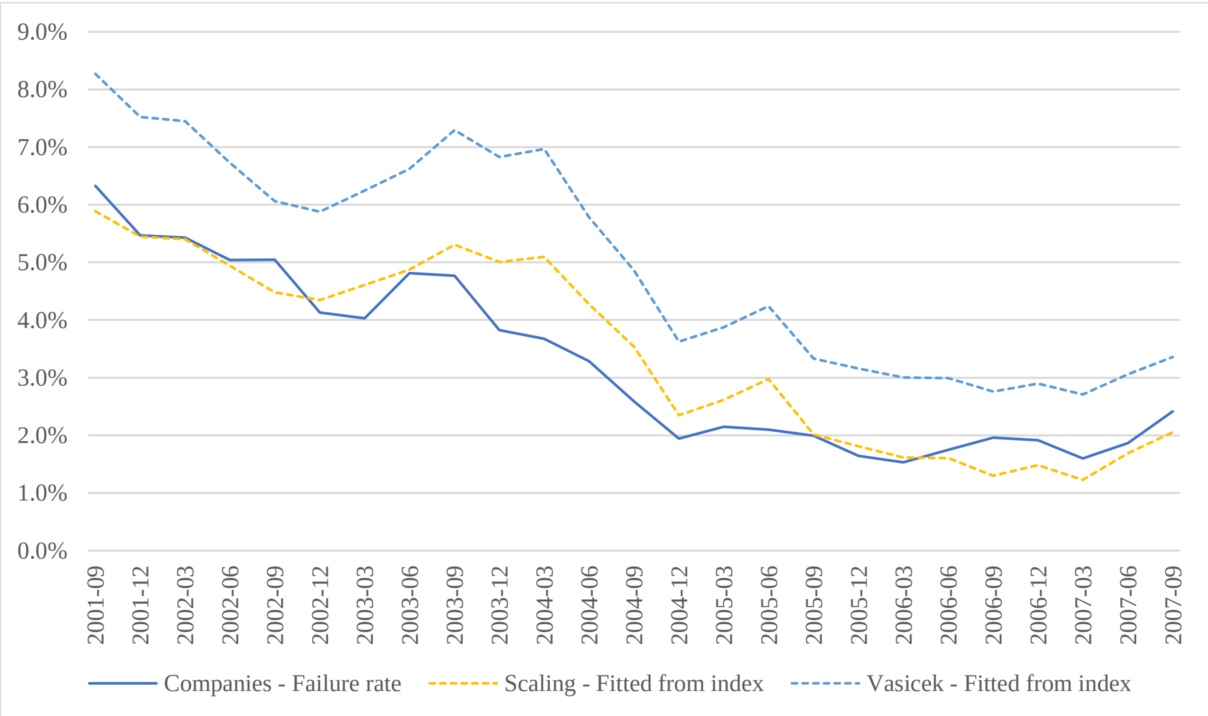

Figure 19: Comparison of Vasicek and scaled index approaches to modelling company credit risk

A comparison of fitted results and actual default risk measure per category is depicted in Figure 20 to Figure 23 below. It shows that the modelling accounts for changes in various default risk categories. The exception is the South African sovereign rating that was not downgraded despite the level of economic strain that was experience.

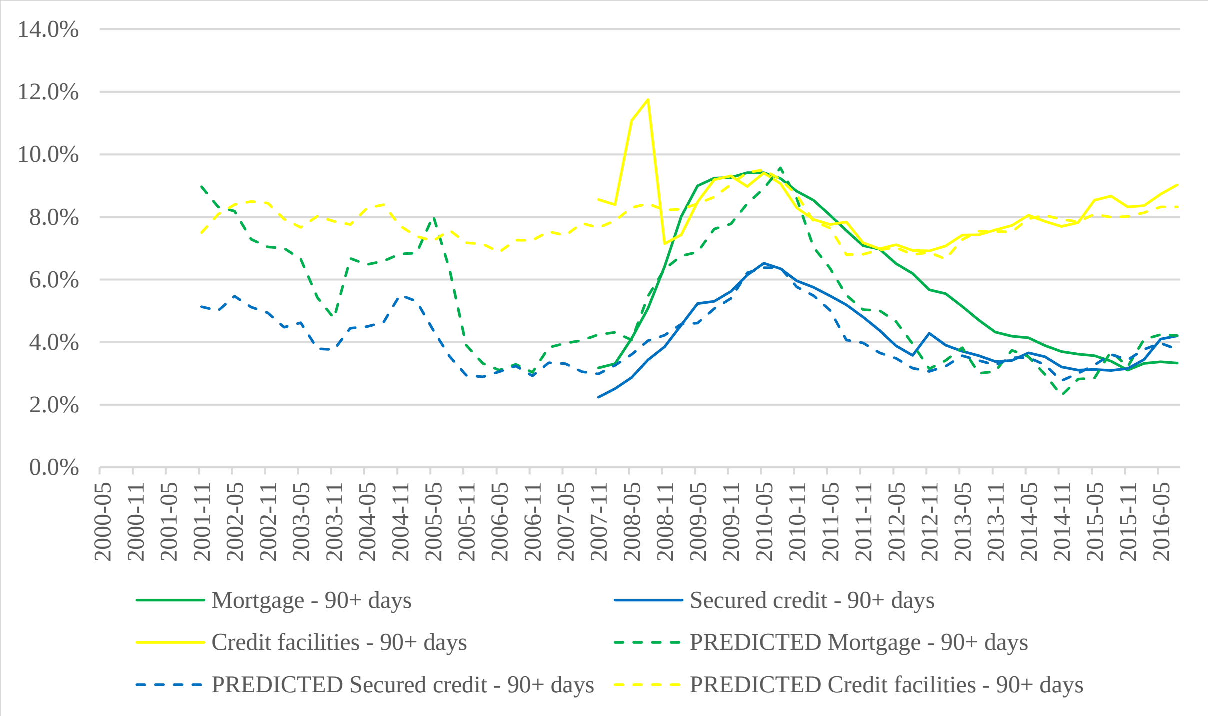

Figure 20: Fitted retail default risk measure compared to actual default risk measure (mortgages, secured credit and credit facilities)

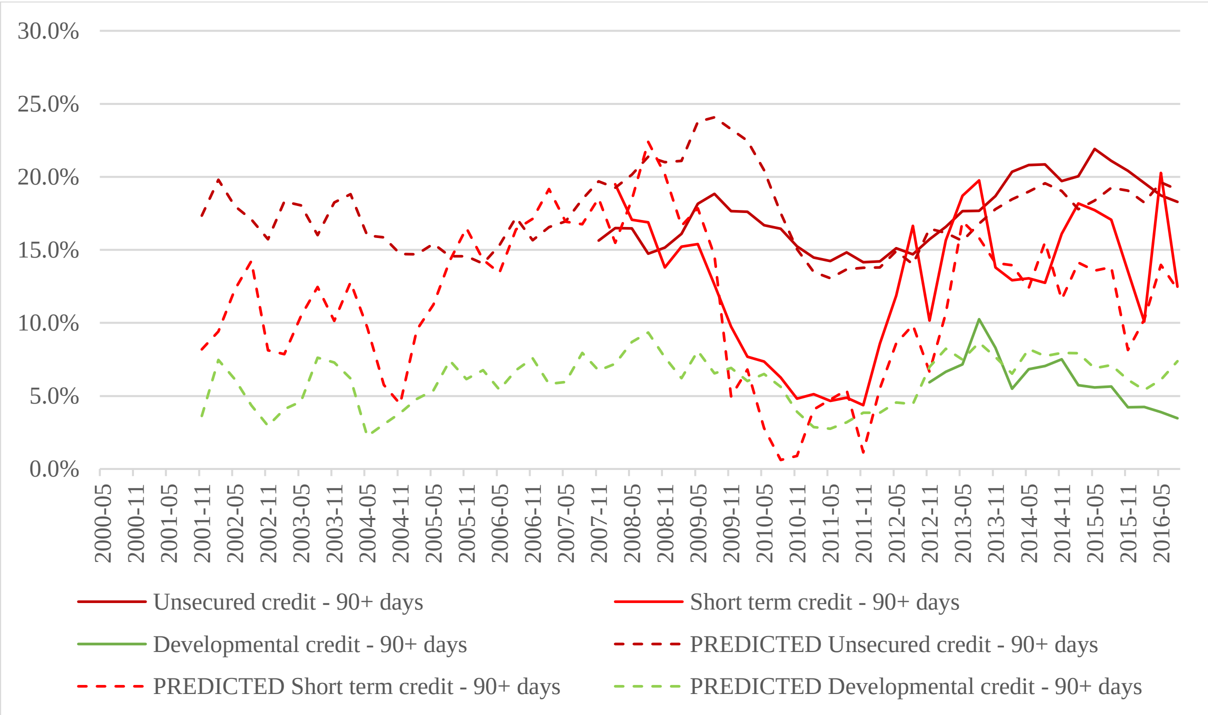

Figure 21: Fitted retail default risk measure compared to actual default risk measure (unsecured credit, short term credit and developmental credit)

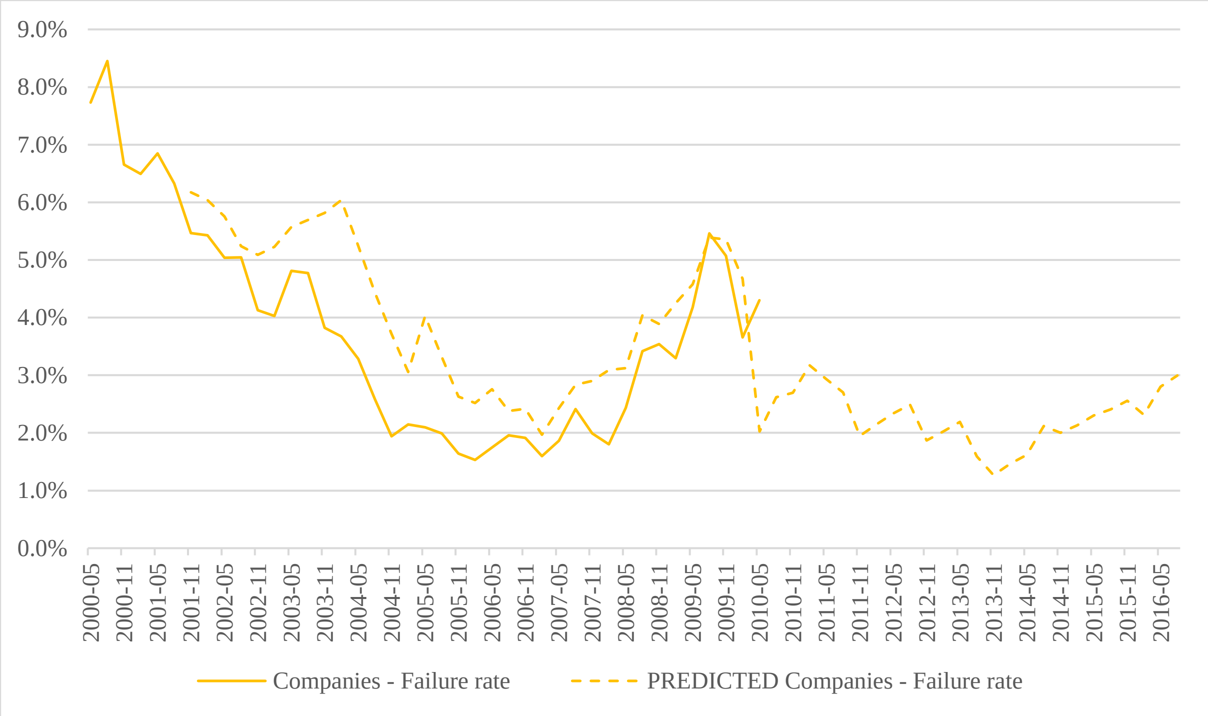

Figure 22: Fitted retail default risk measure compared to actual default risk measure (company credit)

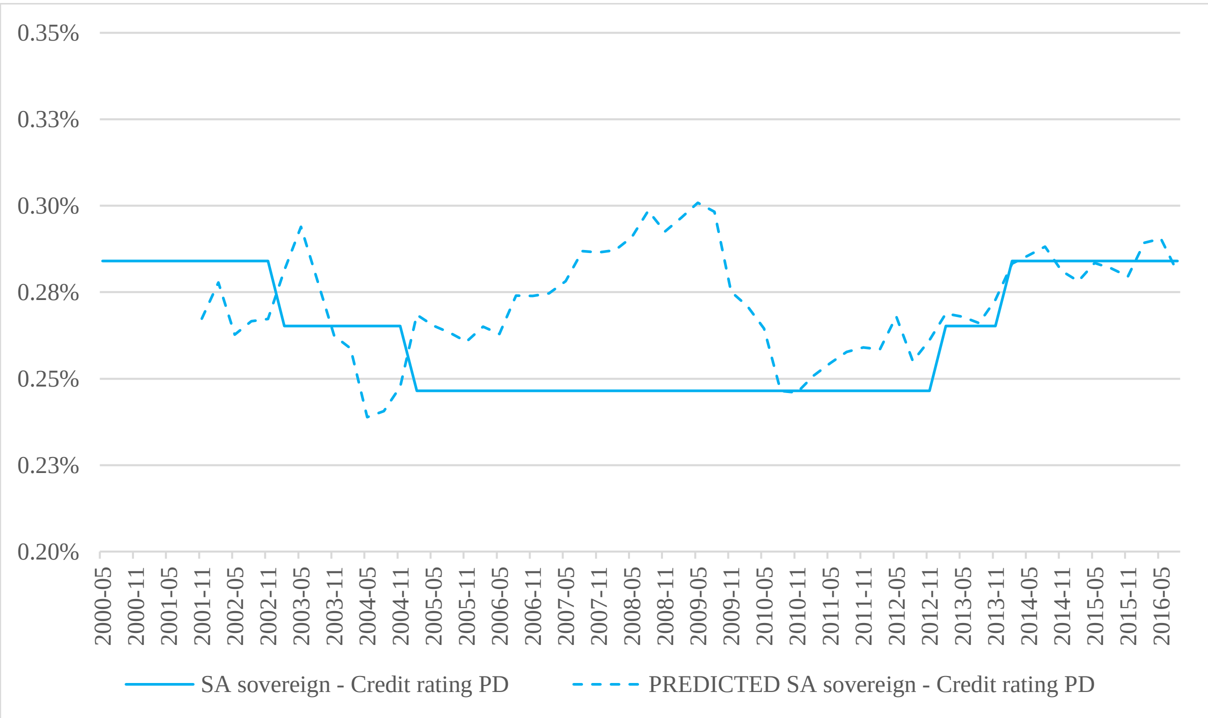

Figure 23: Fitted retail default risk measure compared to actual default risk measure (sovereign credit)

This modelling demonstrates that the various default risk measure indices ($SMA_{x,t}^{credit}$) is an accurate reflection of the default risk for various loan types. It can therefore serve as an input into the modelling of bank impairments. The R^2 values for each loan category is highlighted below.

Loan category	R^2
Mortgage	77%
Secured credit	88%
Credit facilities	78%
Unsecured credit	57%
Short term credit	72%
Developmental credit	18%
Corporate credit	84%
Sovereign credit	43%

Table 5: Fit of the scaled index model to actual historic default rates as represented by R^2 values for each loan category

The fit for each loan category is very good apart from developmental credit. This is due a shorter historic period that only starts in 2012. It should however, not affected overall results since it represents an insignificant proportion of the overall lending in the market.

3.3 Modelling bank impairment

Bank credit losses are typically reflected by credit loss impairments that should be enough to cover all losses from loans that are written-off. To model credit loss impairments per bank the default risk measures need to be linked to the level of impairments (impairment for credit losses) that the banks hold. Note that the historic BA900 is based on impairments under the previous IAS39 accounting standard while current impairment calculation is governed under the new IFRS9 standard. While IFRS9 would lead to quicker recognition of impairment losses due to the use of forward looking information, the peak impairment levels should be similar when default volumes peak. The historic IAS39 data is therefore a suitable proxy in the absence of historic IFRS9 that is only available since 2018.

The BA900 data from the SARB is used to calculate the overall impairment coverage ratio for the big five banks. Impairment coverage is defined as the total impairments held divided *b*y the total loans values for each bank. Each loan category will contribute to the overall bank risk to a different degree. This will not only depend on the proportion of loans and advances made up by each loan category but also the underlying level of risk and sensitivity to changes in risk. Two layers of weighting is therefore proposed. The first layer is simply the proportion of total loans and advances made up by each loan category. The second weight applied to each loan category represents the sensitivity of the bank impairments to changes in the default risk category. The choice of weighting method is determined by considering the combined impairment of the five banks to prevent bank level risk appetite changes from distorting results. A Vasicek approach and linear combination of index values is considered to link impairment coverage to the default risk measure indices. A regression approach is not considered since it could reverse the variable directions and therefore require the entire index construction process to be repeated in an iterative manner. Initial testing also showed that a regression may artificially increase the weight assigned to smaller loan categories which would lead to a spurious fit. The two approaches we applied as follows:

3.3.1 Method 1 – Linear combination of default risk measure indices

The use of a linear regression would not be appropriate since the coefficients assigned to the index values ($SI_{x,t}^{credit}$) could be negative which would be counter intuitive since the deterioration in the credit quality of some loans should not lead to a reduction in the overall impairments of a bank. A set of weights for each default risk measure index is therefore solved based on the following criteria:

1. All weighs should be positive but less than 100 to set a reasonable range for the solver algorithm to search within.
2. The sum of squared errors should be minimised with errors after 2009 receiving a weight four times bigger than errors before 2005.
3. The average fitted impairment over 2009 and 2010 should match the average actual impairment over the same period as closely as possible. This difference carried a weight of 48 which is equivalent to adding double the weight to each of the 24 observations during this period.

The aim of the second criteria is to use more recent information that better reflected the current loan portfolios of the banks. The third criteria ensures that the model fits well over a period of severe stress. The forecasted bank impairment is then calculated using the following formula:

$$IC_{x,t}^{lin} = \sum_{y=1}^{8} \theta_{x,y,t} \omega_y^{imp\ lin} SI_{y,t}^{credit} \quad (10)$$

Where:

$IC_{x,t}^{lin}$ is the forecasted impairment coverage ratio for bank x at time t using a linear combination of the loan category indices;

$\theta_{x,y,t}$ is the proportion of total loans and advances of bank x that is made up by loan category y at time t;

$\omega_y^{imp\ lin}$ is the weight of default risk measure index y.

3.3.2 Method 2 – Average index based on correlation transformed with Vasicek approach

An overall default risk measure index first needs to be constructed. The volume of loans per customer and product type varies over time so a primary weighting based on the proportion of loans for each default risk measure index first needs to be calculated. The subsegments of the loans in the BA900 returns are not the same as the subsegments that underpin the default risk measure indices. The following mapping rules are applied:

1. All loans to the corporate sector, non-profit organisations and other loans not mentioned below are classified as company loans. Note that factoring debtors relating to unincorporated business enterprises of households are also included.
2. Loans to the central government, social security entities, provincial government, local government, the Land Bank, government financial corporates such as the IDC and public sector corporates such as state owned enterprises are classified as government or sovereign loans.
3. Mortgage loans, secured loans, credit facilities, unsecured loans, short term loans and developmental credit to the household sector is classified as retail loans of the corresponding category. Note that this includes overdrafts of unincorporated business enterprises of households.

For retail loans unsecured loans, short term credit and developmental credit could not be separately identified in the BA900 data. These categories are therefore combined based on everything that isn't a mortgage, secured credit or a credit card debtor. The combined category is subsequently split into three parts based on the proportion of unsecured loans, short term credit and developmental credit in the NCR data. It should be noted that more than 79% of credit in this category relates to unsecured credit making the contribution of short term credit and developmental credit small.

A weighted average index could then be constructed based on the default risk measure index value at each point in time and the proportion of total loans for the bank that correspond to the specific default risk measure index. This ensures that a change in the mix of loan types is reflected in the forecasting of impairments.

A secondary weighting can then be applied to create the final index. This is done by calculating the Pearson correlation between each loan weighted default risk measure index and the impairment coverage ratio. This correlation is then used to calculate an index using the following formula:

$$I_{x,t}^{impairment} = \sum_{y=1}^{8} \sigma_{x,y} \theta_{x,y,t} SI_{y,t}^{credit} \tag{11}$$

Where

$I_{x,t}^{impairment}$ is the credit impairment index for entity or grouping x at time t

$\sigma_{x,y}$ is the maximum of zero and the correlation between weighted default risk measure index ($\theta_{x,y,t} SI_{y,t}^{credit}$) for loan category y and the impairment coverage ratio of entity or grouping x

The index is then standardised using the following formula:

$$SI_{x,t}^{impairment} = \frac{I_{x,t}^{impairment} - \mu_x}{\sigma_x} \tag{12}$$

Where

$SI_{x,t}^{impairment}$ is the standardised credit impairment index for entity or grouping x at time t;

μ_x is the average index value of category x;

σ_x is the standard deviation of the index of category x.

The standardised index is the single factor that represents an increase or decrease in the credit impairment coverage ratio for a given set of macroeconomic factors. This standardised index needs to be transformed into a prediction of a credit impairment coverage ratio. This can be done using the Vasicek adjustment [62]:

$$VMA_{x,t}^{impairment} = \phi\left(\frac{\sqrt{1-\rho_x^{impairment}}\,\phi^{-1}\left(g_{x,t}^{TTCimp}\right)+\sqrt{\rho_x^{impairment}}\,\phi^{-1}\left(SI_{x,t}^{impairment}\right)}{\sqrt{1-\rho_x^{impairment}}}\right) \tag{13}$$

Where:

$VMA_{x,t}^{impairment}$ is the Vasicek macroeconomic adjusted credit impairment coverage ratio for entity or grouping x at time t

$g_{x,t}^{TTCimp}$ is the long run average (through the cycle) credit impairment coverage ratio for entity or grouping x

ϕ is the standard normal density function

ϕ^{-1} is the inverse of the standard normal density function

$\rho_x^{impairment}$ is the correlation between $g_{x,t}^{TTCimp}$ and $SI_{x,t}^{impairment}$

The fit has two main objectives:

1. Provide a good fit to the actual historic credit impairment coverage ratios
2. Account for large increases in the credit impairment coverage ratios

The second criteria is important since the aim of stress testing is to evaluate the impact of extreme events rather than accurately predicting long term trends.

In equation (13) the only unknown variable is $\rho_x^{impairment}$ which is the correlation between the index and the credit impairment coverage ratio. Shifts in the risk appetite and portfolio structure of the banks however, also mean that $g_{x,t}^{TTCimp}$ is not known. The correlation and long run average impairment coverage is therefore solved so that the sum of squared errors from 2007 to 2012 is minimised.

3.3.3 Choice of impairment modelling method

The two methods are evaluated by considering:

1. goodness of fit to full time series of the default risk measure
2. extent to which stress is represented by the method

Based on the above criteria a choice between the Vasicek and scaled index approach is therefore needed.

A comparison of fitted results and actual default risk measure per category for the combination of the five banks being modelled is depicted below:

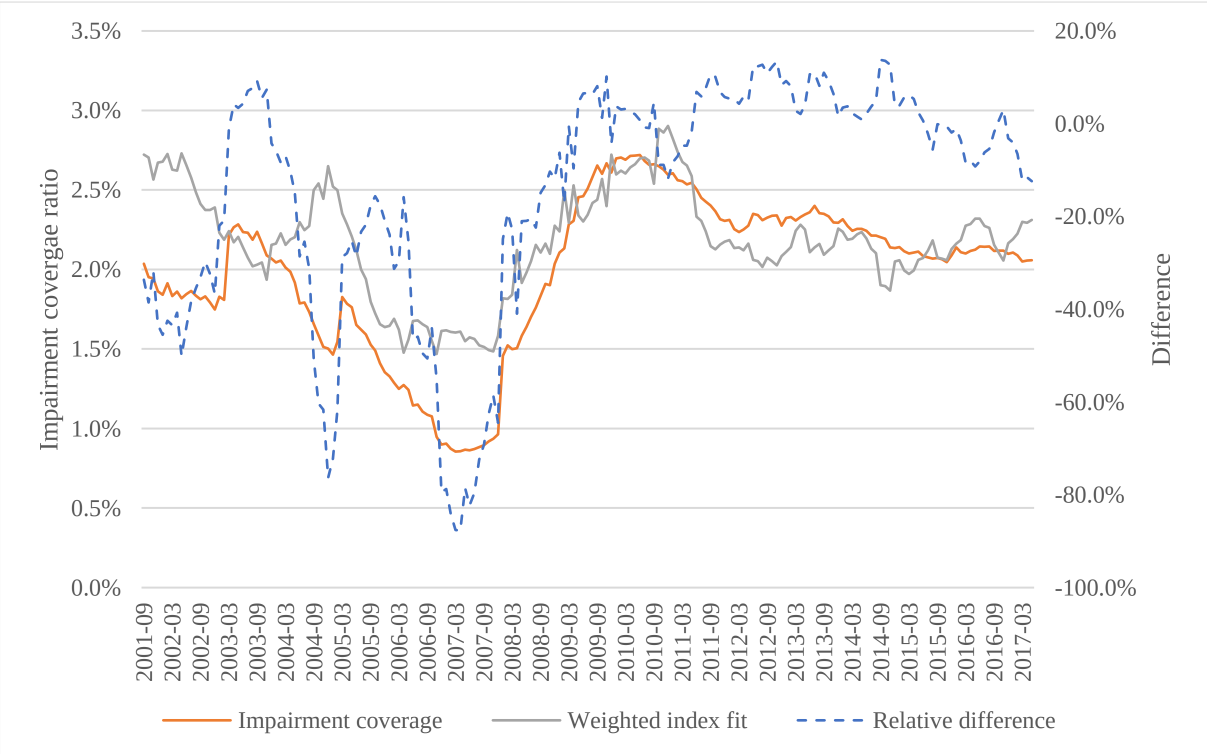

Figure 24: Fit compared to actual impairment coverages for the linear combination of default risk measure indices

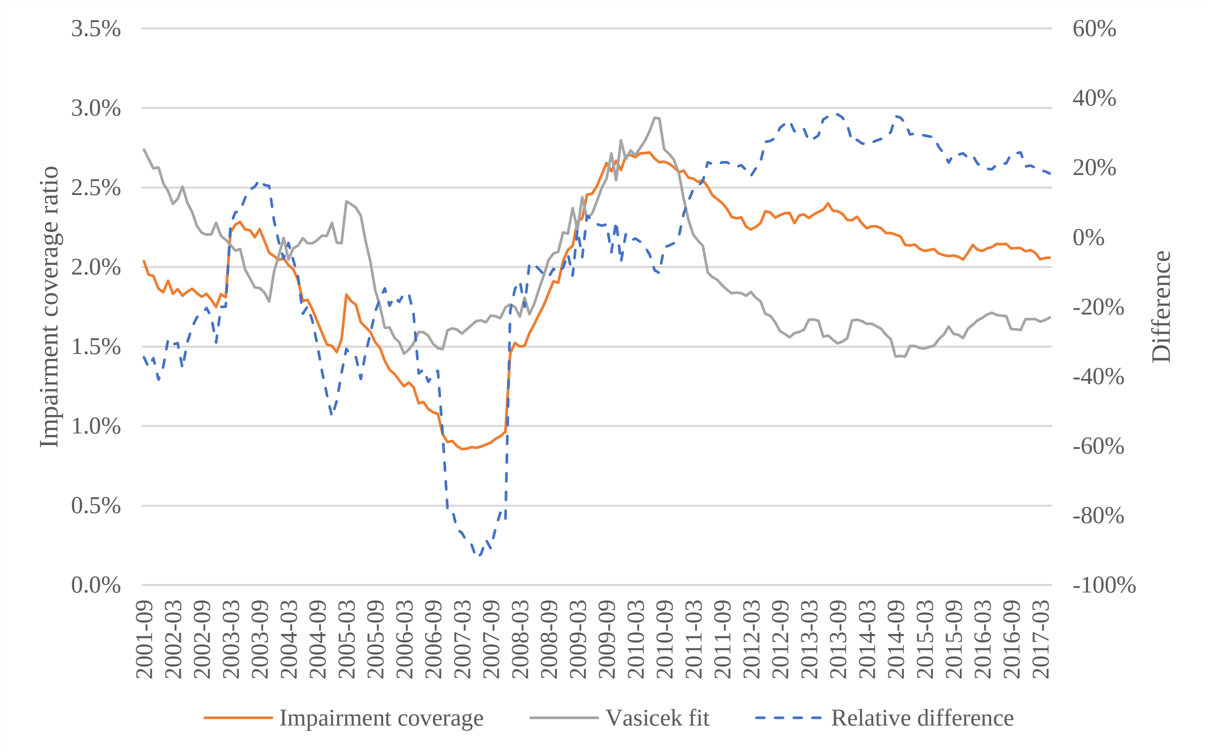

Figure 25: Fit compared to actual impairment coverages for the correlation transformed with Vasicek approach

The weight assigned to each default risk measure index ($Avg\ Wgt_{lin} = \frac{\sum_{t=1}^{N} \theta_{y,t}\omega_y^{imp\ lin} SI_{y,t}^{credit}}{N}$ for the linear combination and $Avg\ Wgt_{corr} = \frac{\sum_{t=1}^{N} \theta_{y,t}\sigma_y SI_{y,t}^{credit}}{N}$ for the correlation based Vasicek approach) for all five banks combined is shown below. Note that the weight is defined as the average index value multiplied by the volume of loan per category and coefficient assigned to it.

	Method 1 - Linear combination of default risk measure indices ($Avg\ Wgt_{lin}$)	**Method 2 - Correlation transformed with Vasicek approach ($Avg\ Wgt_{corr}$)**
Mortgage	0.22%	0.62%
Secured credit	1.25%	0.13%
Credit facilities	0.05%	0.00%
Unsecured credit	0.04%	0.17%
Short term credit	0.01%	0.00%
Developmental credit	0.16%	0.00%
Corporate credit	0.03%	0.04%
Sovereign credit	0.42%	0.00%

Table 6: Contribution of each default risk measure index to the final impairment model

Figure 24 and Figure 25 show that method 1 seems to fit the actual data better. The average difference for method 1 is however, a 15% overstatement compared to a 4% overstatement of method 2. This is due to the apparent increased sensitivity of the method to macroeconomic changes as seen in 2002 and 2004. Method 1 is also more sensitive to sovereign and developmental credit risk which is not intuitive since the impairment on sovereign exposures should be very small and developmental credit exposures are also small. Method 2 on the other hand is primarily driven by mortgage exposures which is aligned to the size of the mortgage risks that the banks have. The difference between the predicted and actual impairments following the 2008 global financial crisis can also be explained by the way that banks calculated credit risk impairments for the period being considered. Credit impairment models typically reference historic data for a number of years and would therefore include the stressed experience from 2008 for a number of years. The large South African banks also tend to be cautious when it comes to credit risk impairments, so the increased credit losses following the 2008 global financial crisis would have been front of mind. The more intuitive weight per loan category, the ability to reflect severe stress and the ability to explain the apparent understatement following stress supports the choice of method 2 as the preferred approach.

Applying this approach to each individual bank yields the results in Table 7 below.

	Absa	**FirstRand**	**Standard Bank**	**Nedbank**	**Investec**
Long run average impairment coverage ratio	1.90%	2.20%	2.06%	2.01%	0.71%
Sensitivity to changes in economic conditions	0.56%	0.59%	1.24%	0.35%	0.36%
Maximum fitted impairment coverage ratio over 2008 financial crisis	2.57%	3.09%	4.01%	2.52%	1.12%
Maximum fitted impairment coverage ratio as a % of long run average impairment coverage ratio	135%	140%	195%	125%	158%
Forecasted impairment coverage ratio if 2008 macroeconomic conditions are repeated in 2020	2.30%	2.93%	3.05%	2.57%	1.17%
Forecasted 2008 condition repeat impairment coverage ratio as a % of long run average impairment coverage ratio	121%	133%	148%	128%	165%

Table 7: Long run average impairment coverage ratio, sensitivity to changes in macroeconomic factors and impact of stress on impairment coverage ratios

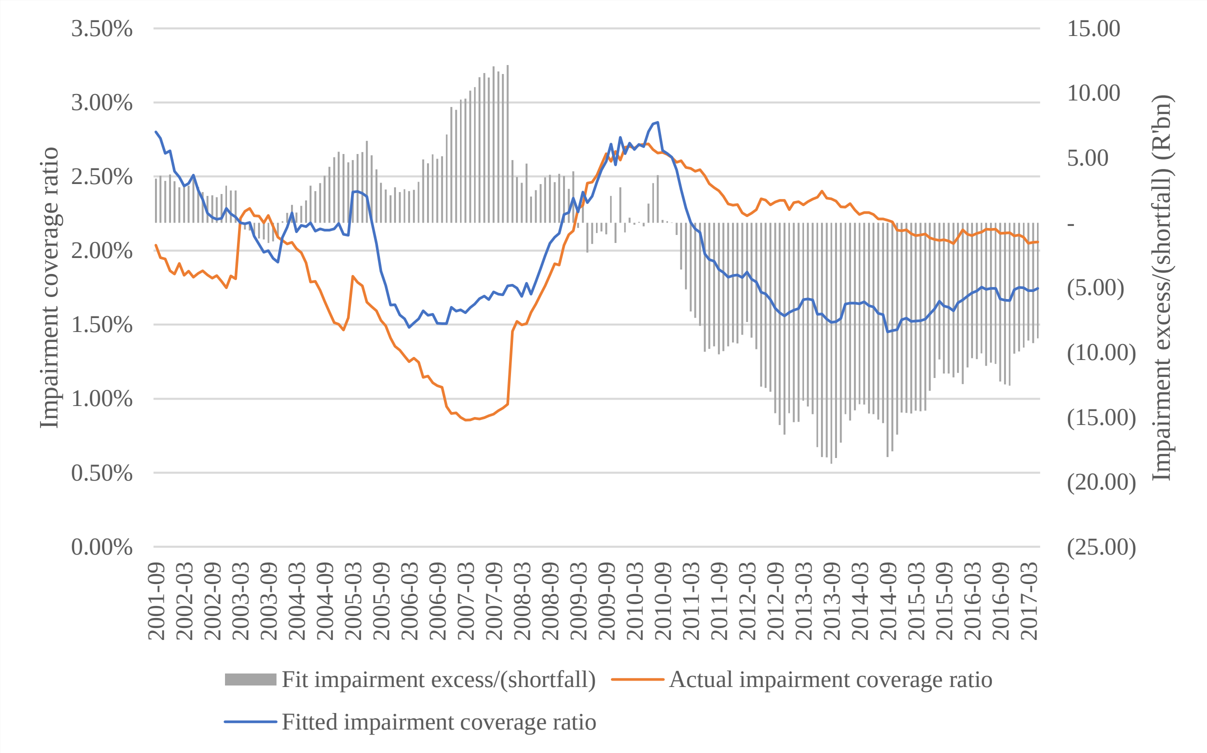

Figure 26: Actual combined impairment coverage ratio compared to the fitted impairment coverage ratio with an indication of the Rand difference in impairment for the five banks

Combining the long run average default rates, sensitivity to changes in macroeconomic factors, historic macroeconomic factors and loan volumes per category yields Figure 26 that shows the fitted impairment coverage ratios for the combined five banks. The results per individual bank is shown in Figure 86 to Figure 90 in Appendix A.

Each bank has different policies as it relates to the calculation of impairments. The use of past data to estimate expected impairments is also subjective and for the period under consideration, credit risk impairments did not include a forward-looking view as is the case under the current accounting requirements. From Table 7 it can be seen that Absa, FirstRand, Standard Bank and Nedbank have similar long run average impairment coverage ratios and that Investec's level is lower. This is reasonable based on the client base of Investec that is more focussed on the upper end of the market. It can also be seen that Absa and FirstRand show a similar level of sensitivity to macroeconomic conditions while Standard Bank seems to be more sensitive and Nedbank and Investec less sensitive. If economic conditions observed during the 2008 global financial crisis is repeated then Standard Bank will see a dramatically reduced increase, Absa and FirstRand will see a somewhat reduced increase while Nedbank and Investec will see a bigger increase in impairment coverage ratio based on the change in loan product mix between 2008 and 2020. This change is mix can be seen is the following figure:

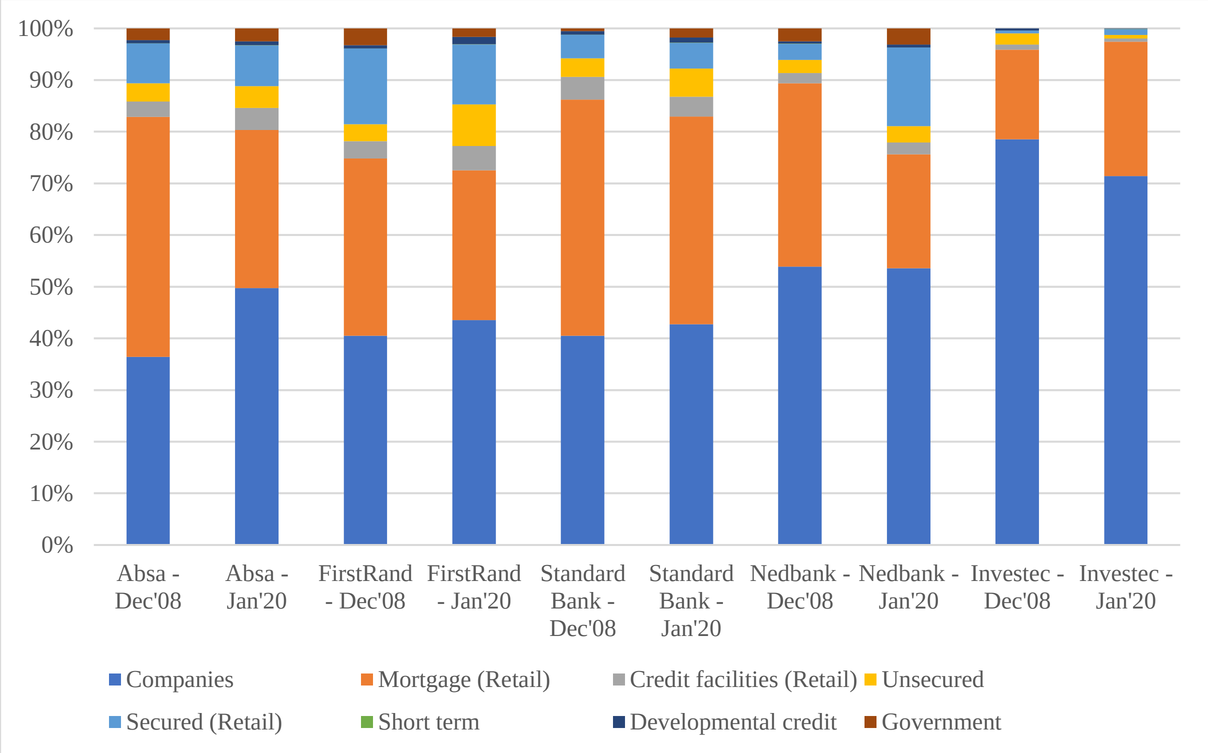

Figure 27: Change in mix between loan category for each bank between December 2008 and January 2020

From Figure 26 above it can be seen that the five banks tended to be more conservative following the global financial crisis and that a higher level of impairment was held even after the economy recovered. It can also be seen that credit impairment levels are generally too optimistic before the global financial crisis. The focus of the modelling is stress testing, so the most important feature is quick and timeous reaction to stress. All the bank level forecasts show reaction to stress that is either in line with or before the impairments raised by the banks. Simulating stressed conditions will therefore be reflected in increased impairments.

3.3.4 Public sector interest bearing securities

Another asset subject to credit risk that makes up 12% of the assets of the five banks is public sector interest bearing securities. These instruments include interest bearing securities of central, provincial, local government, public sector entities and treasury bills. Figure 28 illustrates the volume of these securities that each bank held over time:

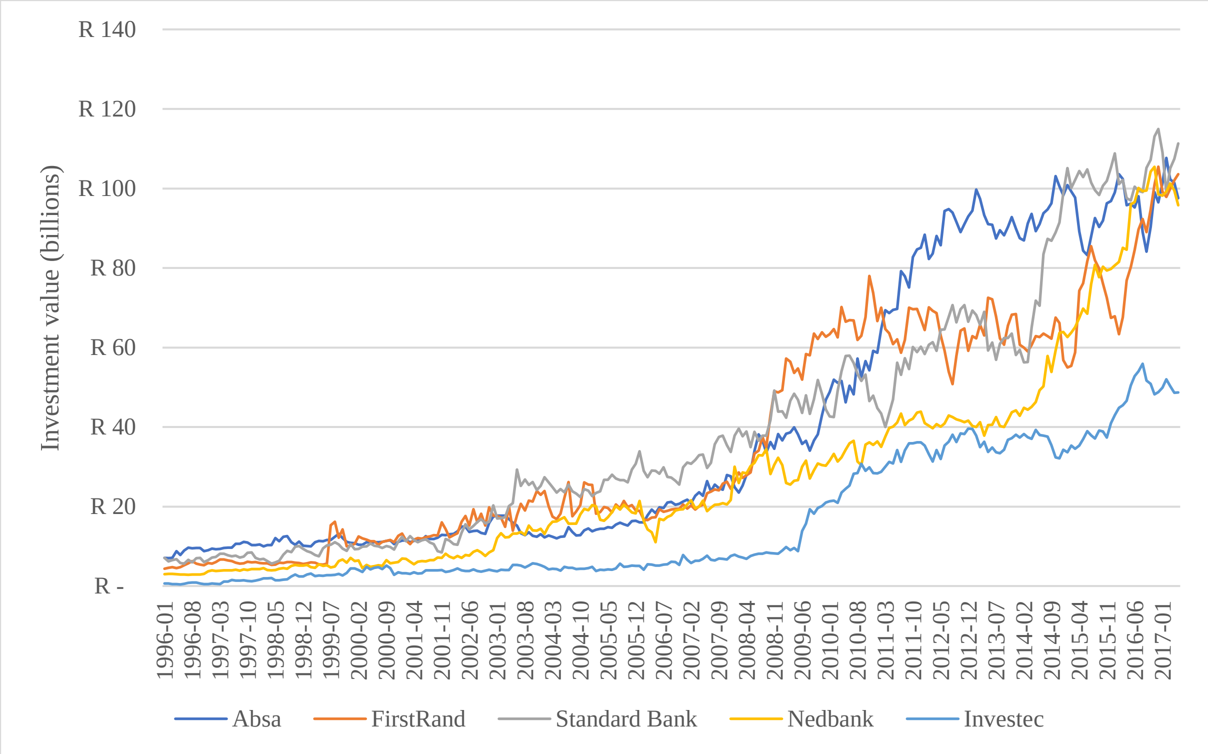

Figure 28: Volume of public sector interest bearing securities held by each bank over time

These instruments will be subject to impairment in line with the sovereign credit risk of South Africa. Banks tend to invest reserve funds as required under regulation in such instruments. Deposits that are also not lent out would be invested in such instruments since other assets classes such as equities carry high capital requirements. It is therefore reasonable to assume that the volume of public sector interest bearing securities would be correlated with the difference between the bank's deposits and loans. Figure 29 below illustrate this relationship for the five banks:

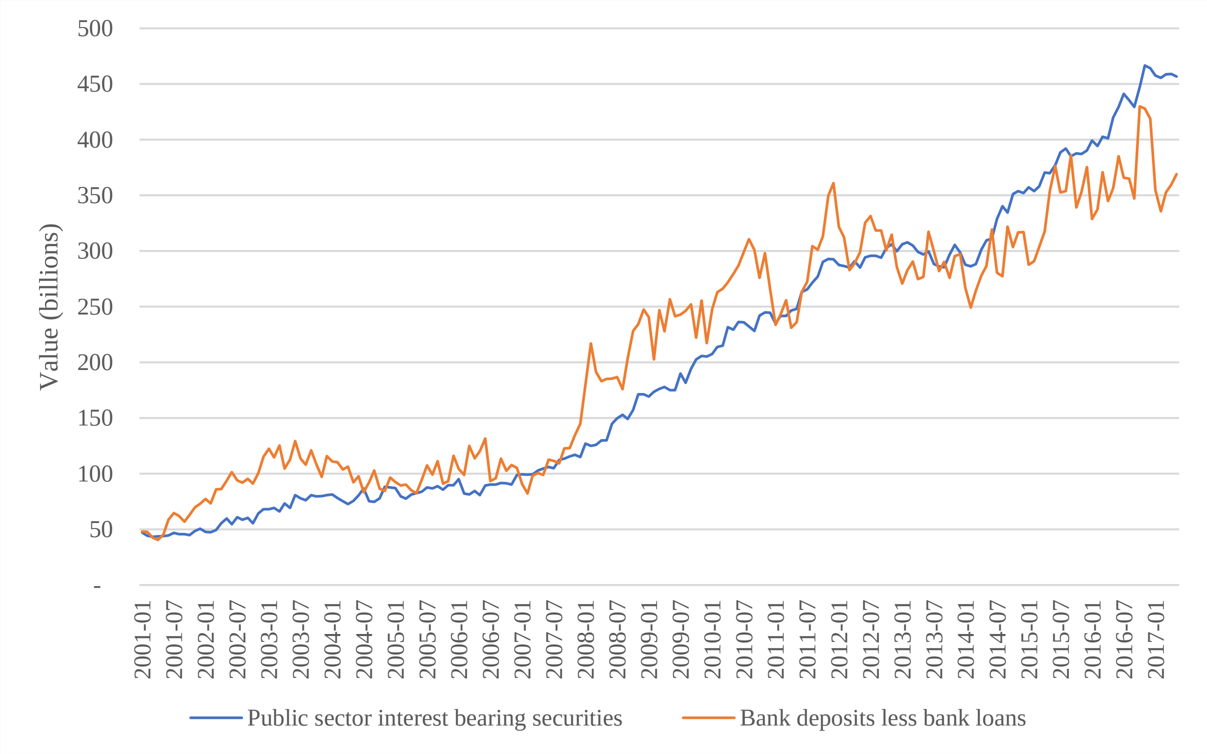

Figure 29: Bank public-sector interest-bearing securities compared to the difference between total bank deposits and loans granted over time

Figure 29 shows a close relationship between public sector interest bearing securities and the difference between total deposits and total loans granted. The relationship for each individual bank is illustrated in Figure 91 to Figure 95 in Appendix B. A linear regression is therefore fitted to relate the change in the gap between deposits and loans and advances to a change in public sector interest bearing securities. This is separately done for each bank. This yielded good fits for Absa, FirstRand, Standard Bank and Investec with R^2 values of 82%, 88%, 48% and 92% respectively. For Nedbank there is no clear relationship identified. Since this asset class has very low risk it is not expected to be the primary driver of a bank failure in the event of stress. The regression coefficient for Nedbank is therefore set as the average of the other banks. The model is therefore defined as:

$$PSIBS_t = PSIBS_{t-1} + \partial_g((Dep_t - Dep_{t-1}) - (LA_t - LA_{t-1})) \tag{14}$$

Where:

$PSIBS_t$ is the volume of public sector interest bearing securities at time t

LA_t is the volume of loans and advances at time t

Dep_t is the volume of deposits at time t

∂_g is the sensitivity of PSIBS to the gap between deposits and loans and advances

Applying the fitted model over a three year horizon to each bank yields the following:

The final values of ∂_g per bank is:

	Absa	FirstRand	Standard Bank	Nedbank	Investec
% of difference movement to apply	93%	91%	68%	79%	65%

Table 8: Proportion of change is difference between deposits and loans that is assumed to lead to a corresponding change in public sector interest bearing securities

Applying these assumptions to historic movements in the difference between deposits and loans over three year periods yields the results in Figure 30 below:

Figure 30: Backtest of public sector interest bearing security values as predicted by changes in the difference between deposits and loans

The overall fit is sufficient for purposes of a bank stress test model since these instruments carry very little credit risk. The relationship for each individual bank is illustrated in Figure 96 to Figure 100 in Appendix C. These predicted volumes of public sector interest bearing securities will carry a credit risk impairment coverage ratio equal to the sovereign credit index value that applies to other government related loans.

3.4 Loan volume modelling

The impairment coverage ratio per bank depends on the mix of loans per product category. The exact growth rates of each individual bank will be directly dependent on strategic choices such as increased or reduced risk appetite for a given product and marketing efforts and pricing that would influence the volume of loans that flows to each bank for a given level of demand. It is however, expected that macroeconomic environment would drive the overall demand and supply for credit. Demand and supply could be affected by economic conditions in various ways. For example, deteriorating economic conditions may lead to increased demand for unsecured while banks may reduce the supply of unsecured credit during such periods to limit their risk. Conversely good economic growth could also increase the demand and supply in cases where credit is used for investment and developmental purposes. The loan volumes per product category is outlined in the below figures.

The industry loan volume growth rates per product category is linked to macroeconomic factors through the use regression formulas. It is then assumed that these growth rates would be the same for the five banks being modelled. The main reason for deviations from this growth rates per bank would be specific strategic decisions that would not be driven by macroeconomic factors.

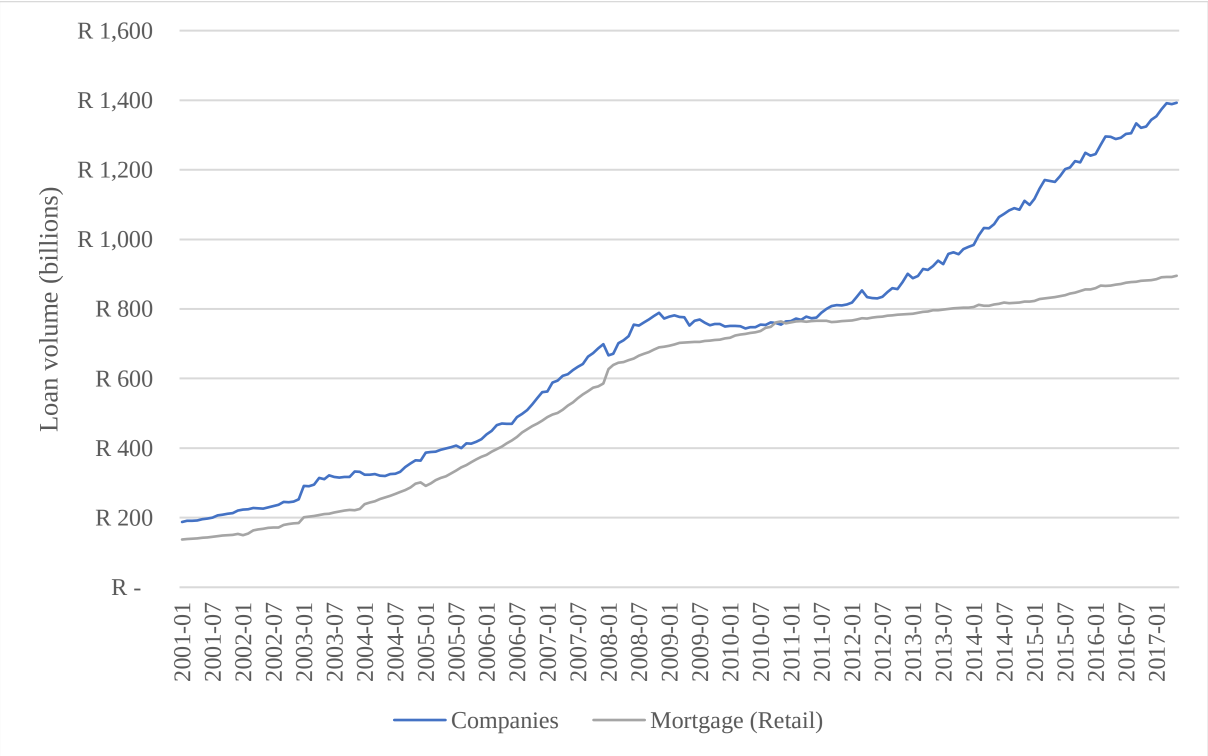

Figure 31: Total loan volumes for retail mortgage and company products of big five banks

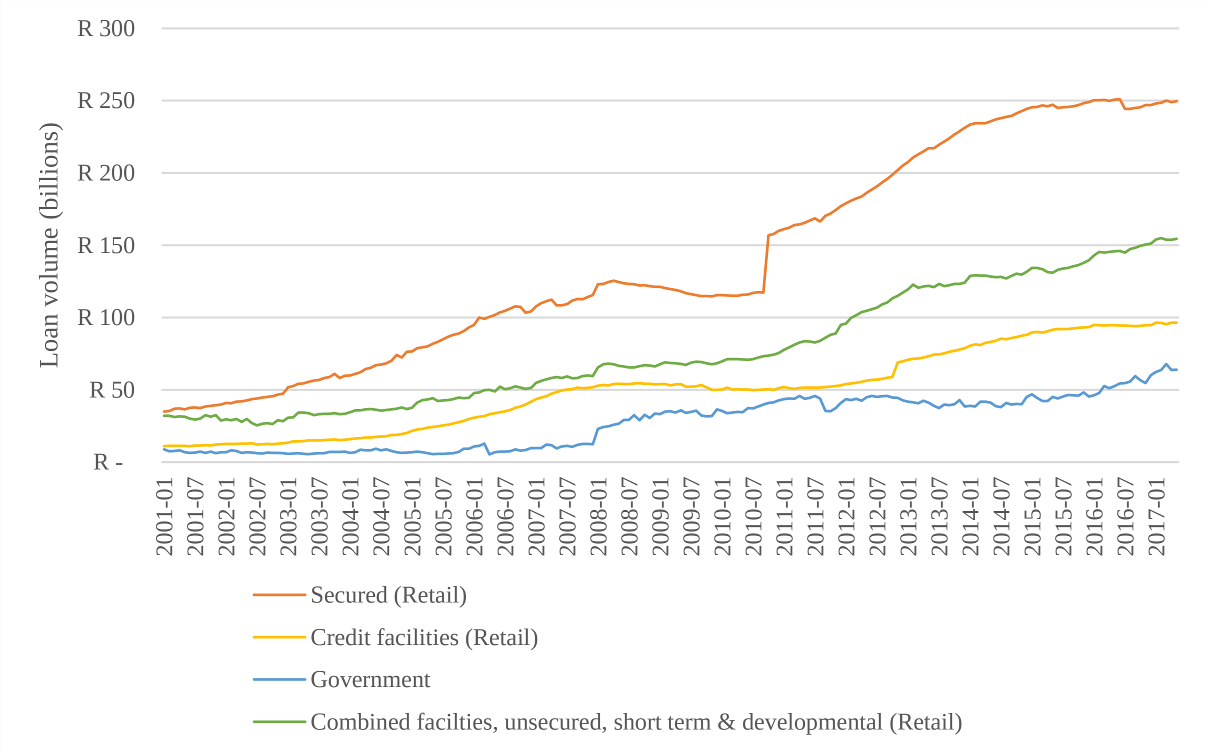

Figure 32: Total loan volumes for retail secured, unsecured, short term, credit facilities, government loans and developmental credit products of big five banks

Any cuts in risk appetite following a macroeconomic stress is also not modelled since the volume and mix of loans just as the stress hits cannot be changed by the banks. The banks also can't demand immediate repayment of riskier loans although they may have the ability to cut some facility limits.

Linear regression modelling is chosen since the purpose is to model loan growth per product category leading up to the macroeconomic stress. The primary stress for loan assets would be driven by the increase in credit losses and not rapid movements in the underlying loan volumes per product. The general form of the linear regression formula is:

$$LR_t^x = \alpha_0 + \alpha_1 MF_t^1 + \alpha_2 MF_t^2 \ldots + \alpha_q MF_t^q \qquad (15)$$

Where:

LR_t^x is the forecasted loan product category growth rate for loan product category x at time t;

α_0 is a constant;

α_p with p > 0 is the coefficient weight of macroeconomic variable p;

MF_t^q is the value of macroeconomic factor q at time t with q <= 15.

A stepwise process is followed to fit the linear regression for each product category type:

1. A reasonability check is first performed on the data. Periods with disproportionate growth or reductions (more than 50% in a single quarter) followed by a reversal is excluded from the data.
2. A regression fit using the least squared error method is then fitted using all 15 macroeconomic variables.
3. The p-value of each independent variable is then considered. Based on a 95% confidence level all variables with a p-value above 5% is excluded. This includes the use of a constant.
4. A subsequent regression is then fitted on the remaining variables.
5. Steps 3 and 4 above are repeated until a model is found where each variable (including the intercept) has a p-value below 5%

The final fitted model values for α_p are shown in Table 9 below:

	Companies	**Secured (Retail)**	**Mortgage (Retail)**	**Credit facilities (Retail)**	**Government**	**Combined facilities, unsecured, short term & developmental (Retail)**
Prime overdraft rate (End of Period)	-2.10		3.79	-3.23	8.35	
All monetary institutions: Total credit extended to the private sector 12-Term % change	1.47					
CPI: Total country (All items)		-9.31	-8.94	-6.80		-15.06
Government bond yield - 0-3 years		8.17		12.86		18.86
Government bond yield - 3-5 years		-11.34		-11.70		-41.22
Government bond yield - 5-10 years			16.59			28.23
Government bond yield - 10 years and over			-25.87			
J203 - ALSI Value			-0.13			
CONSUMER CONFIDENCE						
BUSINESS CONFIDENCE						2.81
GDP at market prices			-0.96			-1.53
Disposable income of households				-0.51	1.74	
National government deficit / surplus as % of GDP						0.70
Ratio of gross savings to GDP						
Household debt to disposable income		1.13	1.40			3.07
Constant	0.18			0.78	-0.87	-2.43

Table 9: Linear regression coefficients for each macroeconomic factor and loan category

The final fitted values are then visually compared to the actual growth rates and loans volumes that would be predicted over a three year period using this model. The fitted results are illustrated below:

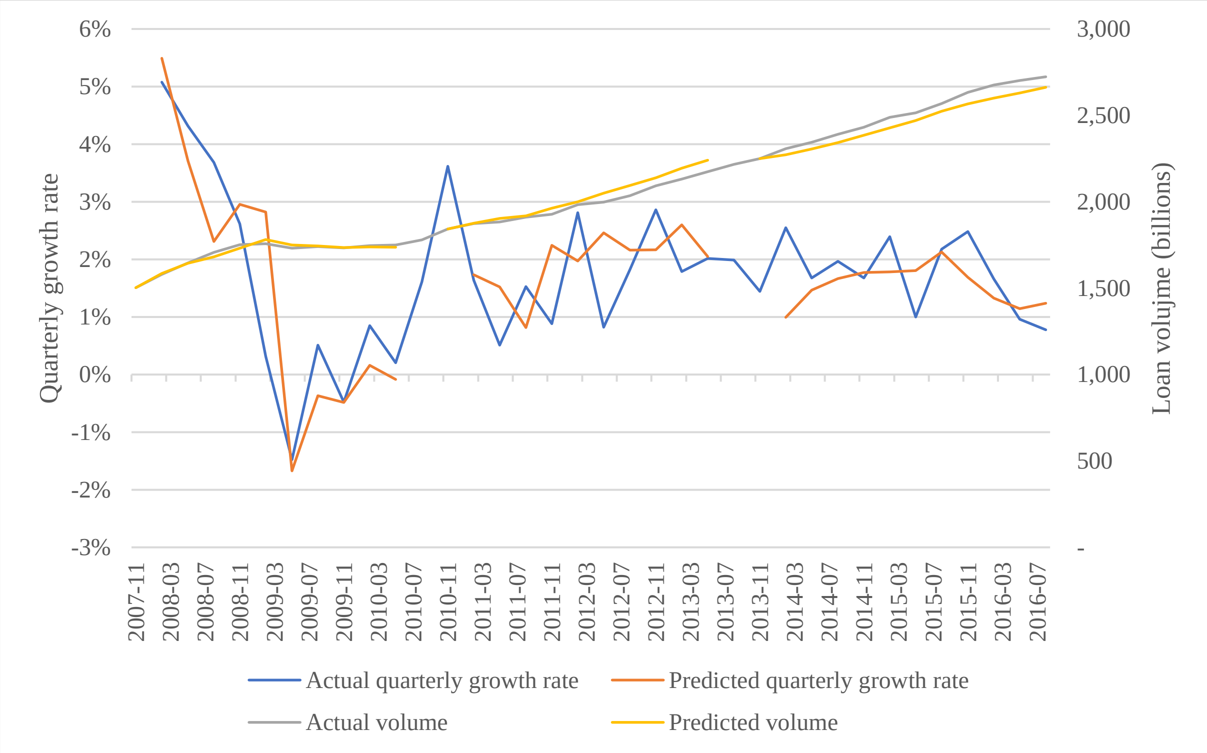

Figure 33: Fitted quarterly loan growth rates including 30 month forecast of loan volumes using fitted growth rates

Figure 33 shows that the general growth in loan volumes can be forecasted with a reasonable degree of accuracy to serve as an input into credit risk stress test modelling where the level of credit risk applied to these volumes is the most important consideration.

3.5 Results

3.5.1 Key factors that drive changes in credit impairments

The analysis that is performed shows that different macroeconomic drivers affect different default risk measures and the overall impairment in different ways. The sensitivity of each category to each of the macroeconomic factors is assessed by individually increasing each macroeconomic factor by one standard deviation to assess the impact on the predicted default risk measure indices and forecasted overall bank impairment for each category.

	Mortgage	Secured credit	Credit facilities	Unsecured credit	Short term credit	Developmental credit	Corporate credit	Sovereign credit	Combined impairment fit
Prime overdraft rate (End of Period)	10.8%	7.1%	0.8%	N/A	N/A	N/A	11.2%	N/A	6.3%
All monetary institutions: Total credit extended to the private sector 12-Term % change	3.3%	2.0%	2.1%	3.9%	12.1%	7.7%	N/A	1.6%	2.4%
CPI: Total country (All items)	8.8%	5.4%	2.3%	4.0%	5.2%	9.6%	N/A	2.1%	5.4%
Government bond yield - 0-3 years	11.5%	6.1%	0.4%	3.0%	N/A	N/A	11.8%	0.7%	7.1%
Government bond yield - 3-5 years	11.8%	6.6%	2.4%	2.2%	N/A	N/A	12.1%	0.1%	7.2%
Government bond yield - 5-10 years	11.1%	5.7%	1.9%	1.8%	N/A	N/A	10.7%	0.3%	6.6%
Government bond yield - 10 years and over	6.6%	5.7%	1.8%	N/A	N/A	N/A	10.3%	N/A	4.1%
J203 - Alsi Value	N/A	N/A	-0.9%	N/A	N/A	N/A	-8.6%	-0.7%	-0.3%
CONSUMER CONFIDENCE	N/A	N/A	-0.1%	-1.8%	-3.8%	-5.0%	N/A	N/A	-0.3%
BUSINESS CONFIDENCE	N/A	-2.1%	-1.3%	-2.2%	-3.6%	-3.7%	N/A	-0.2%	-0.6%
GDP at market prices	N/A	-1.2%	N/A	-2.9%	-1.5%	N/A	N/A	-1.4%	-0.6%
Disposable income of households	N/A	-4.7%	-1.8%	-3.3%	-8.0%	-8.6%	N/A	-1.9%	-1.1%
National government surplus as % of GDP	4.7%	3.9%	0.5%	N/A	5.3%	N/A	N/A	0.6%	2.6%
Ratio of gross savings to GDP	N/A	N/A	-1.8%	-3.0%	-12.7%	-8.9%	N/A	-1.8%	-0.5%
Household debt to disposable income	10.0%	7.4%	N/A	N/A	N/A	N/A	N/A	N/A	5.5%

Table 10: Movement in default risk measure indices and forecasted overall impairment following a single standard deviation macroeconomic variable increase

The results in the table above shows that the key drivers of default risk and impairments are interest rates that include the prime rate and government bond yields over various terms. Inflation and household debt to disposable income are also key drivers. This is particularly true for secured and mortgage lending where an increase in interest rates lead to increases in repayments that are relatively big. It is also expected that credit facilities, unsecured credit would be affected less since these products tend to have fixed interest rates or large interest rates that lead to smaller relative impacts when interest rates change. Companies/corporate clients are mostly affected by the level of the ALSI index that represent the strength and profitability of companies in aggregate. Sovereign default risk is mostly driven by GDP growth, CPI and total credit extended to the private sector which is an indication of the general strength of the economy and therefore by extension the government.

It should be noted that the disposable income of households, national government deficit/surplus as % of GDP, ratio of gross savings to GDP and household debt to disposable income are not included as variables in the final models since the directional impacts of these variables aren't reasonable. GDP has been shown to be correlated to past banking crises [26][32]. These variables are, however, indirectly represented since macroeconomic factors are highly correlated. The other variables may therefore simply be stronger indicators of default risk that are correlated with these variables.

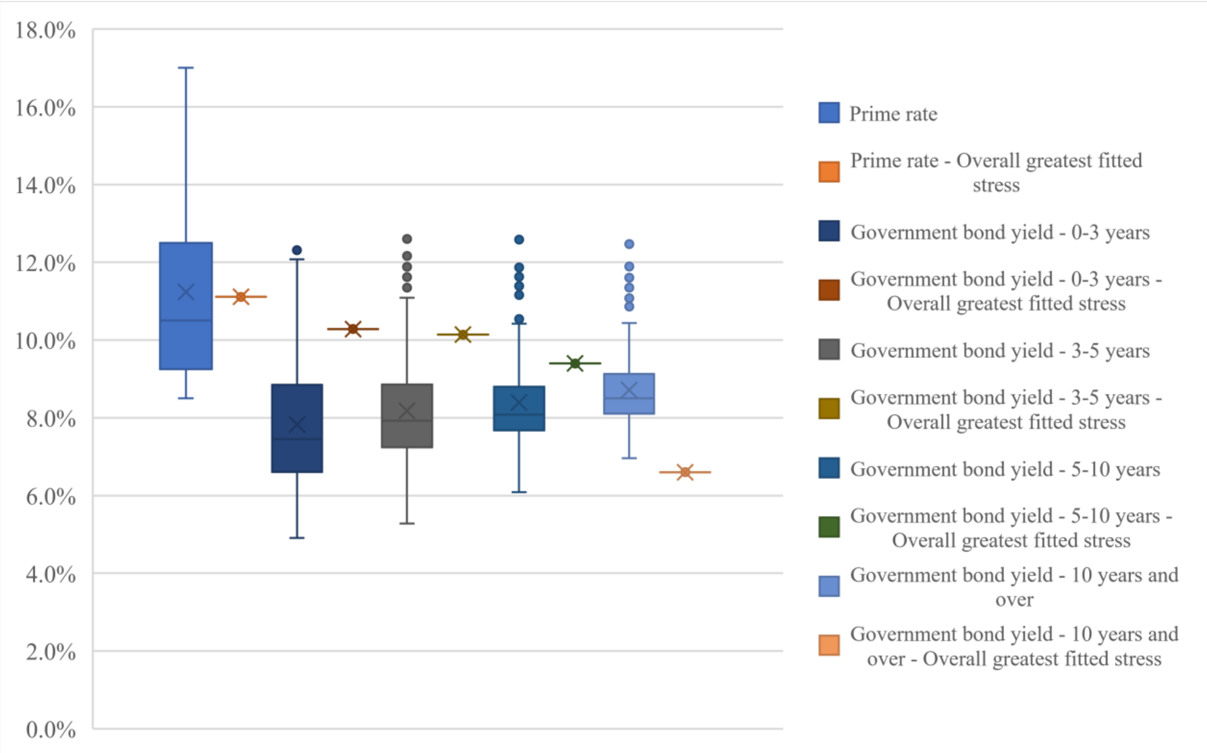

Figure 34: Box plot of historic macroeconomic variables compared to levels that lead to the greatest modelled impairment coverage ratio (interest related variables)

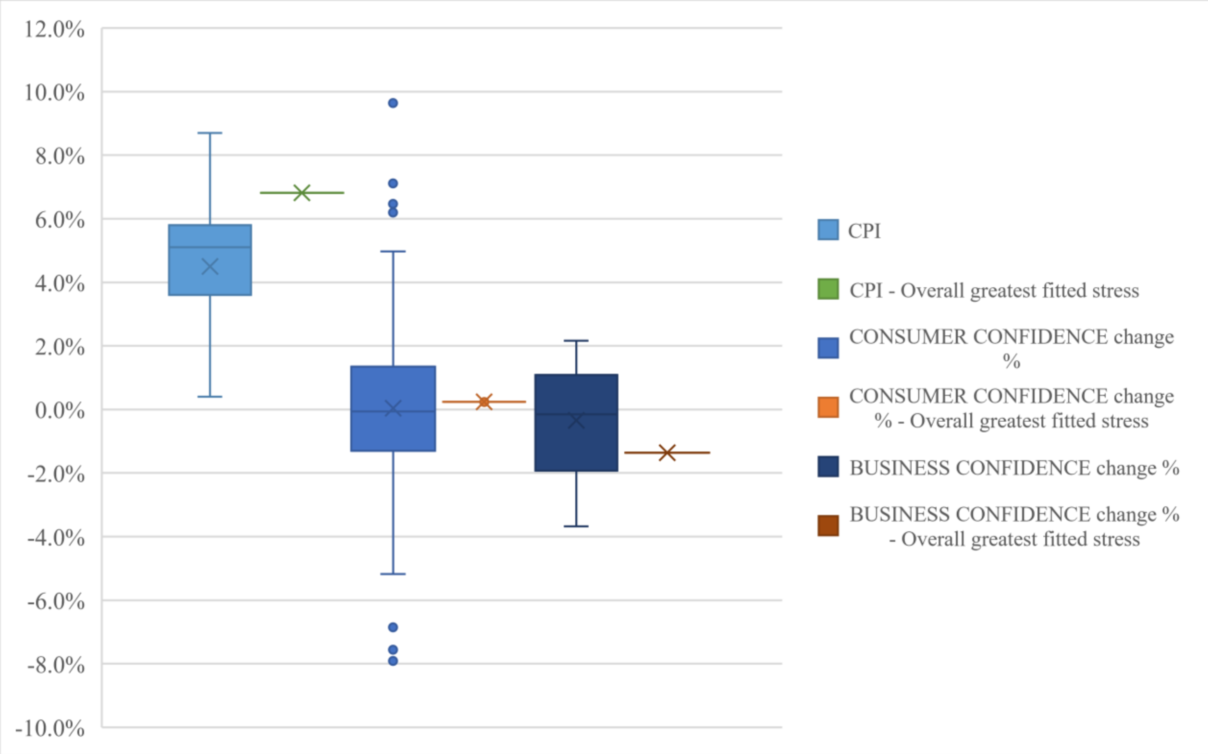

Figure 35: Box plot of historic macroeconomic variables compared to levels that lead to the greatest modelled impairment coverage ratio (CPI and confidence levels)

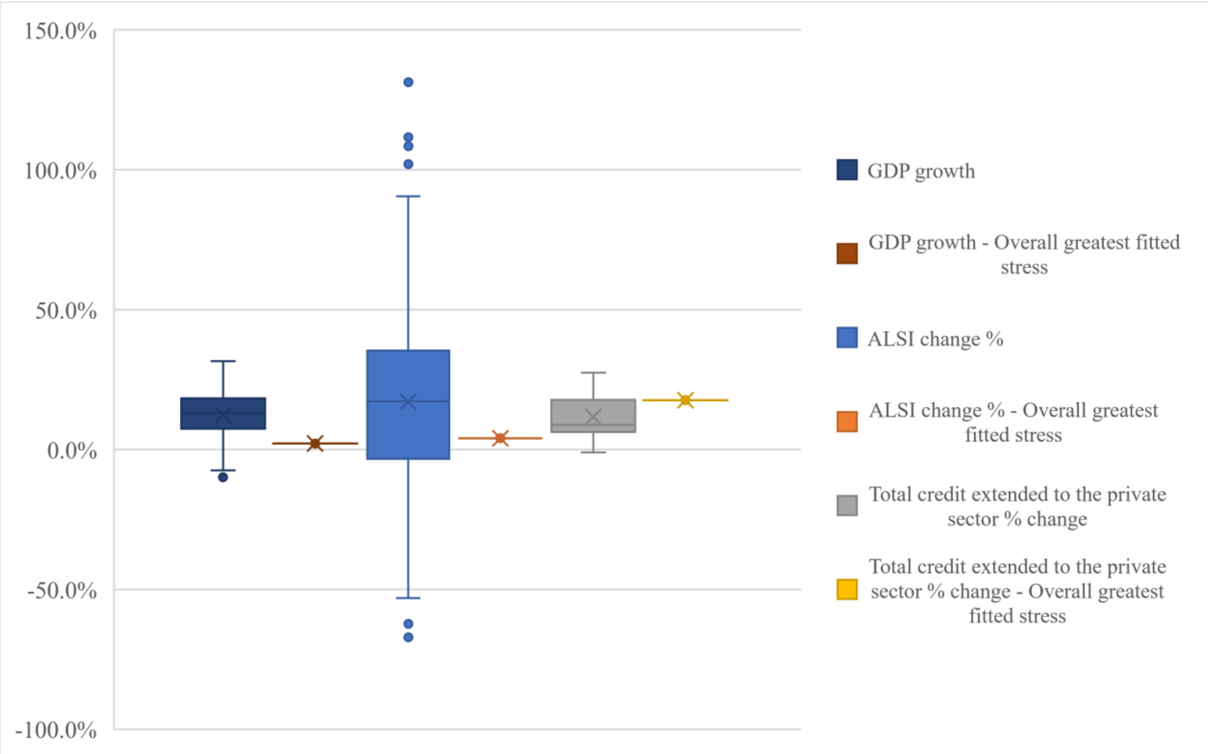

Figure 36: Box plot of historic macroeconomic variables compared to levels that lead to the greatest modelled impairment coverage ratio (GDP and ALSI growth and private sector credit extension)

The principle component analysis will also reduce the individual sensitivity to specific factors that are correlated with other factors. For example, GDP is a key indicator of the general state of the economy and would therefore be correlated to other factors such as the All Share Index, CPI and interest rates. Shocks in isolation are therefore also unlikely. A combination of factors that lead to the greatest stress is therefore investigated by considering the prevailing factors that correspond to the biggest predicted increase in default risk per category. Figure 34 to Figure 36 highlight the extent to which a factor varies and the value of the variable during the period of greatest stress in overall impairment levels. The bottom of the box represents the second quartile while the top half of the box represents the third quartile. The cross is the mean while the line in the middle is the median. The whiskers extend up to 1.5 times the size of the box. Any points beyond the whiskers are represented as dots. Next to each box plot is a line with a cross at the centre that represents the value of the variable during the period with the highest forecasted impairment coverage ratio.

From Figure 34 to Figure 36 it can be observed that the greatest stress is generated when bond yields and inflation are high while GDP and growth in the ALSI is low. There is also a drop in business confidence and increased lending to the private sector which would lead to increased levels of credit risk. A local or global economic crisis can, however, happen in many different ways so this should just be seen as one example of a stressed scenario.

3.5.2 Key drivers of increased market loan volumes

	Companies	**Secured (Retail)**	**Mortgage (Retail)**	**Credit facilities (Retail)**	**Government**	**Combined facilities, unsecured, short term & developmental (Retail)**	**Total loan volume**
Prime overdraft rate (End of Period)	-5%		8%	-7%	18%		0.5%
All monetary institutions: Total credit extended to the	8%						4.0%

private sector 12-Term % change							
CPI: Total country (All items)		-12%	-12%	-9%		-19%	-5.9%
Government bond yield - 0-3 years		14%		22%		32%	3.7%
Government bond yield - 3-5 years		-14%		-15%		-51%	-4.5%
Government bond yield - 5-10 years			13%			22%	5.3%
Government bond yield - 10 years and over			-15%				-4.8%
J203 - ALSI Value			-4%				-1.4%
CONSUMER CONFIDENCE							0.0%
BUSINESS CONFIDENCE						6%	0.3%
GDP at market prices			-7%			-11%	-2.8%
Disposable income of households		-6%		-6%	19%		-0.3%
National government deficit / surplus as % of GDP						7%	0.4%
Ratio of gross savings to GDP							0.0%
Household debt to disposable income		4%	5%			10%	2.3%

Table 11: Change in loan volume growth rate due to an increase of one standard deviation in the macroeconomic variable for each loan category

Table 11 shows that total loan growth in the market is most sensitive to the total amount of credit extended to the private sector, CPI, government bond yields and GDP. The interrelated nature of these variables also needs to be considered. For example, the relationship to CPI can also reflect the inflation targeting policy followed by the SARB that would lead to higher interest rates and therefore reduced lending when inflation increases. Indicators such as credit extended to the private sector would in turn be directly correlated to company loan volumes. The varying impacts of government bond yields over various terms should also be considered bearing in mind that the rates across all terms would tend to change at the same time. The exact sensitivity and expected impact will therefore depend on the shape of the government bond yield curve.

3.6 Key bank credit risk impairment modelling conclusions

Distressed economic conditions such as the 2008 global financial crisis leads to large increases in the credit risk impairments held by banks. It can also be seen that banks tended to be conservative in reducing their impairment levels following the downturn. The modelling and analysis show that interest rates, CPI, growth in the ALSI index and GDP growth are key drivers of credit risk. It is reasonable that these macroeconomic factors represent the key drivers since these factors directly relate to the cost of borrowing, income available to service debt and general economic growth that would increase the income of individuals, companies and the government. Each loan category is however, affected by a different set of macroeconomic factors as noted in Table 10 above.

The level of stress that an individual bank experiences during an economic downturn will therefore depend on the exact nature of the stress, the volume of loans that each bank has in loan category and the risk profile of the bank’s clients in that loan category. All five banks being considered had significant mortgage exposures during the 2008 global financial crisis and consequently suffered large credit risk impairments when interest rates increased rapidly. Mortgage lending makes up a smaller proportion of overall lending for all the banks apart from Investec. Conversely lending to companies have increased as a proportion of overall lending for all banks apart from Investec. Other changes that stand out in increased unsecured lending at FirstRand and increased secured lending by Nedbank. These changes all contribute changes in the risk profile of each of the banks.

Chapter 4

4. Modelling Deposit volumes

Liquidity is one of the key risks that banks face. For large commercial banks, liquidity and profitability depend on the volume of deposits since these deposits are the primary source of funding for their loan portfolios. A stress test model therefore requires a reliable model that estimate the volume of bank deposits.

Historic data shows that there is variability in the total volume of deposits per deposit category in the market [35].

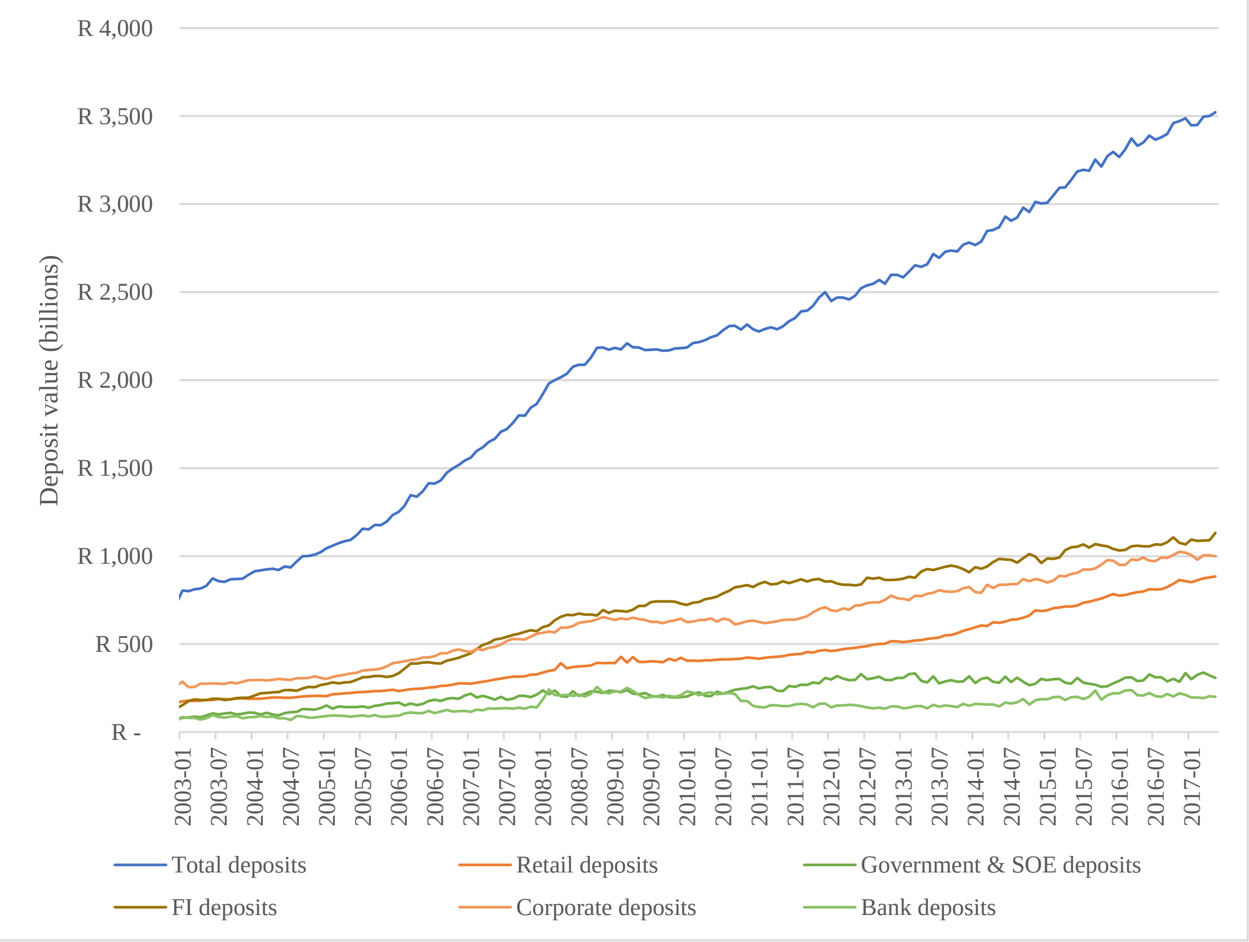

Figure 37: Total volume of deposits per category in the South African market

Figure 37 above shows that the total volume of deposits experiences different rates of growth and short term volatility and that the individual deposit categories also exhibit their own trends and periods of stress.

4.1 *Method*

Although the scale of the big five banks make them more resilient to stress than smaller banks, it does introduce a significant amount of concentration risk if one of these banks were to fail [63]. The top-down model module that forecasts deposit volumes under stressed macroeconomic conditions for the biggest five banks (by deposit volumes) is therefore proposed:

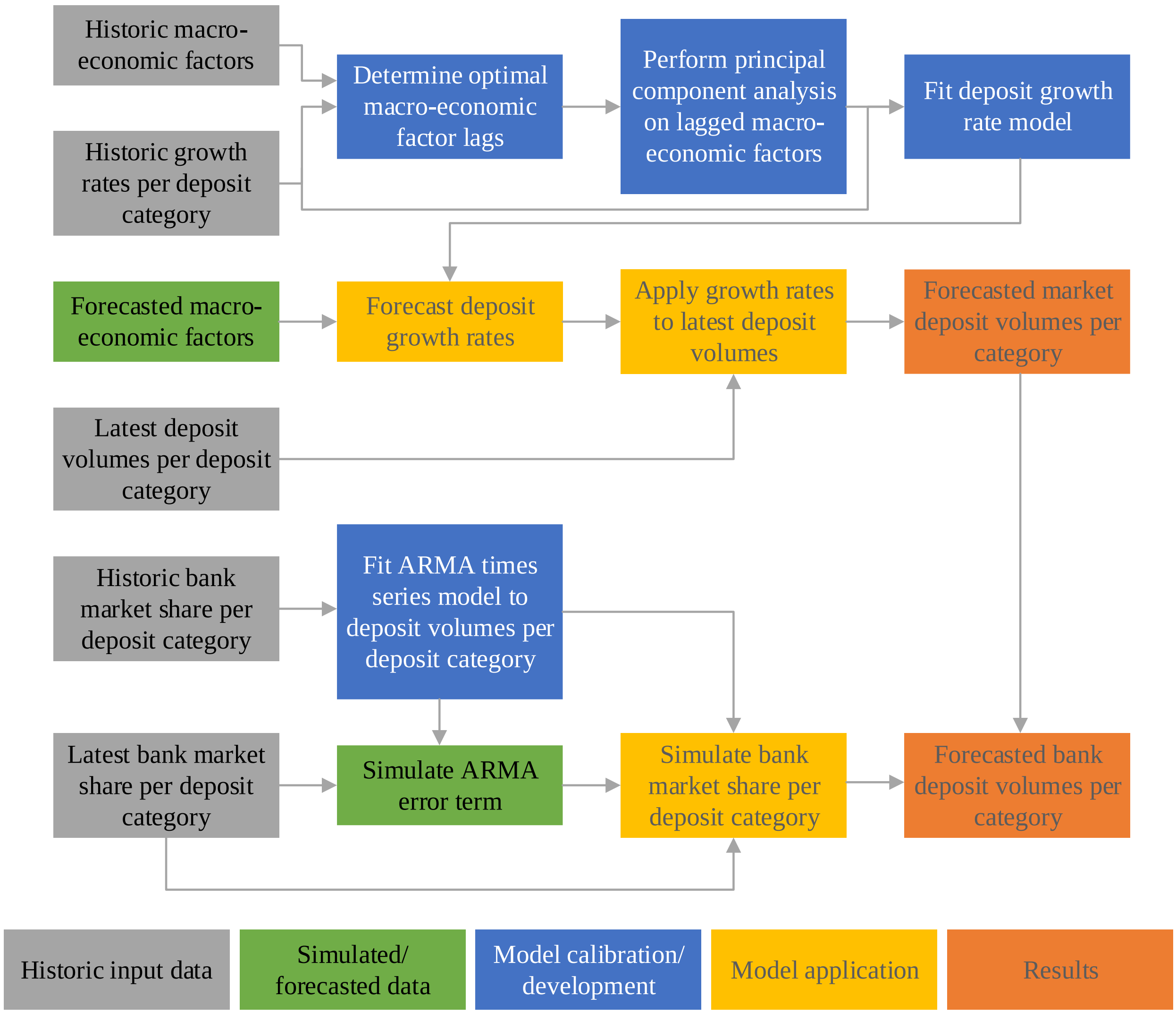

Figure 38: Top-down deposit stress test model structure

The components in the structure outlined above is covered in more detail in the subsequent sub-sections. The development of a deposit growth model per deposit category is outlined in section 4.2 . The simulation of each bank's market share of the predicted deposit volumes per category is outlined in section 4.3 .

4.2 Modelling deposit growth rates per deposit category

The observed deposit volumes for each of the five deposit categories shown in Figure 37 and the fourteen macroeconomic factors shown in Figure 8 to Figure 11 are first transformed by calculating monthly, quarterly and half-yearly growth rates. For the macroeconomic information, monthly values are not available for all variables. Where monthly values are not available, the quarterly growth rate is transformed into a monthly growth rate using the following formula:

$$rate_{monthly} = (1 + rate_{quarterly})^{\frac{1}{3}} - 1 \quad (16)$$

It is assumed that the rate remains constant throughout the period. Similarly, quarterly and half-yearly growth rates could then be derived from these monthly rates using the following formulas:

$$rate_{quarterly} = (1 + rate_{monthly})^{3} - 1 \quad (17)$$

$$rate_{half-yearly} = (1 + rate_{monthly})^{6} - 1 \quad (18)$$

The monthly rates used for the modelling are depicted in the Figure 8 to Figure 11 in section 2.2 .

The monthly deposit volumes are first converted into monthly growth rates using the following formula:

$$g_t = \frac{Value_t}{Value_{t-1}} \quad (19)$$

Where:

g_t is the deposit growth rate between time t - 1 and time t.

This rate is then converted into quarterly and half-yearly rates using equations (17) and (18). A conversion to half-yearly rates is only used where the quarterly rates exhibited volatility that exceeded that of the macroeconomic factors since the purpose of the model is to link deposit growth rates to macroeconomic factors. The growth rates per deposit category is shown in Figure 39 to Figure 43 below.

The correlation between monthly, quarterly and half-yearly macroeconomic factors and deposit categories was considered. From Figure 39 to Figure 43 it can be seen that the monthly growth rates tend to exhibit a large degree of volatility that cannot be explained by corresponding economic changes represented by Figure 8 to Figure 10. A balance is therefore needed between undue volatility and a sufficiently short period to capture shocks driven by macroeconomic factors.

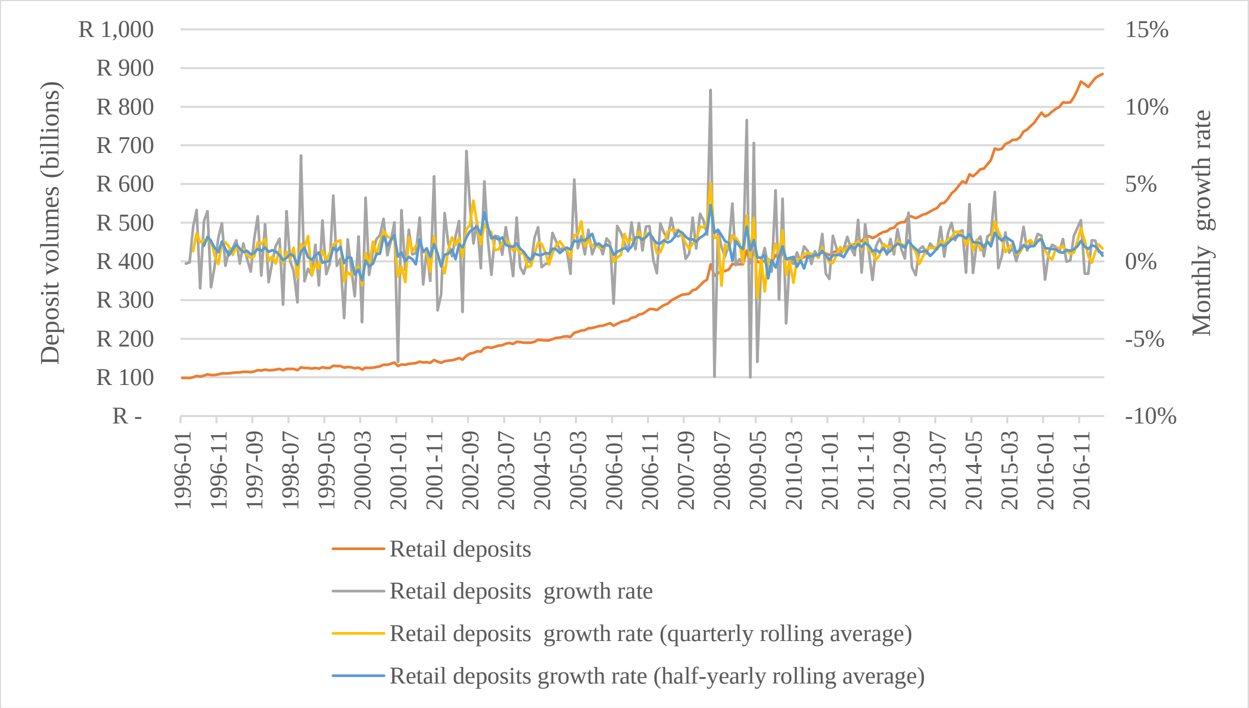

Figure 39: Retail deposit volumes and growth rates

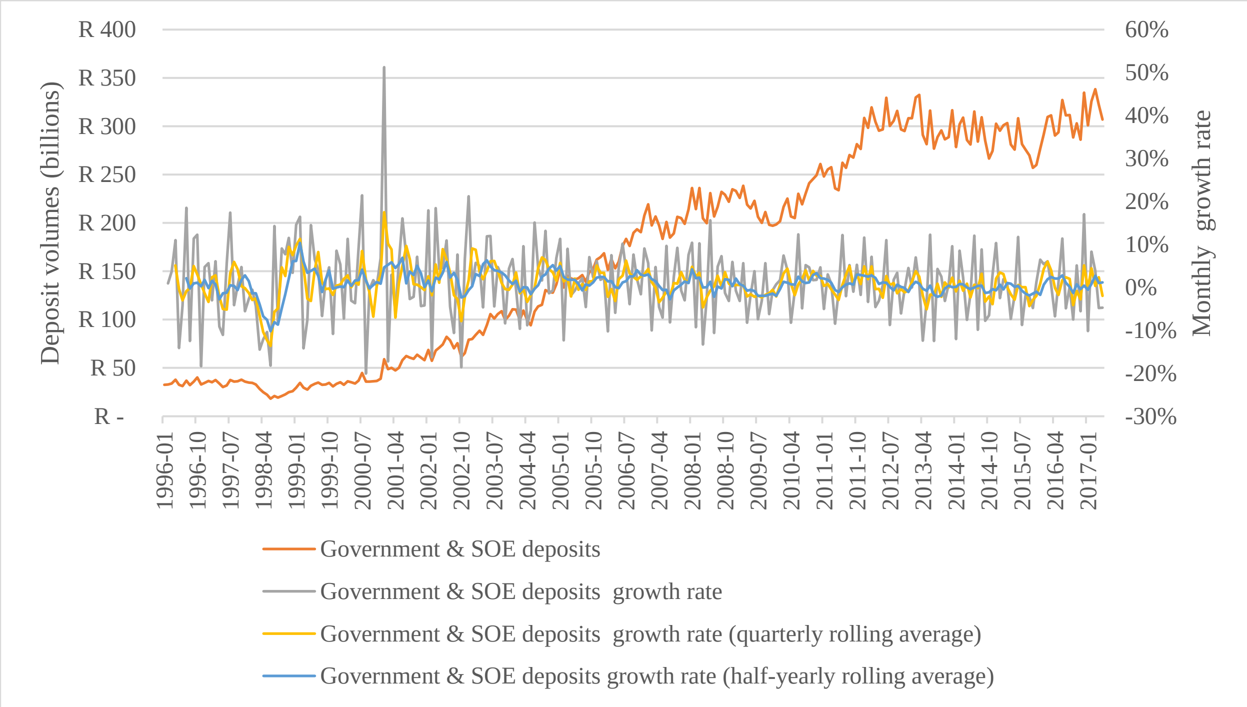

Figure 40: Government and SOE deposit volumes and growth rates

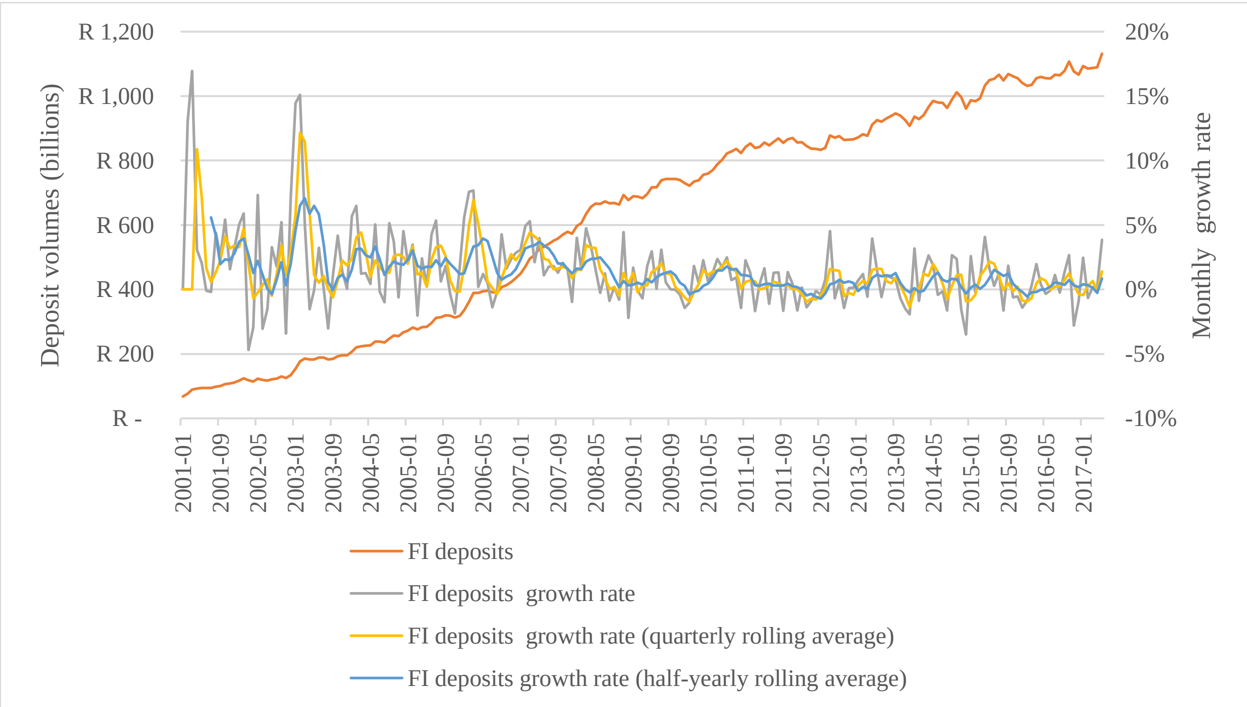

Figure 41: Financial institution deposit volumes and growth rates

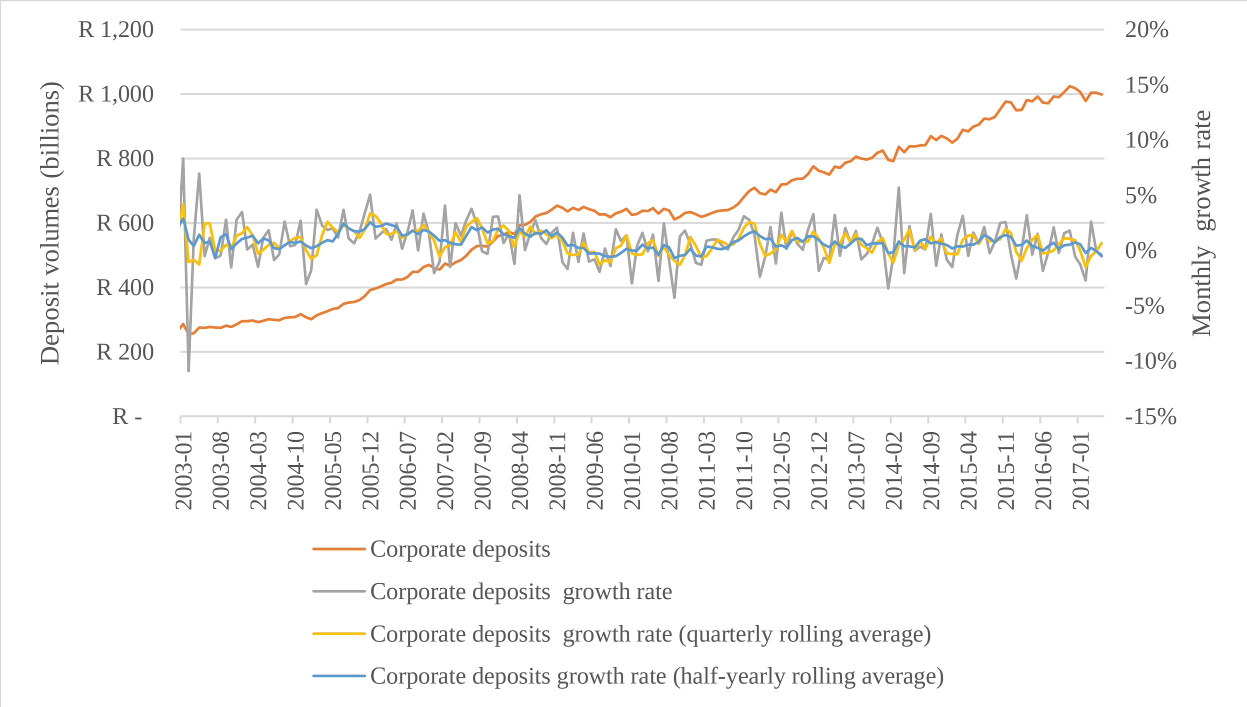

Figure 42: Corporate deposit volumes and growth rates

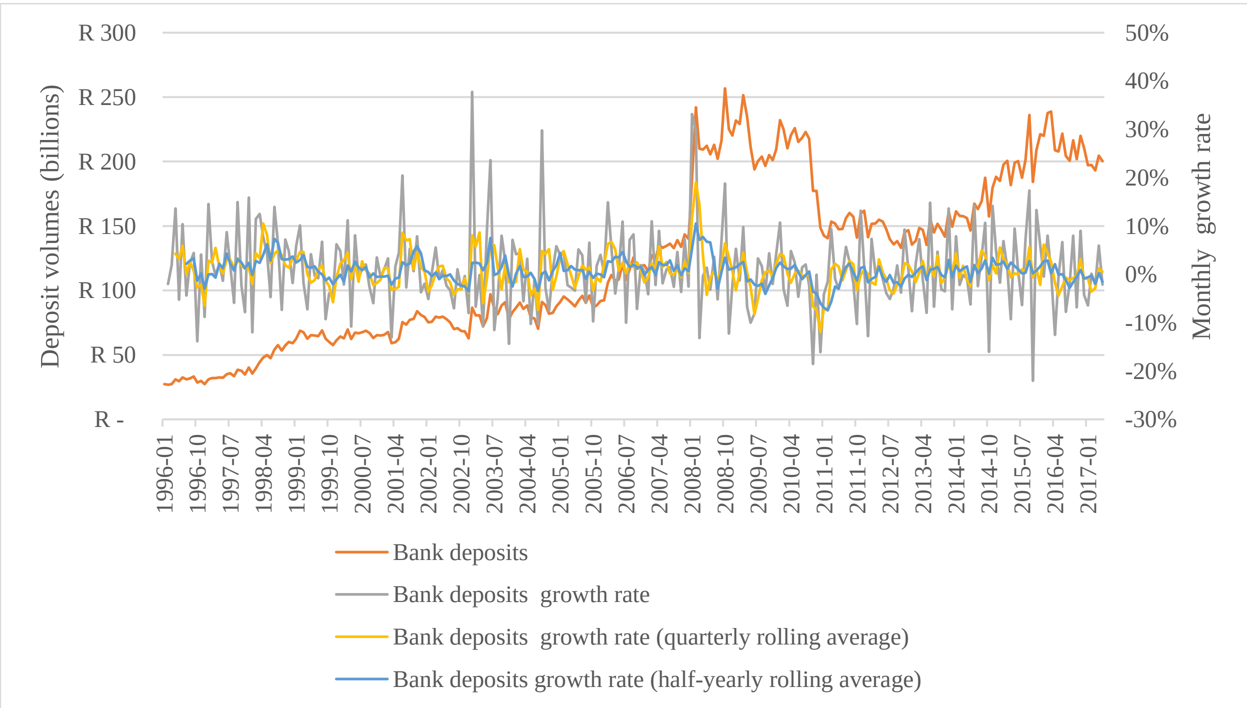

Figure 43: Bank deposit volumes and growth rates

The effect of macroeconomic factors could also take a while to have an effect on deposit volumes. For example, individuals may only withdraw deposits after an extended period of reduced interest rates. The time between a macroeconomic factor changing and the deposit volumes changing can therefore be incorporated by lagging the macroeconomic factors. The following process is followed to arrive at the final deposit growth rate averaging and macroeconomic factor lags:

1. Calculate the Pearson correlation between the macroeconomic factors and deposit growth rate. This is done using monthly, quarterly and half-yearly sets of macroeconomic and deposit growth rate figures.
2. Determine the lag period (in months) that leads to the maximum absolute level of correlation between the macroeconomic factors from Figure 8 to Figure 10 and the deposit growth rates from Figure 39 to Figure 43. The lag period is limited to a maximum of 24 months to reduce the risk of finding a spurious link between variables.
3. Consider the increase in correlation when moving from monthly to quarterly to half-yearly values.
4. Balance increased correlation against the need for more granular information.

Using this analysis, the lags and averaging periods in Table 12 are chosen:

	Retail	**Government and SOE**	**Financial institution**	**Corporate**	**Bank**
Prime overdraft rate	14	24	0	25	0
All monetary institutions: Total credit extended to the private sector 12-Term % change	0	9	6	10	11
CPI: Total country (All items)	14	6	21	16	24
Government bond yield - 0-3 years	14	24	5	24	0
Government bond yield - 3-5 years	15	24	6	24	0
Government bond yield - 5-10 years	14	24	7	18	0
Government bond yield - 10 years and over	14	24	24	17	15
Monthly ALSI Growth rate	18	11	15	7	24
Change in consumer confidence index	0	16	22	8	0
Change in business confidence index	0	12	17	15	0
GDP growth rate (annualised rate change)	5	0	3	4	13

Disposable income of households (quarterly rate change)	16	24	10	10	22
National government deficit / surplus as % of GDP	4	0	1	13	1
Ratio of gross savings to GDP	14	0	16	6	2
Household debt to disposable income	0	19	11	10	19

Table 12: Lag in months applied to macroeconomic variables for each deposit category

	Data averaging period
Retail	Quarterly
Government and SOE	Half-yearly
Financial institution	Half-yearly
Corporate	Quarterly
Bank	Half-yearly

Table 13: Averaging period for macroeconomic and deposit growth rates per deposit category

Using the specified lagged macroeconomic variable directly to predict deposit volumes per category could lead to volatile results due to multicollinearity. The same approach as the default risk modelling that used principle component analysis is therefore followed. This is addressed by apply principle component analysis to the final lagged macroeconomic variables. The Eigen values resulting from the principle component analysis is used to choose the number of principle components to use. An Eigen value level of one is used as a benchmark. Using five principle components ensures that all principle components with an Eigen value above one is included in the final model.

To forecast deposit volumes the principle components needed to be linked to deposit growth rates. Three potential methods are considered:

4.2.1 Method 1 - Index based on correlation transformed with Vasicek approach

An index representing deposit volumes is constructed in a manner similar to the credit risk modelling and literature that demonstrates the use of a linear combination of factors that can be used to predict an outcome [59]. An index is first constructed by calculating the Pearson correlation between each principle component and the deposit growth rate. This correlation is then used to calculate an index using the following formula:

$$I_{x,t}^{deposit} = \sum_{y=1}^{5} \sigma_y PC_{y,t}^{deposit} \tag{20}$$

Where

$I_{x,t}^{deposit}$ is the deposit growth rate index for deposit category x at time t

σ_y is the correlation between principal component y and the deposit growth rate

$PC_{y,t}^{deposit}$ is the value of the principal component y of deposit category x at time t

The index is then standardised using the following formula:

$$SI_{x,t}^{deposit} = \frac{I_{x,t}^{deposit} - \mu_x^{deposit}}{\sigma_x^{deposit}} \tag{21}$$

Where

$SI_{x,t}^{deposit}$ is the standardised deposit growth rate index for deposit category x at time t;

$\mu_x^{deposit}$ is the average index value of deposit category x;

$\sigma_x^{deposit}$ is the standard deviation of the index of deposit category x.

The standardised index is the single factor that represents an increase or decrease in the volume of deposits for a given set of macroeconomic factors. This standardised index needs to be transformed into a prediction of deposit growth rates. This can be done using the Vasicek adjustment [62]:

$$VMA_{x,t}^{deposit} = \phi\left(\frac{\sqrt{1-\rho_x^{deposit}}\,\phi^{-1}\left(g_{x,t}^{TTCdg}\right)+\sqrt{\rho_x^{deposit}}\,\phi^{-1}\left(SI_{x,t}^{deposit}\right)}{\sqrt{1-\rho_x^{deposit}}}\right) \tag{22}$$

Where:

$VMA_{x,t}^{deposit}$ is the Vasicek macroeconomic adjusted deposit growth rate for deposit category x at time t

$g_{x,t}^{TTCdg}$ is the long run average (through the cycle) deposit growth rate for deposit category x

ϕ is the standard normal density function

ϕ^{-1} is the inverse of the standard normal density function

$\rho_x^{deposit}$ is the correlation between $g_{x,t}^{TTCdg}$ and $SI_{x,t}^{deposit}$

The fit has two main objectives:

3. Provide a good fit for actual historic deposit growth rates

4. Account for severe reduction in deposit volumes.

The second criteria is important since the aim of stress testing is to evaluate the impact of extreme events rather than accurately predicting long term trends.

In equation (22) the only unknown variable is ρ which is the correlation between the index and the deposit growth rate. The correlation is set so that the following value is minimised:

$$\frac{\left|g\ min_x^{Act\ dg} - g\ min_x^{Fit\ dg}\right|}{\left|g\ min_x^{Act\ dg}\right|} \times 3 + \left(R^2_{Regression\ x} - R^2_{Vasicek\ x}\right) \times 3 + \frac{\left|g\ max_x^{Act\ dg} - g\ max_x^{Fit\ dg}\right|}{\left|g\ max_x^{Act\ dg}\right|} \quad (23)$$

Where:

$g\ min_x^{Act\ dg}$ is the minimum observed deposit growth rate for deposit category x

$g\ min_x^{Fit\ dg}$ is the minimum deposit growth rate for deposit category x as predicted by equation (22)

$g\ max_x^{Act\ dg}$ is the maximum observed deposit growth rate for deposit category x

$g\ max_x^{Fit\ dg}$ is the maximum deposit growth rate for deposit category x as predicted by equation (2)

$R^2_{Regression\ x}$ is the R^2 value of the linear regression fitted to the deposit growth rates of deposit category x using the principal components of deposit category x

$R^2_{Vasicek\ x}$ is the R^2 value of the Vasicek equation (22) fitted to the deposit growth rates of deposit category x

4.2.2 Method 2 - Index based on correlation transformed with scaling

The standardised index $SI_{x,t}$ can also be scaled to align to the average and standard deviation of the deposit growth rates. The forecasted deposit growth rate is therefore calculated using the following formula:

$$SMA_{x,t}^{deposit} = SI_{x,t}^{deposit} \times \sigma_x^{dg} + \mu_x^{dg} \quad (24)$$

Where:

$SMA_{x,t}^{deposit}$ is the scaled index macroeconomic adjusted deposit growth rate for deposit category x at time t.

σ_x^{dg} is the standard deviation of deposit growth for deposit category x

μ_x^{dg} is the average of deposit growth for deposit category x

4.2.3 *Method 3 - Regression performed on principle components*

The growth rates can also be estimated through linear regression applied to the principle components. The forecasted deposit growth rate is therefore calculated using the following formula:

$$RMA_{x,t}^{deposit} = \omega_{x,0}^{deposit} + \sum_{y=1}^{5} \omega_{x,y}^{deposit} PC_{y,t}^{deposit} \quad (25)$$

Where:

$\omega_{x,0}^{deposit}$ is the constant estimated through the regression for deposit category x;

$\omega_{x,y}^{deposit}$ is the regression weight of principal component y of deposit category x;

$RMA_{x,t}^{deposit}$ is the linear regression macroeconomic adjusted deposit growth rate for deposit category x at time t.

4.2.4 *Choice of method*

The methods are evaluated by visually considering:

1. goodness of fit to full time series of deposit growth rates
2. extent to which short periods of stress is represented by the method
3. goodness of fit when method is applied as a forecast

The considerations are illustrated in Figure 44 below:

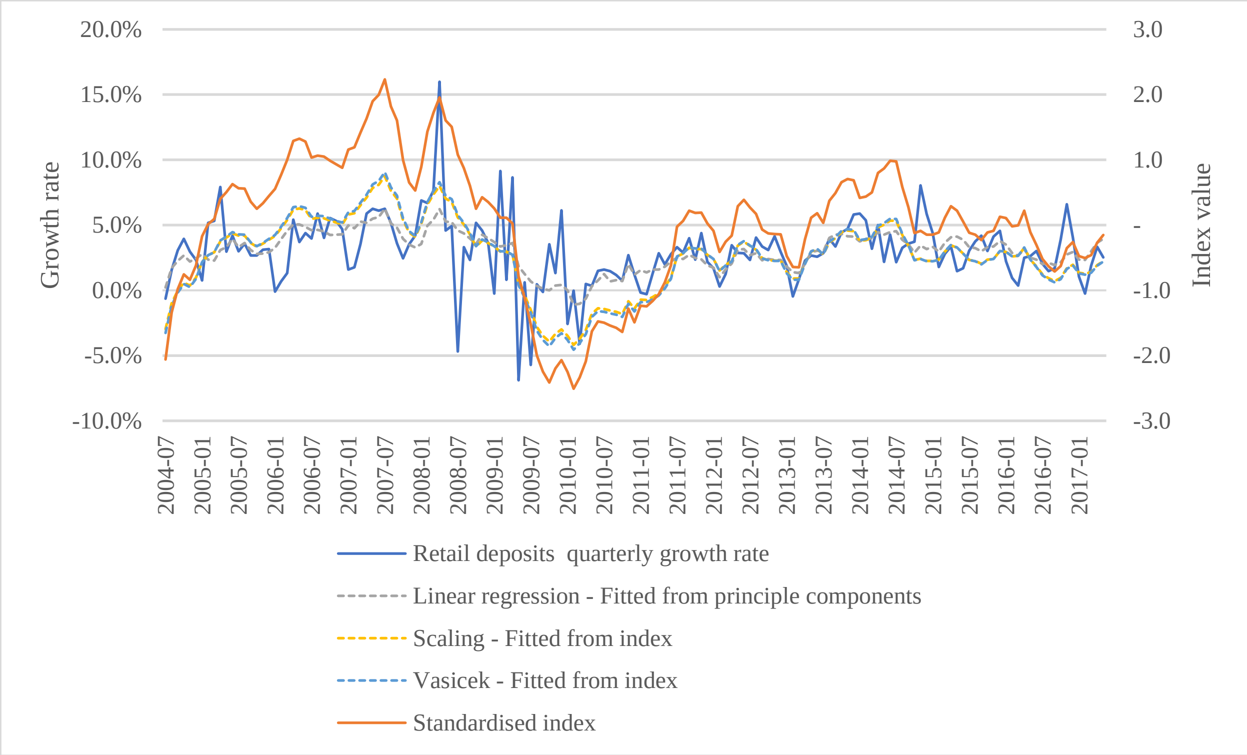

Figure 44: Retail deposits index and fitted growth rates

From Figure 44 the following observations can be made:

1. The linear regression follows the average growth rate closely and does not have any severe increases or decreases.
2. The Vasicek and scaled index fitted values both follow the general trend in growth rates and include larger drops and increases that is represented in the actual growth data.
3. The Vasicek method estimates a slightly bigger reduction than the scaled index method and would therefore be better at representing stressed reductions in deposit volumes.

The Vasicek and scaled index approaches is therefore a better choice when the aim is to predict short term volatility in deposit growth rates. This is also aligned to observations that many stress test models tend to underpredict the severity of stress [26].

From Figure 45 to Figure 47 it can be seen that the regression approach provides the best overall fit. This is expected since it fits the average deposit growth rates well. The Vasicek and scaled index approaches tends to over and underestimate total deposit volumes for periods. The general volume of deposits and observed trends are still plausible.

The use of a Vasicek or scaled index method can therefore capture the effects of short term stress while still producing a reasonable deposit volume forecast over longer periods.

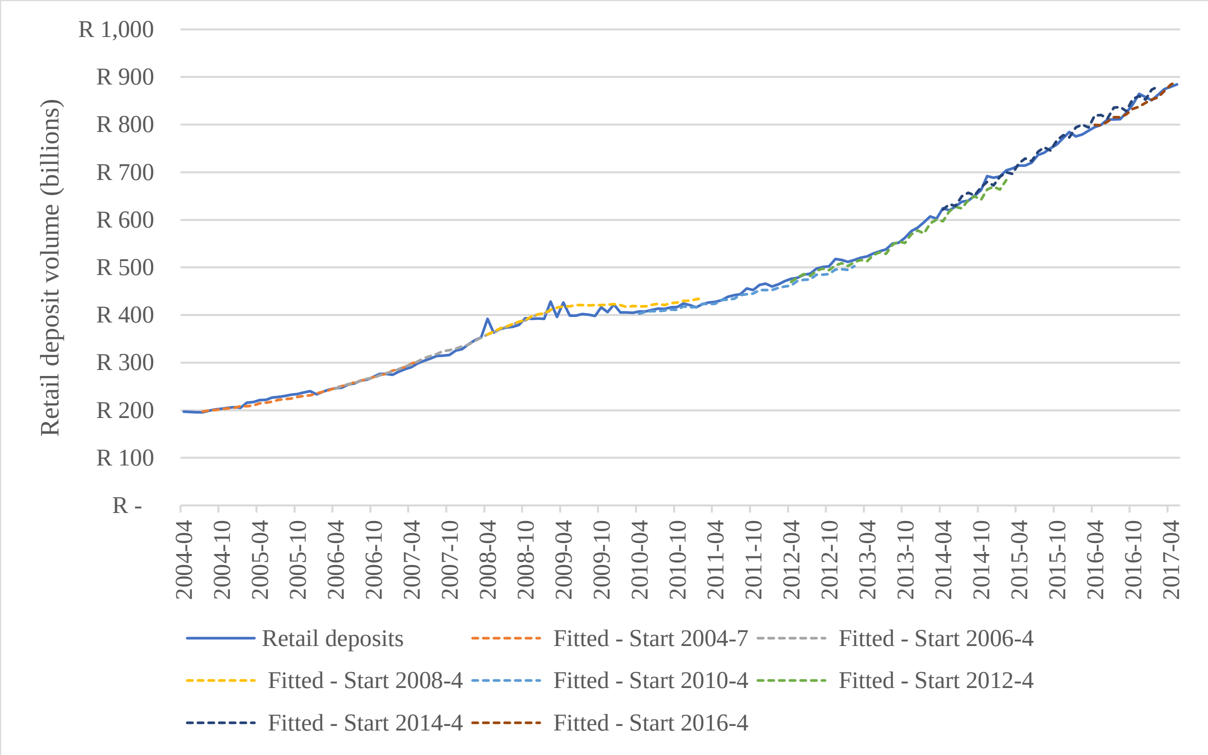

Figure 45: Linear regression fitted deposit volumes compared to actual deposit volumes

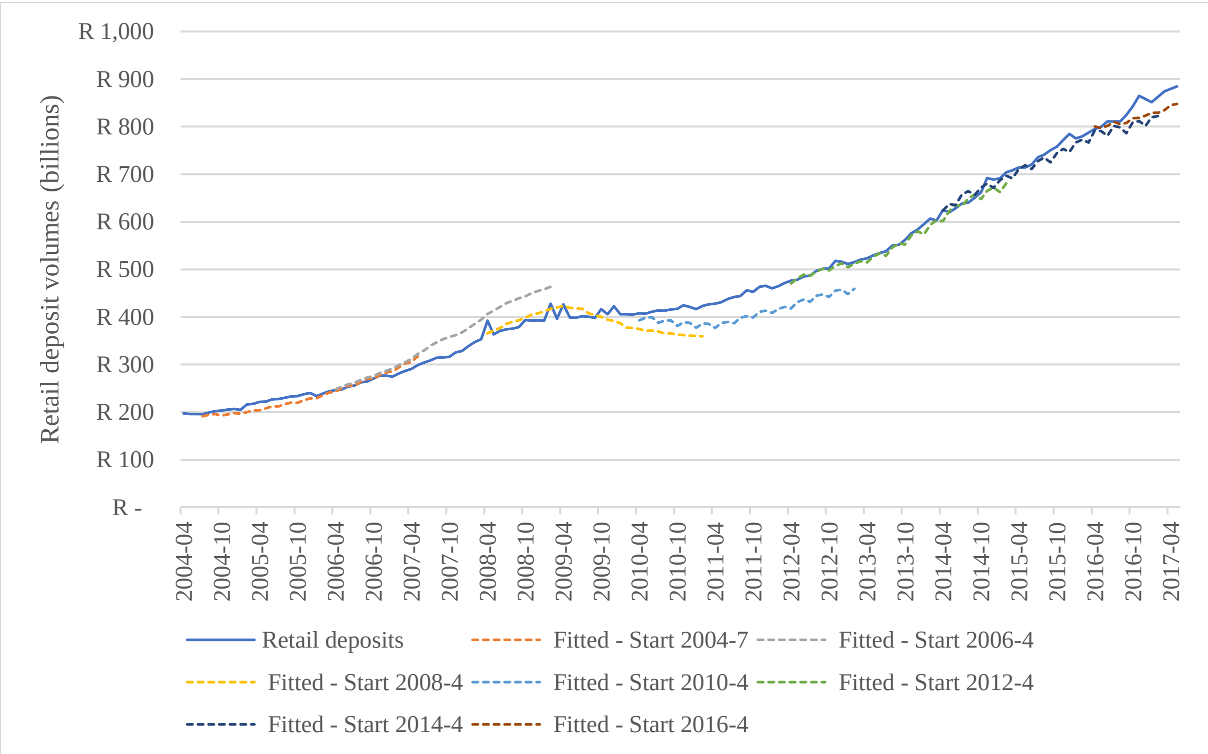

Figure 46: Scaled index fitted deposit volumes compared to actual deposit volumes

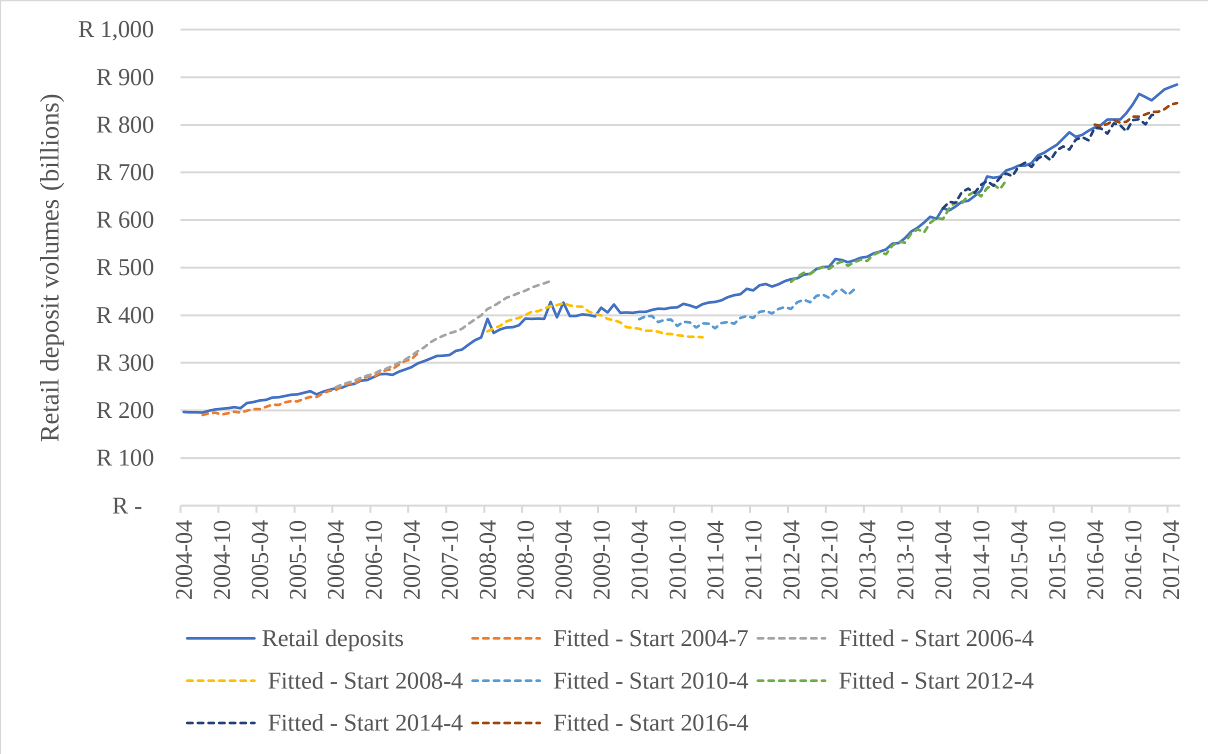

Figure 47: Vasicek fitted deposit volumes compared to actual deposit volumes

The following methods are selected for each deposit category:

	Chosen method
Retail	Vasicek
Government and SOE	Vasicek
Financial institution	Scaled index
Corporate	Scaled index
Bank	Scaled index

Table 14: Selected fitting method for each deposit category

A comparison of fitted results and actual deposit volumes per deposit category is depicted below:

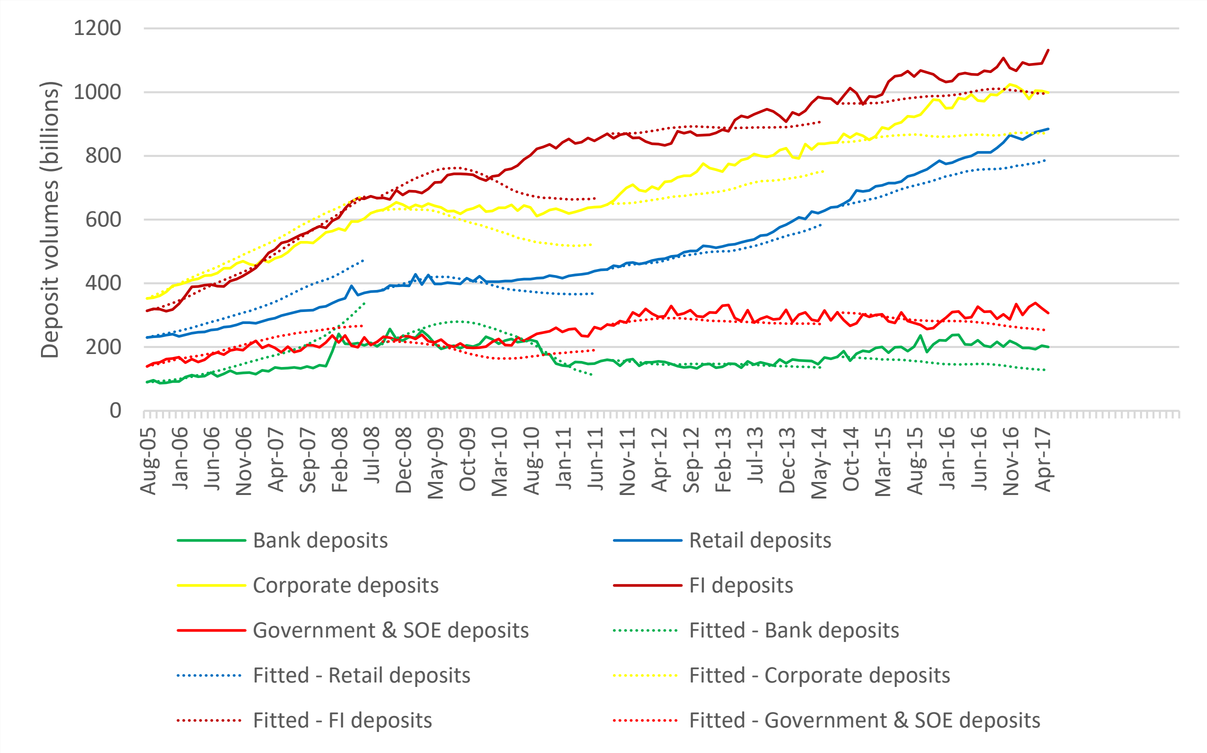

Figure 48: Fitted deposit volumes compared to actual deposit volumes

4.3 Market share modelling

Once the total volume of deposits per category has been forecasted, the deposit volumes for each individual bank can be forecasted by considering each bank's market share at a given point in time. Economic conditions are expected to drive the total volume of deposits in the economy while the specific idiosyncratic actions of the banks are then expected to be the primary driver of the bank's market share at a given point in time. An individual bank can therefore experience additional strain since customers tend to move their deposits from weaker to stronger banks [64]. The monthly market share values are volatile as demonstrated by the below figures.

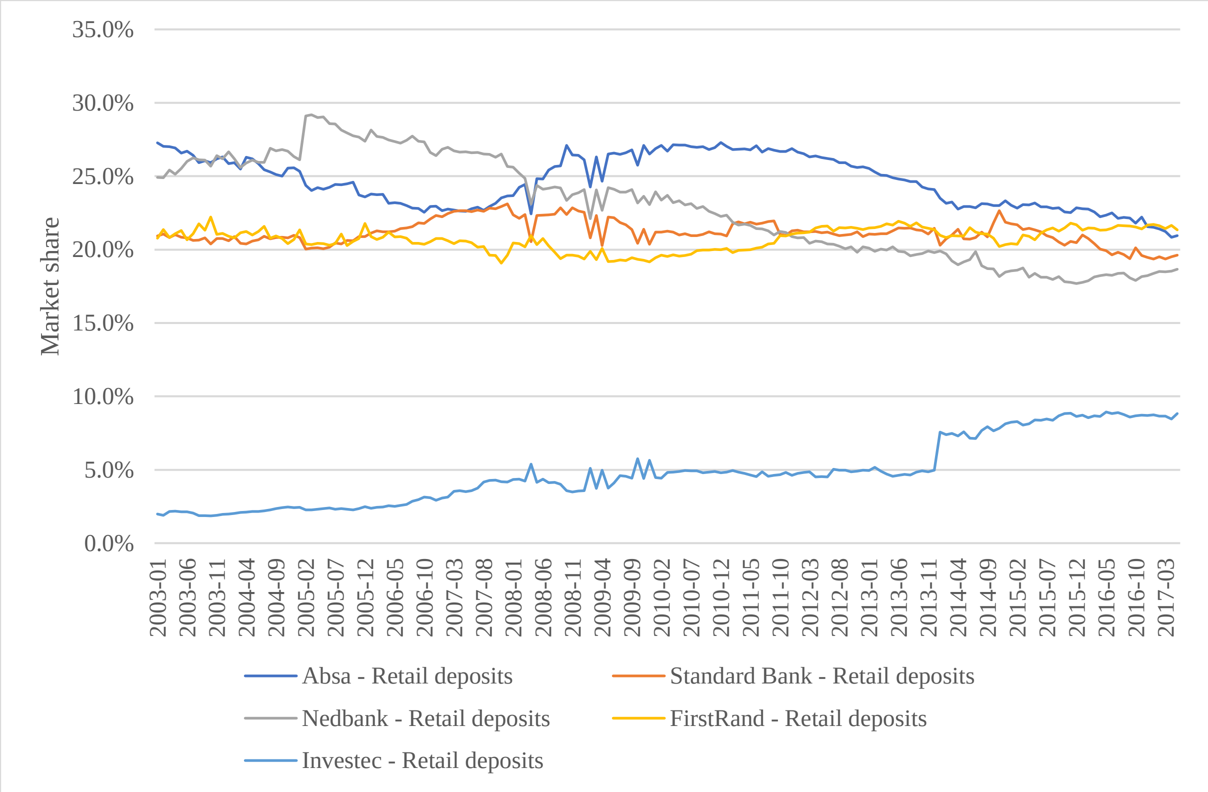

Figure 49: Retail deposit market share of big five banks

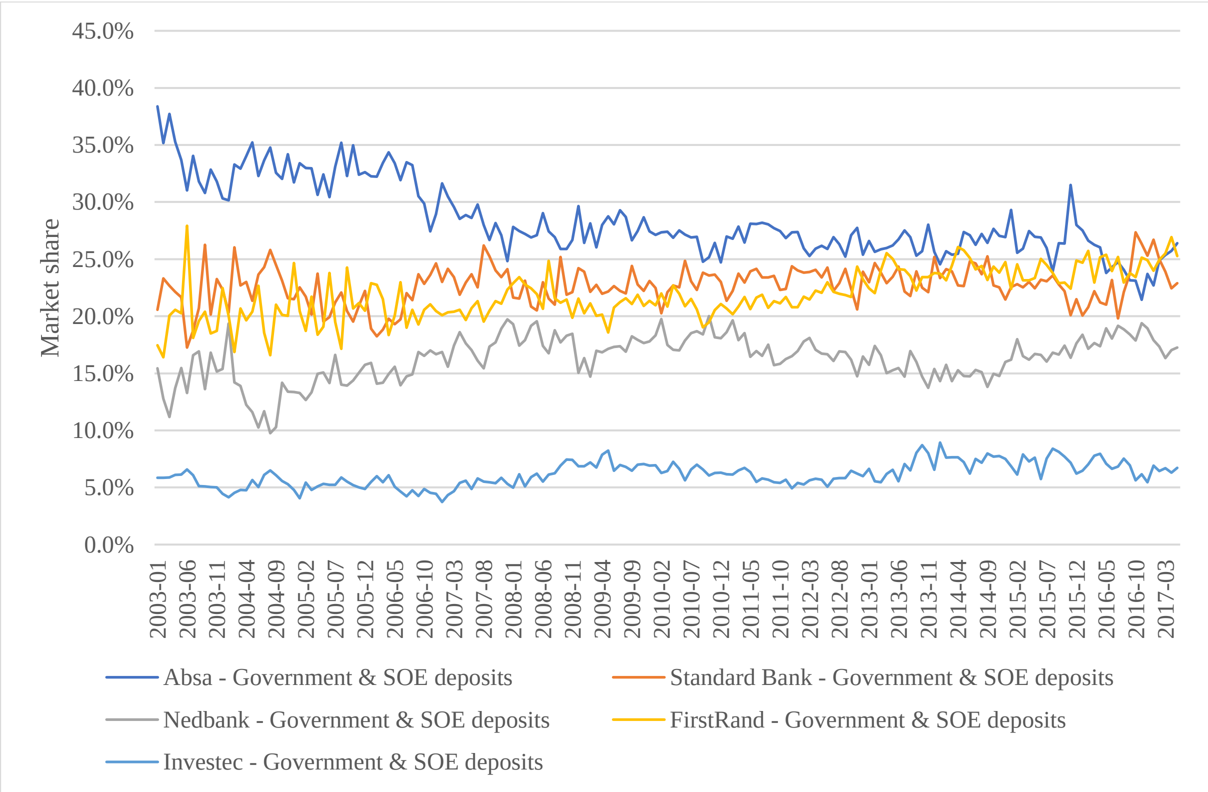

Figure 50: Government and SOE deposit market share of big five banks

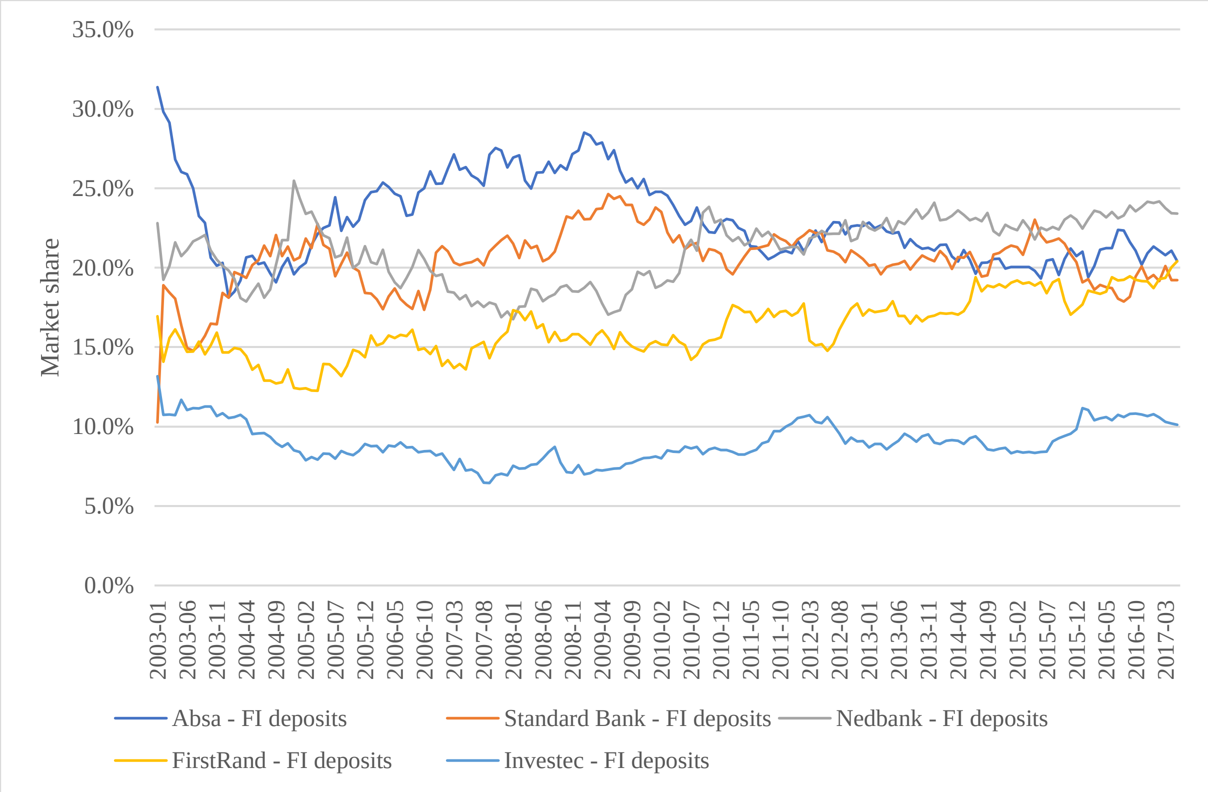

Figure 51: Financial institution deposit market share of big five banks

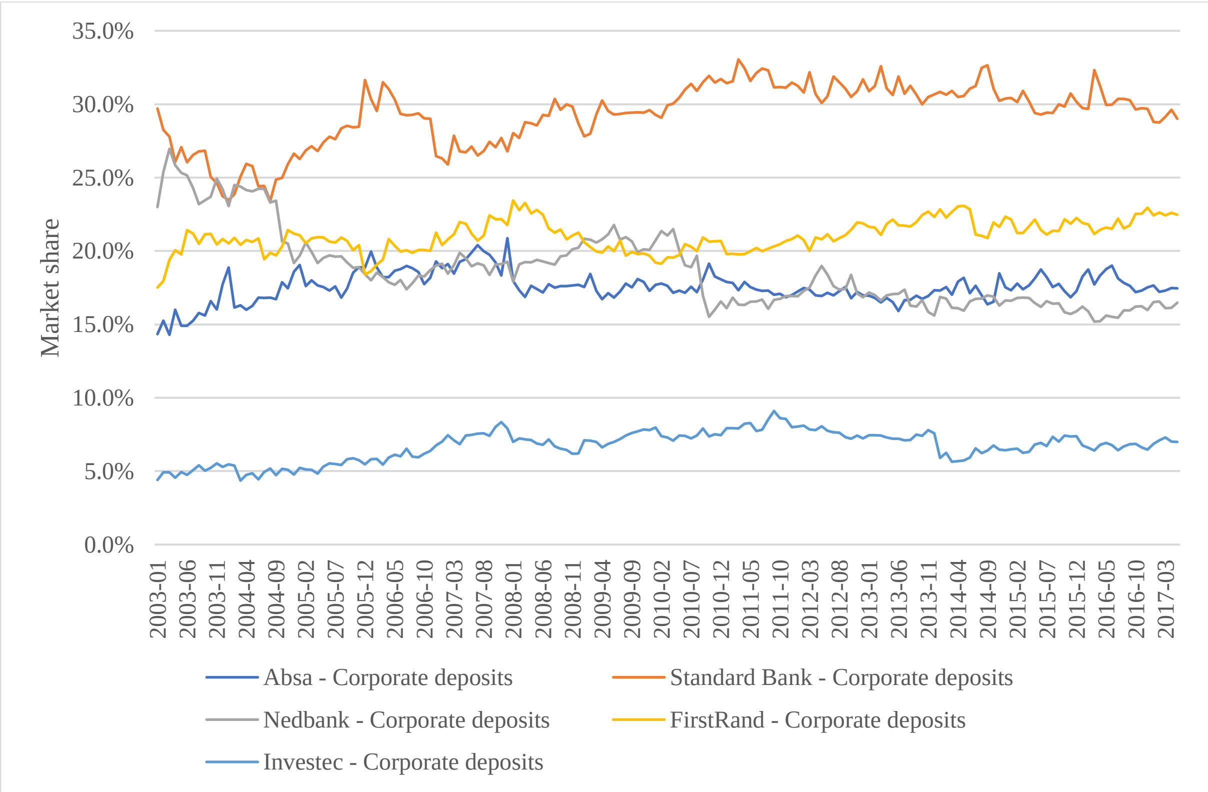

Figure 52: Corporate deposit market share of big five banks

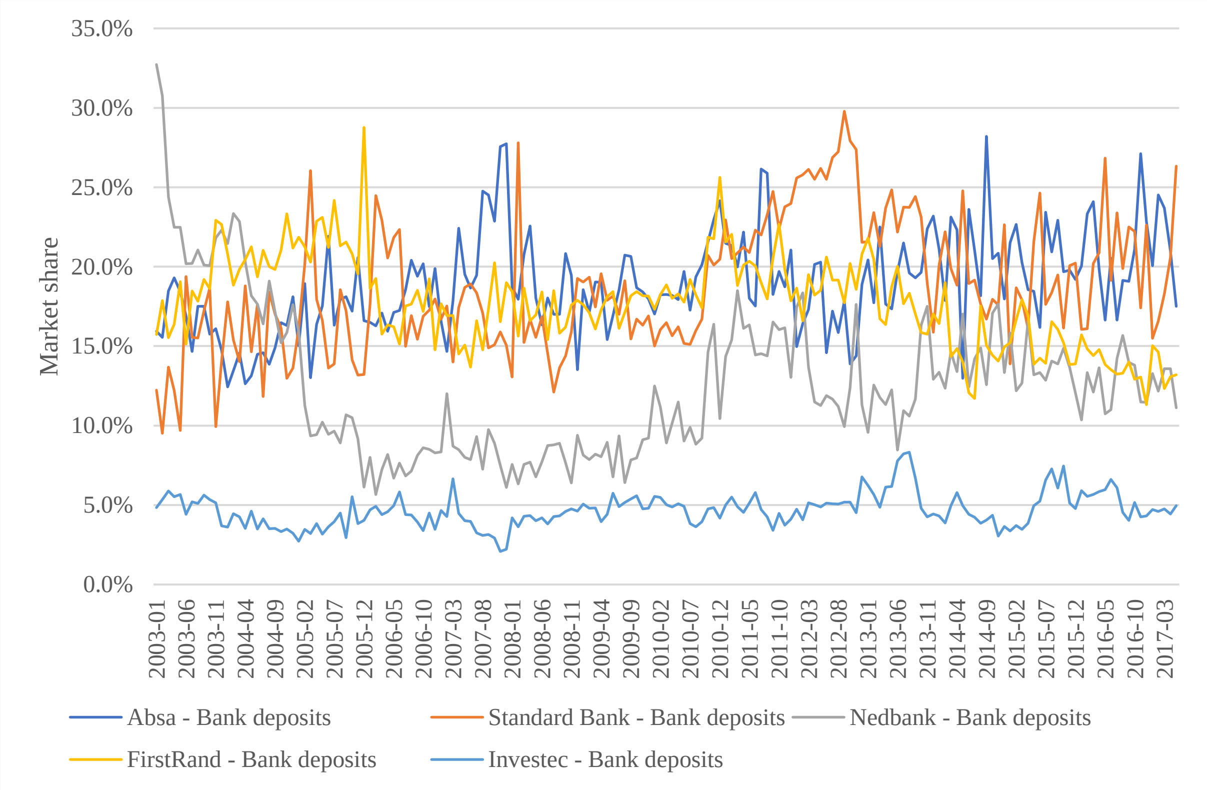

Figure 53: Bank deposit market share of big five banks

Figure 49 to Figure 53 above illustrates the volatility in bank market share and that some deposit categories such as bank deposits tend to be more volatile. Trends of banks growing and losing market share over time can also be observed.

Due to the monthly volatility, autoregressive moving average ("ARMA") models are fitted to each bank's market share per deposit category. This also allows the simulation of idiosyncratic impacts through the error term of each ARMA model.

The general form of an ARMA(p,q) model is:

$$Z_t^{x,y} = \theta_0 + \phi_1 Z_{t-1}^{x,y} + \phi_2 Z_{t-2}^{x,y} + \cdots + \phi_p Z_{t-p}^{x,y} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - -\theta_q a_{t-q} \quad (26)$$

Where:

$Z_t^{x,y}$ is the market share of bank y for deposit category x at time t;

θ_0 is a constant with average $\mu = \frac{\theta_0}{1-\phi_1-\phi_{2-\cdots-}\phi_p}$;

ϕ_p is the autoregressive parameter corresponding to a lag of p applied to the market share time series;

a_t is the normally distributed error term at time t with an average of 0 and a standard deviation of σ_a;

θ_q is the moving average parameter corresponding to a lag of q applied to the error term time series.

To fit an ARMA model the following parameters need to be estimated:

- Values of p and q
- θ_0
- ϕ_1 to ϕ_p
- θ_1 to θ_q

An estimate of σ_a is also needed to simulate the random variance of the time series.

The values of p and q where estimated using the following tests:

- Smallest canonical correlation method
- Extended sample autocorrelation function method
- Minimum information criterion

The hypothesis that the error terms or residuals are normally distributed is also tested once a model is fitted based on selected values of p and q.

Once a model has been fitted, a progression of market shares can be simulated by simulating random values of a_t in equation (26) with the fitted parameters.

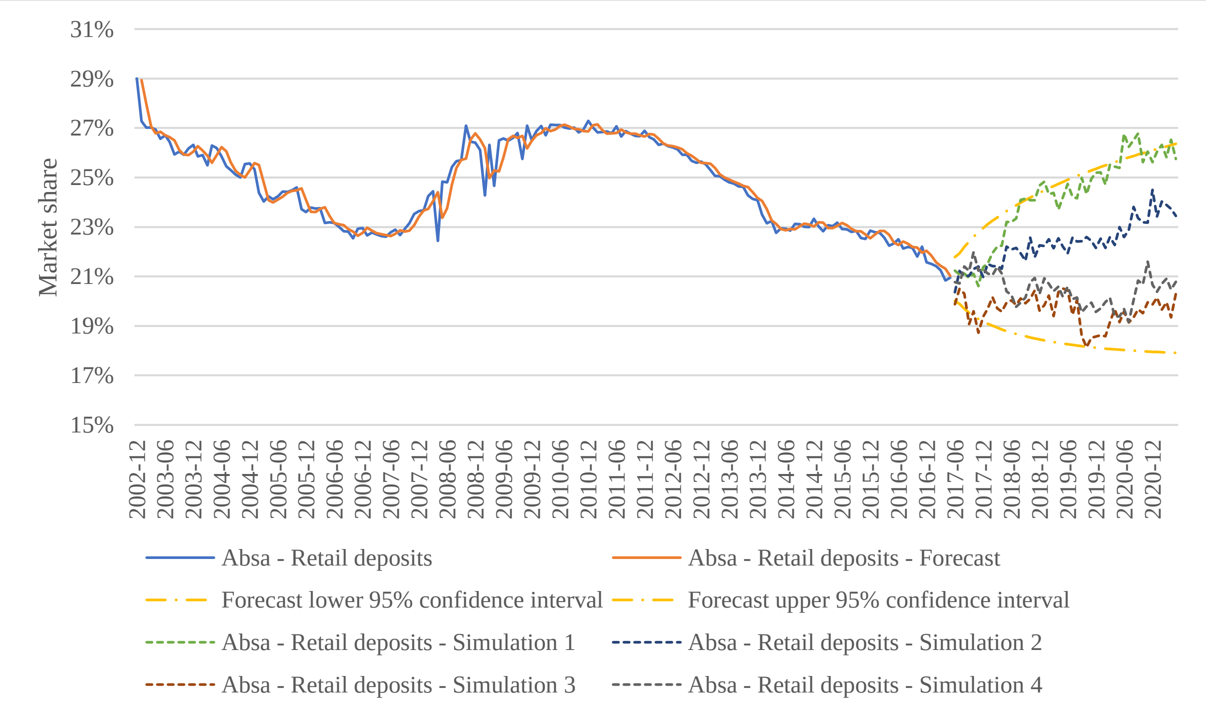

Figure 54: Fitted and simulated retail deposit market share of Absa

The simulated retail deposit market share for Absa using a fitted ARMA(1,2) model is illustrated above in Figure 54. It shows that goodness of fit on the historic market share time series and the range of potential market share outcomes between June 2017 and May 2021. The simulation allows for general short term trends in market share and short term volatility. ARMA models are fitted for each bank and deposit category:

	Retail	Government & SOE	Financial institution	Corporate	Bank
Absa	ARMA(1,2)	ARMA(1,1)	ARMA(2,1)	ARMA(1,1)	ARMA(1,2)
Standard Bank	ARMA(2,2)	ARMA(3,2)	ARMA(2,1)	ARMA(1,2)	ARMA(1,1)
Nedbank	ARMA(2,2)	ARMA(5,4)	ARMA(1,3)	ARMA(1,1)	ARMA(1,2)
FirstRand	ARMA(1,1)	ARMA(3,3)	ARMA(1,1)	ARMA(1,0)	ARMA(1,1)
Investec	ARMA(2,0)	ARMA(2,1)	ARMA(1,1)	ARMA(1,1)	ARMA(1,1)

Table 15: Fitted ARMA parameter values for each bank and deposit category

4.4 Results

4.4.1 Key factors that drive changes in deposit volumes

The analysis that is performed shows that different macroeconomic drives affect different deposit customer types in different ways. The sensitivity of each deposit customer type to each of the macroeconomic factors is assessed by individually moving each macroeconomic factor by one standard deviation to assess the impact on the predicted deposit growth rate per deposit customer type.

	Retail	Government & SOE	Financial institution	Corporate	Bank	Weighted overall average
Prime overdraft rate (End of Period)	-9.3%	11.8%	8.9%	-2.2%	17.7%	2.0%
All monetary institutions: Total credit extended to the private sector 12-Term % change	20.4%	-2.7%	14.2%	10.7%	25.9%	14.0%
CPI: Total country (All items)	-14.2%	-18.0%	-14.7%	-27.7%	-26.2%	-19.2%
Government bond yield - 0-3 years	-7.0%	10.6%	7.3%	-6.1%	16.1%	0.7%

Government bond yield - 3-5 years	-11.1%	14.0%	4.8%	-0.4%	7.0%	0.3%
Government bond yield - 5-10 years	-10.2%	16.4%	2.7%	5.9%	5.1%	1.7%
Government bond yield - 10 years and over	-14.5%	17.7%	7.4%	6.8%	-16.6%	1.3%
J203 - ALSI Value	8.3%	18.5%	12.8%	11.6%	40.3%	13.4%
Consumer Confidence	-9.6%	22.8%	12.2%	5.5%	-15.7%	4.2%
Business Confidence	-19.9%	8.4%	0.8%	15.1%	-32.9%	-1.6%
GDP at market prices	17.7%	14.3%	12.6%	21.7%	33.6%	17.8%
Disposable income of households	18.1%	-8.1%	14.3%	21.0%	39.4%	16.6%
National government deficit / surplus as % of GDP	-15.1%	-2.8%	-14.6%	-3.7%	-26.8%	-11.3%
Ratio of gross savings to GDP	21.2%	14.6%	7.6%	18.2%	20.0%	15.3%
Household debt to disposable income	-4.2%	-15.1%	-11.3%	-26.5%	-19.0%	-14.6%

Table 16: Movement in deposit growth rates following a single standard deviation macroeconomic variable shock

The results in Table 16 shows that the key drivers of overall deposit volumes are:

- Total credit extended to the private sector
- CPI
- JSE All Share Index
- GDP Growth
- Disposable income of households
- National government surplus or deficit
- Ratio of gross savings to GDP
- Household debt to disposable income

The directions of the impacts are also aligned to the positive or negative nature of these factors. For example, factors that indicate economic growth such as credit extended to the private sector, stock price growth (JSE ALSI), GDP growth, disposable income of households and ratio of gross savings to GDP lead to increased deposits. Conversely, factors associated with increased economic strain such as CPI, national government deficit and household debt to disposable income lead to reduced deposits. These factors also have the same directional impact on all deposit customer types although the level of sensitivity varies.

The individual deposit customer types also reflect the specific features of those customers. For example, retail deposits would be adversely affected by increases in the prime rate and bond yields since this would increase the cost of servicing debt and therefore reduce the funds available to retail customers. Conversely, the government and SOE's, financial institutions, corporates and banks would tend to save more when interest rates are higher. This would be to take advantage of the higher return and since higher interest rates tends to reduce economic growth which in turn leads to savings instead of investment of funds.

A combination of factors that lead to the greatest stress is investigated by considering the prevailing factors that correspond to the biggest predicted reduction in deposit volumes per category. The graphs below highlight the extent to which a factor varies and the value of the variable during the period of greatest stress in overall deposit volumes. The bottom of the box represents the second quartile while the top half of the box represents the third quartile. The cross is the mean while the line in the middle is the median. The whiskers extend up to 1.5 times the size of the box. Any points beyond the whiskers are represented as dots. Next to each box plot is a line with a cross at the centre that represents the value of the variable during the greatest period of reduction in the overall market deposit volumes.

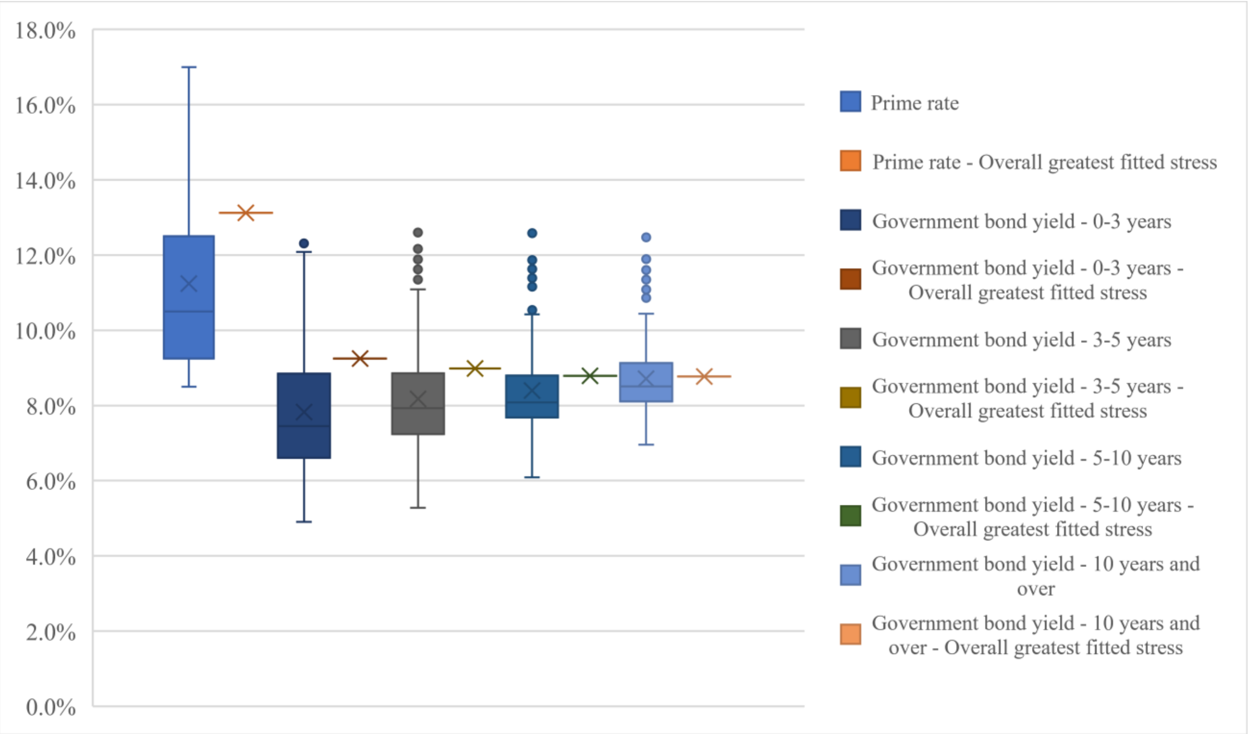

Figure 55: Box plot of historic macroeconomic variables compared to levels that lead to the greatest modelled reduction in overall deposit volumes (interest related variables)

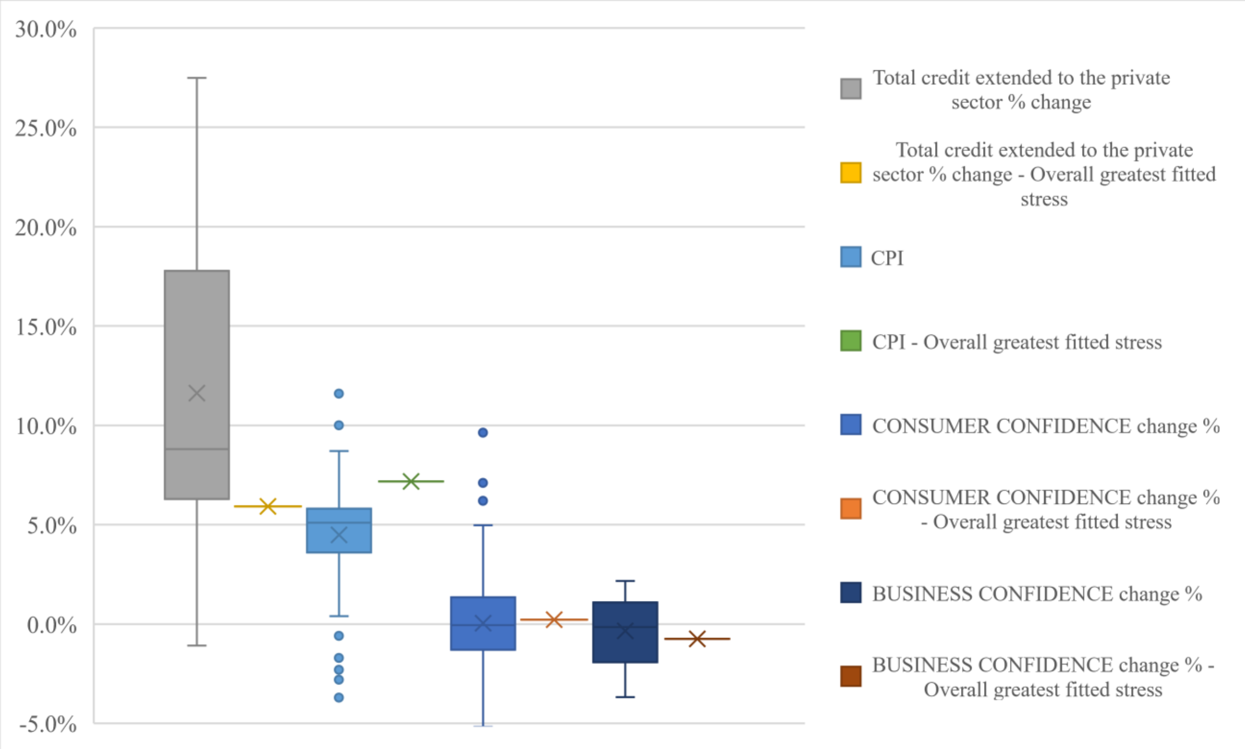

Figure 56: Box plot of historic macroeconomic variables compared to levels that lead to the greatest modelled reduction in overall deposit volumes (credit extension, CPI and confidence variables)

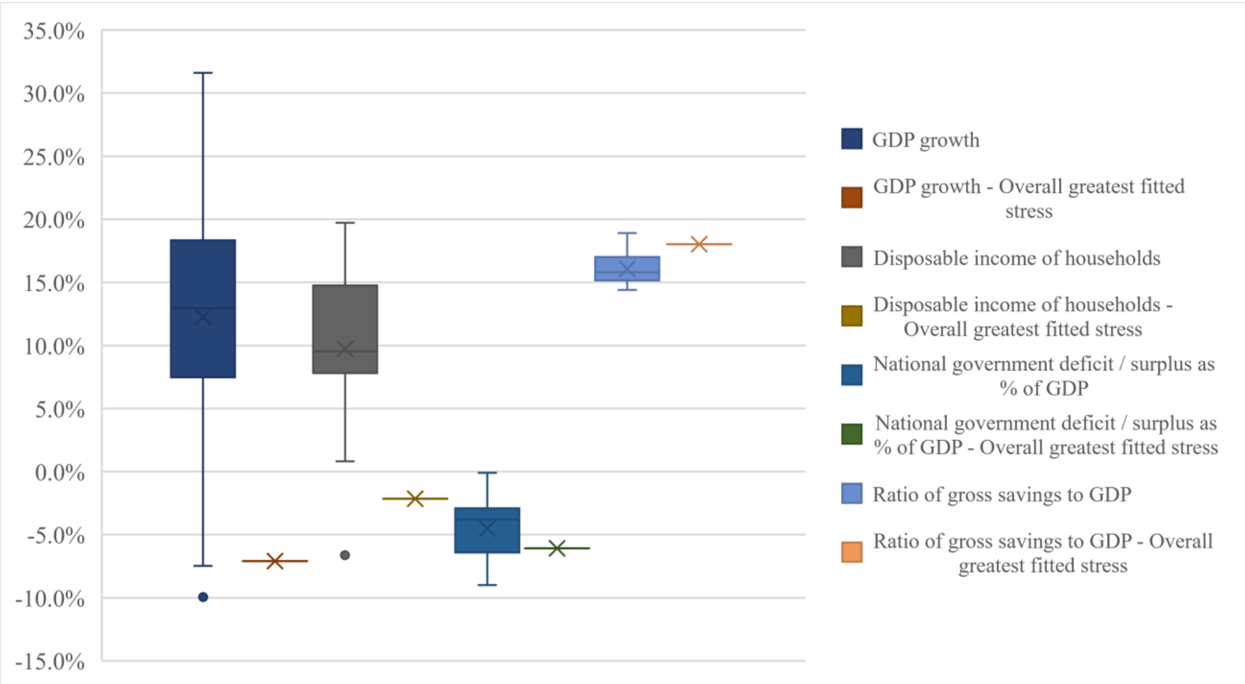

Figure 57: Box plot of historic macroeconomic variables compared to levels that lead to the greatest modelled reduction in overall deposit volumes (GDP, disposable income, government deficit and saving variables)

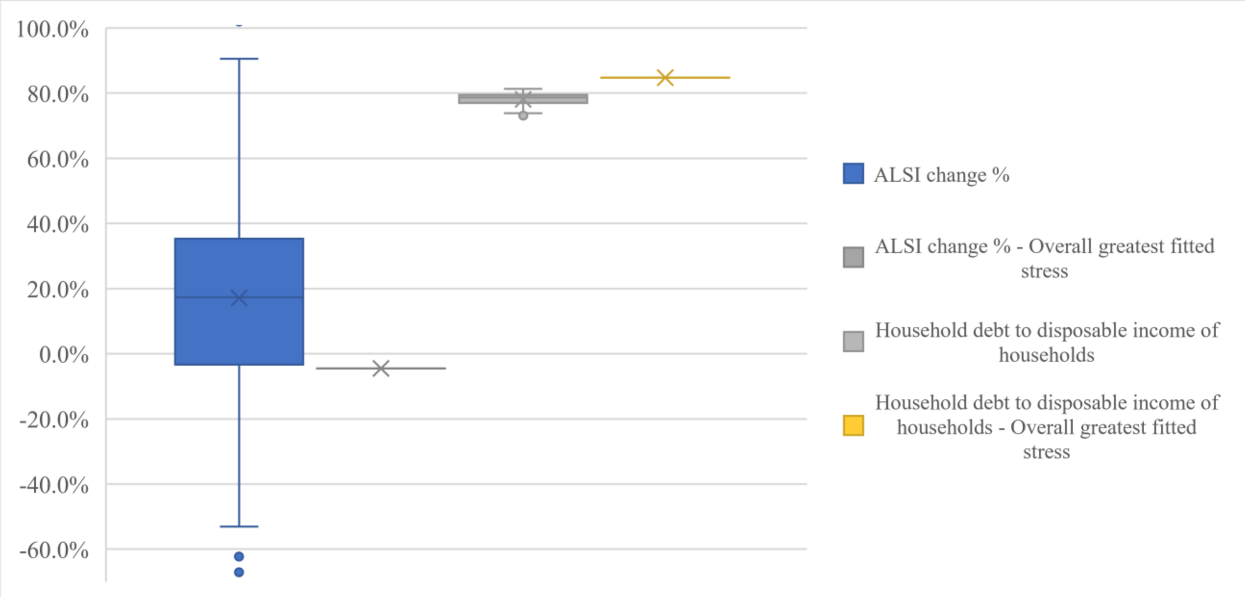

Figure 58: Box plot of historic macroeconomic variables compared to levels that lead to the greatest modelled reduction in overall deposit volumes (ALSI and household disposable income variables)

From Figure 55 to Figure 58 it can be observed that the greatest stress is generated when the majority of macroeconomic variables are stressed. The prime rate, government bond yields, credit extended to the private sector, CPI, GDP growth, ALSI growth rate and household debt to disposable income levels are all at stressed levels with GDP and household disposable income and household debt to disposable income being extremely stressed levels.

4.4.2 Level of variability in bank market share

The time series modelling highlighted that the market share for some deposit categories exhibited a large amount of volatility. The standard deviation of the error term a_t for each bank and deposit category is shown in Table 17:

	Retail	Government & SOE	Financial institution	Corporate	Bank
Absa	0.5%	1.4%	0.8%	0.6%	2.7%
Standard Bank	0.4%	1.4%	1.0%	0.8%	3.0%
Nedbank	0.6%	1.2%	1.0%	0.7%	2.3%
FirstRand	0.3%	1.0%	0.6%	0.6%	1.8%
Investec	0.4%	0.6%	0.4%	0.3%	0.7%

Table 17: Variability in market share based on the standard deviation of time series error term

From Table 17 it can be seen that the deposit categories that make up a smaller proportion of the total deposits of a bank such as government and SOE and bank deposits exhibit more volatility. It can also be seen that Investec and FirstRand experiences less volatility in general while Standard Bank tends to have more volatility.

4.5 *Key deposit modelling conclusions*

The overall volume of deposits in the market is driven by macroeconomic factors and large reductions in the overall volume of deposits can be explained by stress in the economy that will be evident in factors such as economic growth, lending levels, household debt levels and equity markets. The various types of depositors will also react to economic strain in different ways. Retail deposits would be negatively impacted by high interest rates while non-retail deposits may increase as interest rates that can be earned increases.

Individual banks can also be impacted by changes in market share. Historic data shows that market share could exhibit volatility over time although the bigger deposit types such as retail, financial institutions and corporate are less volatile that bank, government and SOE deposits over time. The market share of a bank would not be primarily driven by macroeconomic conditions since all banks operating in the market would be subject to the same macroeconomic conditions.

Stress for an individual bank in terms of deposit volumes would therefore be driven by a combination of macroeconomic and idiosyncratic factors that drive market share. A drop in the overall level of deposits in the market combined with a drop in market share could strain the liquidity of a bank and reduce profitability since alternative sources of funding are more expensive than deposits.

Chapter 5

5. Modelling other movements in bank equity

The assets and liabilities of banks in South Africa is concentrated loans and deposits. From a liability perspective 77% of all bank liabilities are deposits while another 6% relate to derivative and trading liabilities. From an asset perspective 57% of assets are loans with another 13% being public sector interest bearing securities and 8% being derivative and trading assets. Market risk exposures such as derivatives and trading exposures are likely to have complex relationships with macroeconomic factors with further complications such as hedging and mismatches between asset and liability positions. Modelling these exposures are therefore not possible without instrument level information.

It is therefore decided to model the net movement in the remaining 23% of liabilities and 30% of assets (that include market risk exposures) at an aggregate level. Figure 59 and Figure 60 below is derived with equation (27) and shows the movement in equity not related to changes in credit risk.

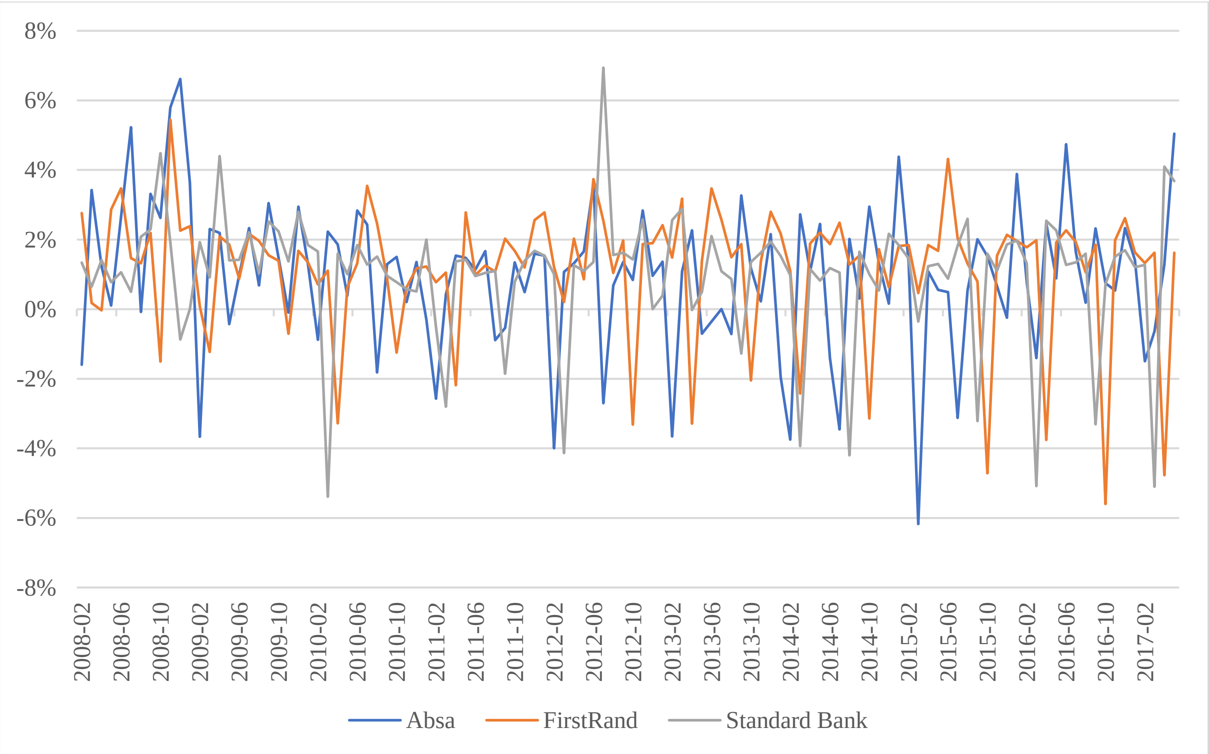

Figure 59: Movement in equity levels not attributable to movement in credit risk impairment for Absa, FirstRand and Standard Bank

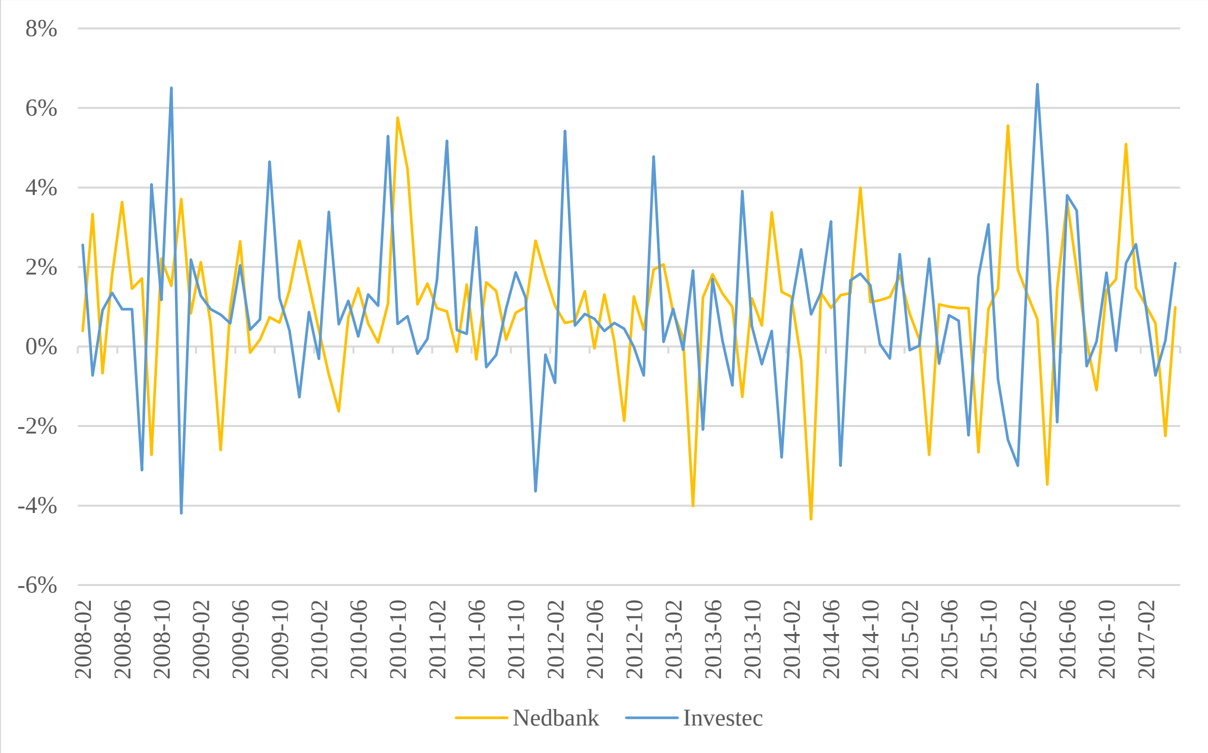

Figure 60: Movement in equity levels not attributable to movement in credit risk impairment for Nedbank and Investec

Note that all movement bigger than 10% (in absolute terms) have been excluded since there are no reported non-credit stress events over the observation period that could have led to such as large reduction or increase in equity. From Figure 59 and Figure 60 it can be seen that there is a fair amount of volatility that doesn't follow a clear economic cycle. The movements for the five banks being considered are also not correlated. This is expected since specific events unique to each bank can drive changes in equity. The varied market risk positions also mean that the same changes in the market could have different effects on each bank.

5.1 *Method*

The movement in bank equity excluding the effects of credit risk impairments is calculated for each bank by deducting the impact on increased credit risk impairments from the change in equity for the month.

$$NCEM_t = \frac{(E_t - E_{t-1}) - (Imp_t - Imp_{t-1})}{E_{t-1}} \qquad (27)$$

Where:

$NCEM_t$ is the percentage change in equity that is not attributable to a change in credit risk impairment

E_t is the bank equity at time t

Imp_t is the bank impairment at time t

This movement in equity is then modelled at an aggregate level. The distribution of NCEM value for the five banks are as follows:

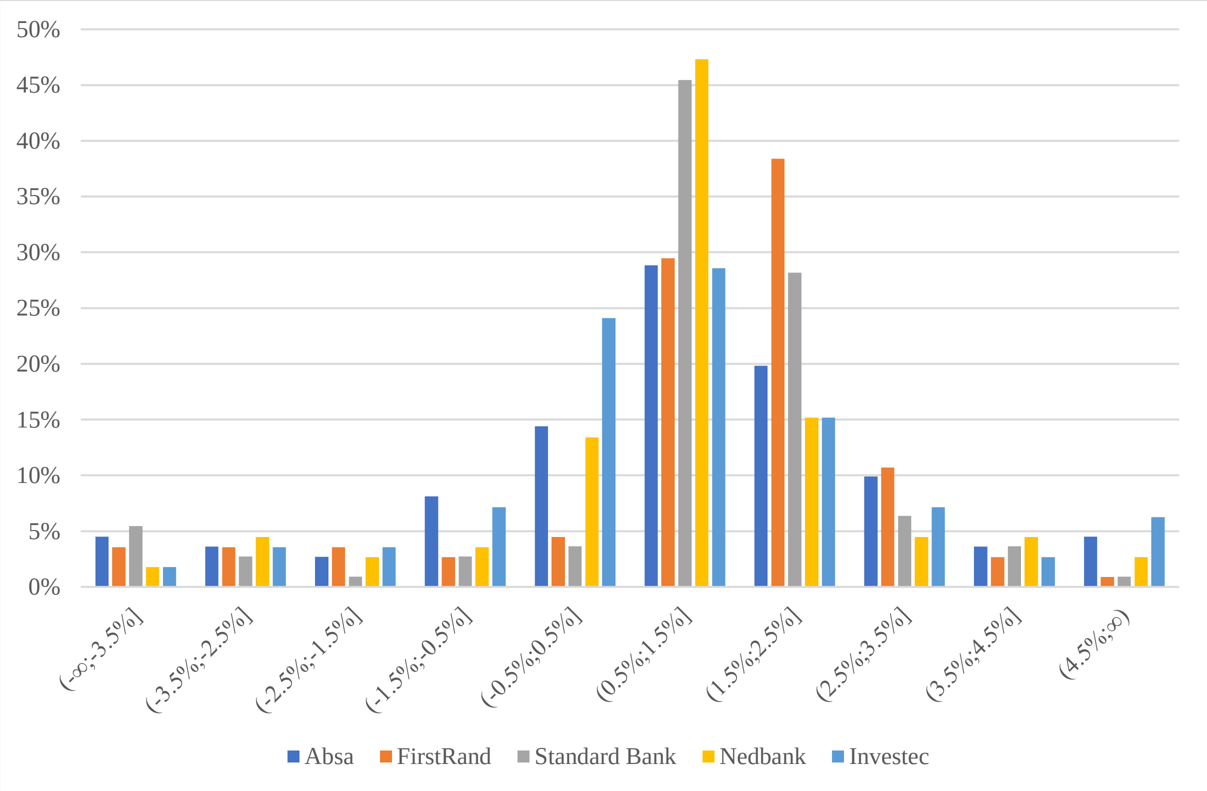

Figure 61: Distribution of equity movement percentages not attributable to changes in credit risk impairments

From Figure 61 above it can be seen that the distribution is fairly symmetrical with a peak in the centre. The first step is therefore to attempt to fit a normal distribution to the observations. Figure 62 illustrates an indicative normal distribution based on the average and standard deviation of the data. It illustrates that the data has a higher concentration of values around the average and thicker tails. This is reasonable since bank equity is expected to show steady growth with the growth in balance sheet with a few outlying events that either increase or decrease equity levels. A Chi-squared test also confirmed that the hypothesis of normality should be rejected. An attempt is also made to fit a Gamma distribution. The hypothesis that the observations follow a Gamma distribution is also rejected.

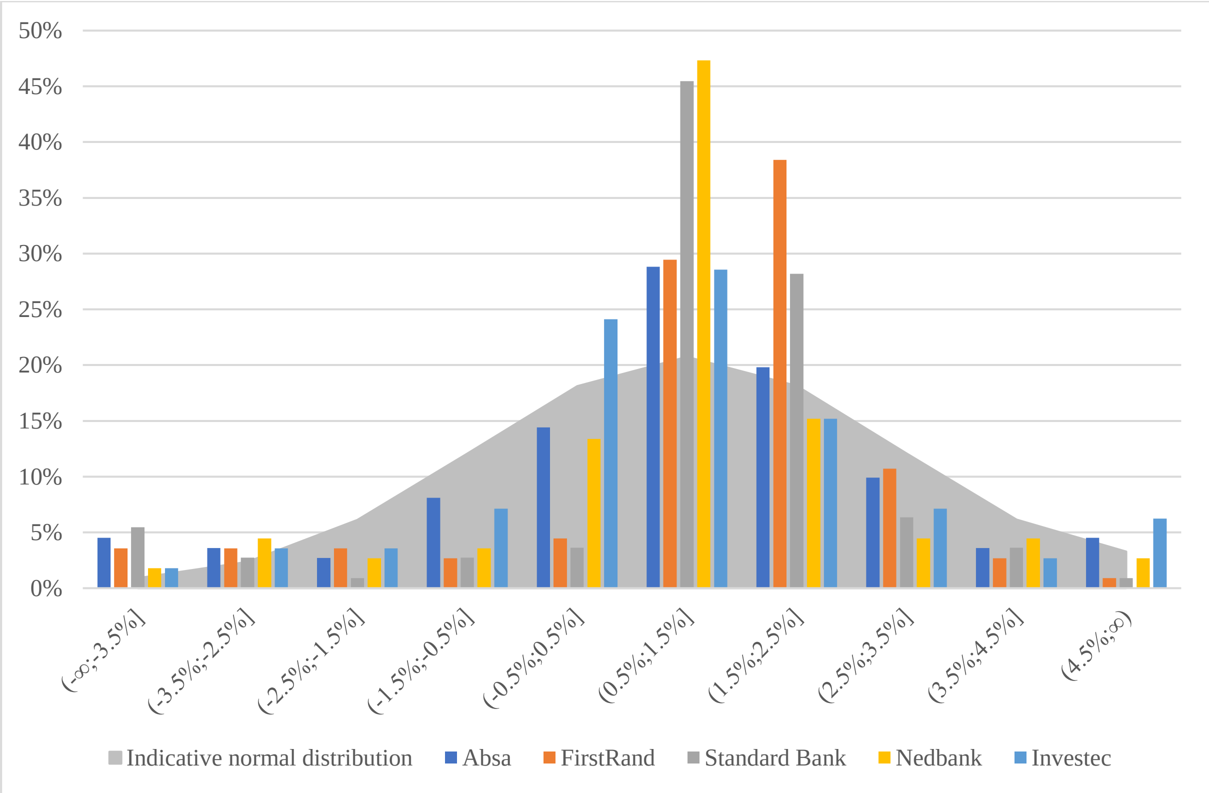

Figure 62: Normal distribution compared to empirical non-impairment equity movements

It was therefore decided that NCEM would be modelled by simulating potential equity movements based on the empirically observed NCEM values of each bank.

Chapter 6

6. Combined stress test model structure

The BA900 returns [35] submitted by each bank every month provides a view of the balance sheet of each bank for every month. The projection of loans and advances, public sector interest bearing securities, deposits and other movements in equity can therefore be projected using the latest BA900 returns [35] as the starting point. January 2020 as a recent available data point is selected as the starting point for the stress test forecast. The following steps are then followed to create a three year projection of the balance sheet of each of the five selected banks:

6.1 Set a macroeconomic forecast

Setting a stressed forecast with coherent variables require a set of econometric models and specialised expertise. The focus of this research is not the forecasting of a coherent macroeconomic stress. For purposes of this section a repeat of the 2008 global financial crisis is therefore created to demonstrate the impact of a severe stress on the current structure of the five biggest South African banks. The ongoing COVID-19 stress was also considered to demonstrate the model. It was however, not used because the COVID-19 stress represents a structural change in the macroeconomic conditions including interest rates not seen since 1965, low inflation and a very large reduction in GDP with stress observed across nearly all sectors. Structural changes in the economy pose a challenge for stress test models based on historic data [26]. The application of this model to such as stress will therefore require careful consideration of the various model components to adequately reflect the severity of the stress and to not overexaggerate the beneficial impact of low interest rates and inflation. The exact impact of the COVID-19 stress from an economic, liquidity and credit risk perspective is also not known at this point in time.

The stress is characterised by large increases in interest rates, a drop in GDP, increasing government deficit and increasing household debt to disposable income. The stress from 2008 is applied as the forecasted macroeconomic outlook from January 2020 to January 2023. Figure 63 to Figure 65 represents a repeat of the 2008 macroeconomic stress over 2020 to 2023. The forecast therefore represents the onset of the stress, the stress itself and the period after the stress that can then be applied as a macroeconomic scenario to the banks as at January 2020.

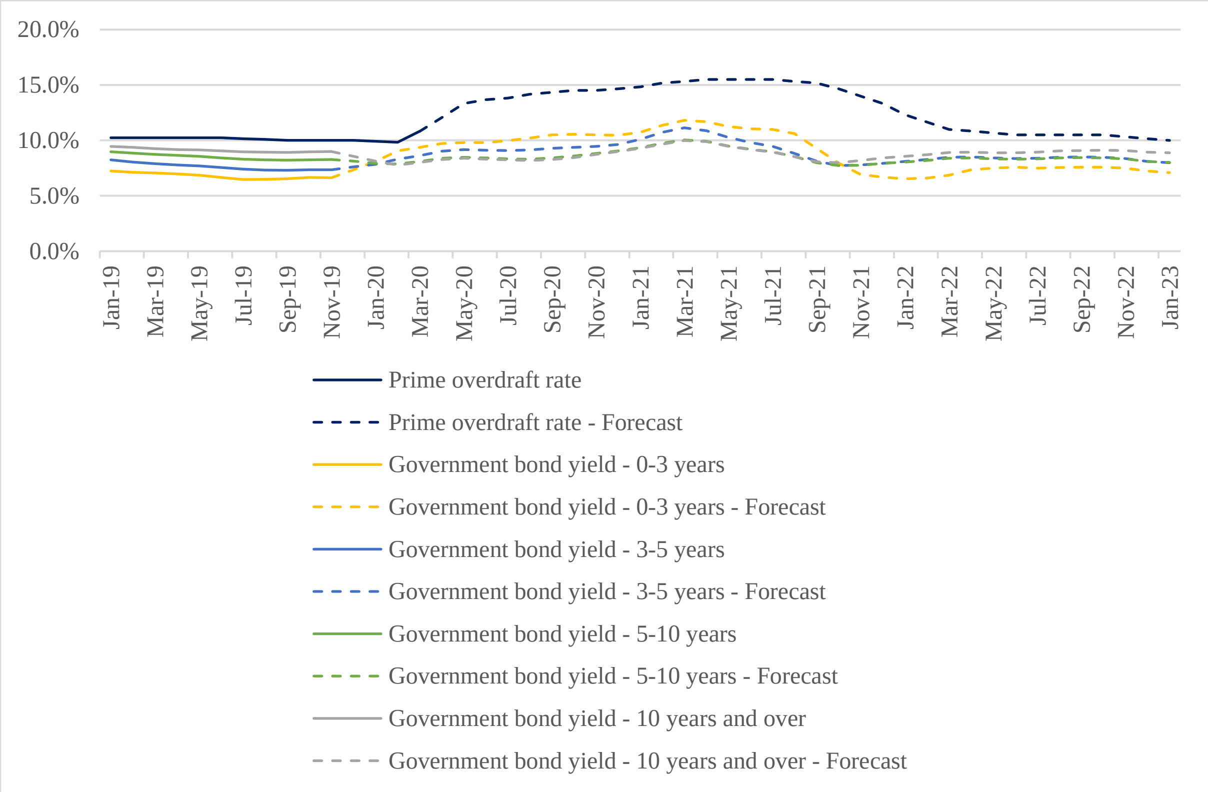

Figure 63: Stressed prime rate and government bond yield forecasts

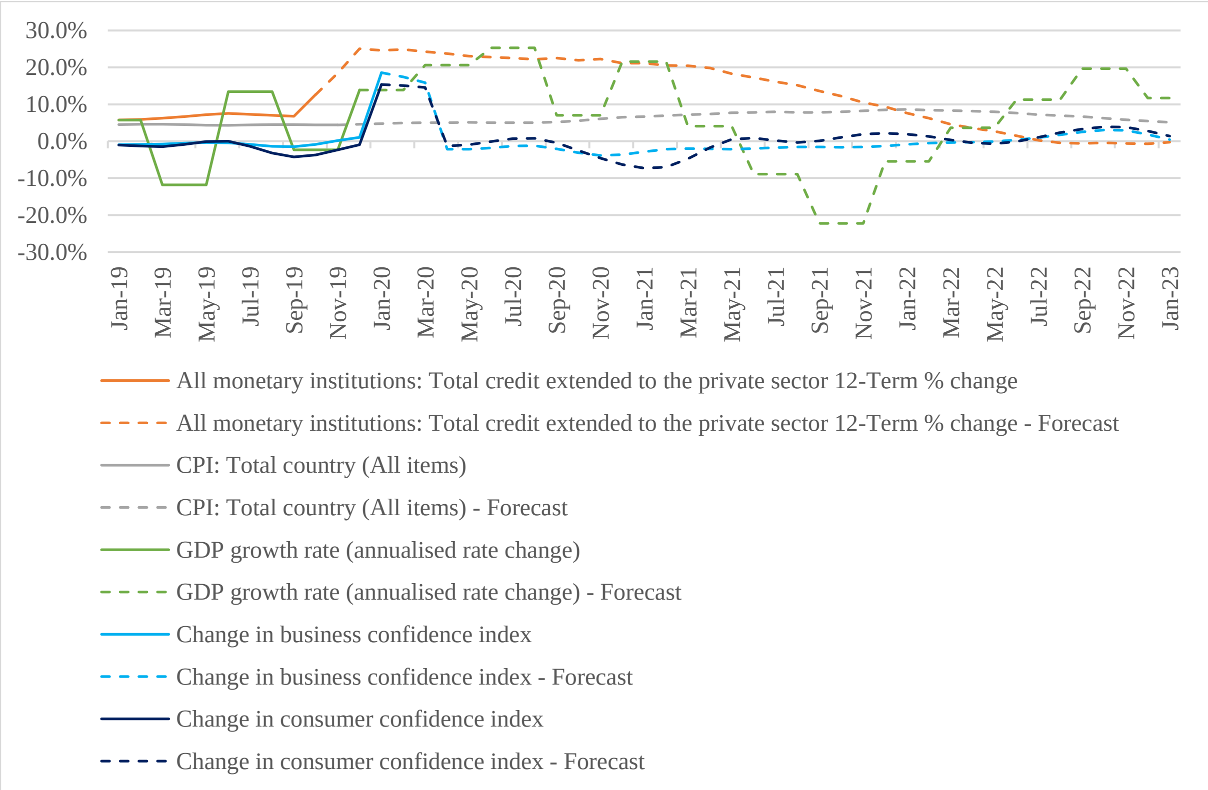

Figure 64: Stressed credit extension, CPI, GDP, consumer and business confidence forecasts

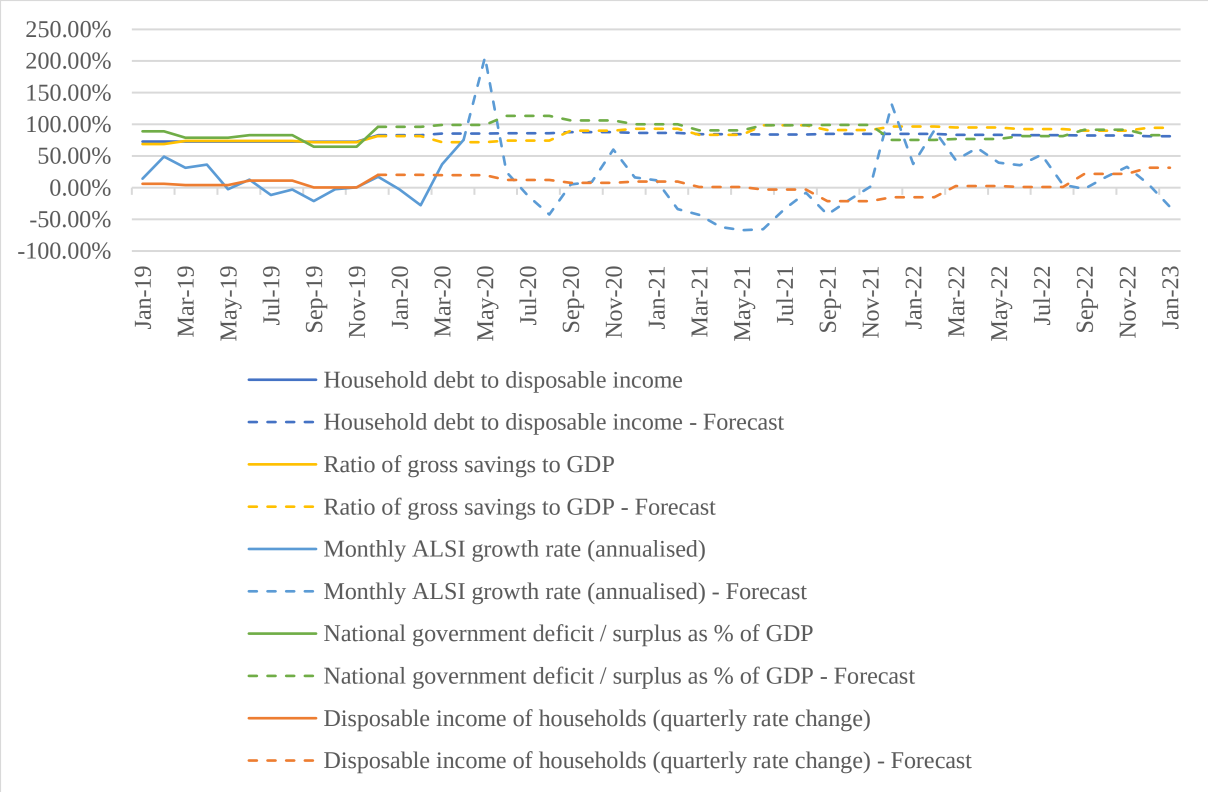

Figure 65:Stressed all share index growth, household disposable income, debt to GDP, saving to GDP and household debt to GDP forecasts

6.2 Project loans and advances volumes per category

The volume of company, secured retail, retail mortgage, retail credit facilities, retail unsecured, government, short term and developmental loans needs to be forecast. This is done by running the forecasted macroeconomic factors through the loan volume forecast model from section 3.4 . Running the indicative forecast through the loan volume projection module produces the following growth rates per loan category:

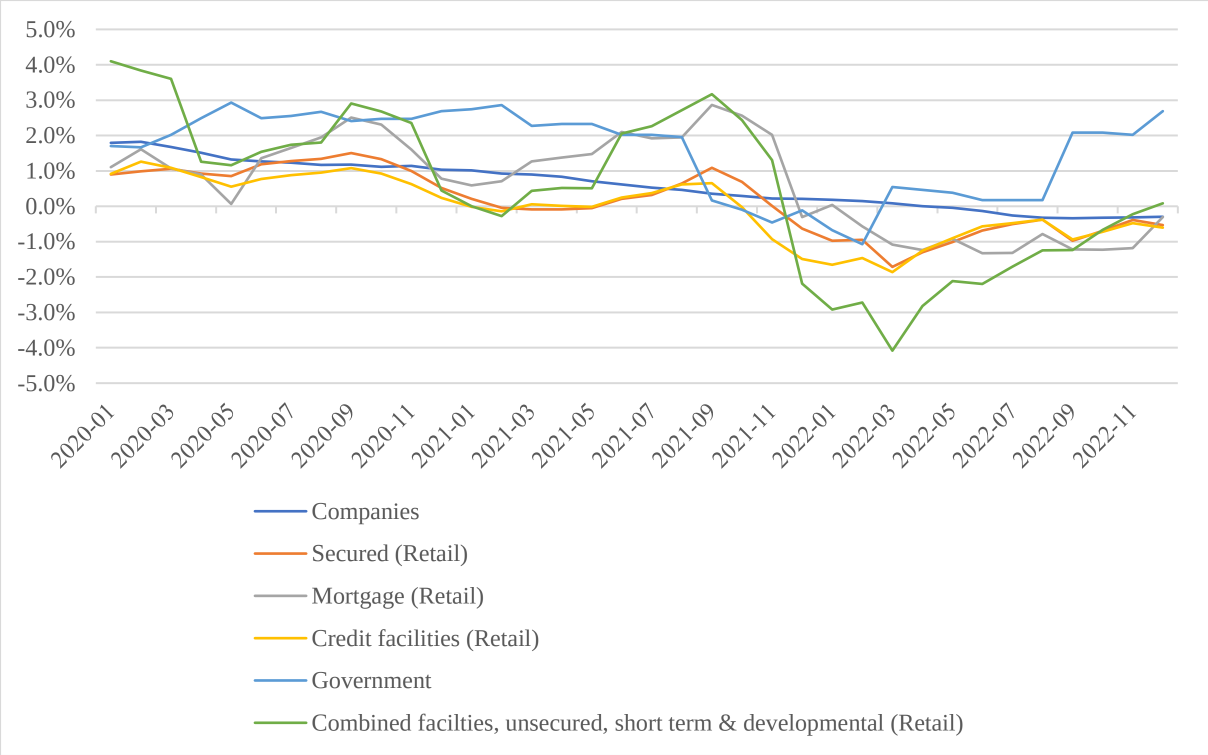

Figure 66: Projected loan growth rates per loan category under indicative stress scenario

These growth rates can then be applied to the starting volume of loans per category for each bank.

6.3 *Forecast changes in credit impairments*

Once the volume of loans per category has been forecasted, the credit impairment per category can be forecasted. This is done by running the forecasted macroeconomic factors through the loan volume forecast model from section 3.2 . Running the indicative forecast through the credit index projection module produces the following growth rates per loan category:

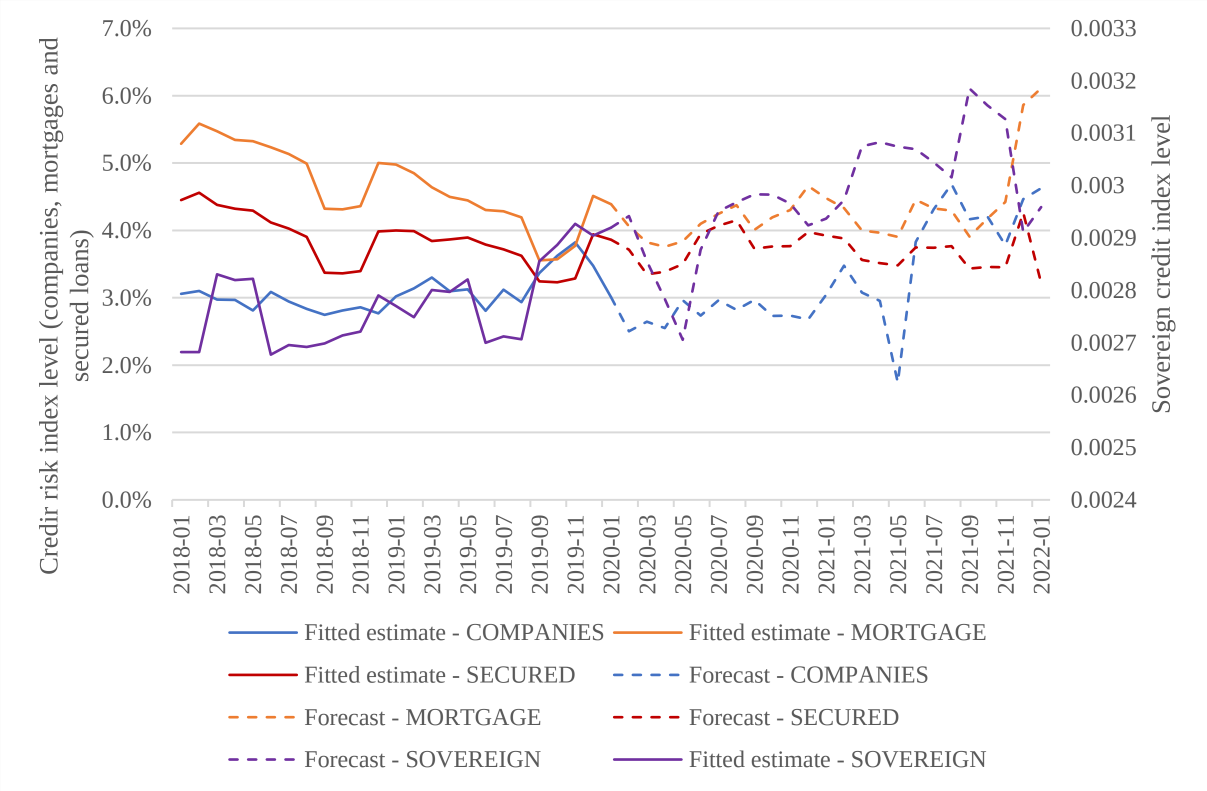

Figure 67: Forecasted credit risk index of companies, mortgages, secured and sovereign loans

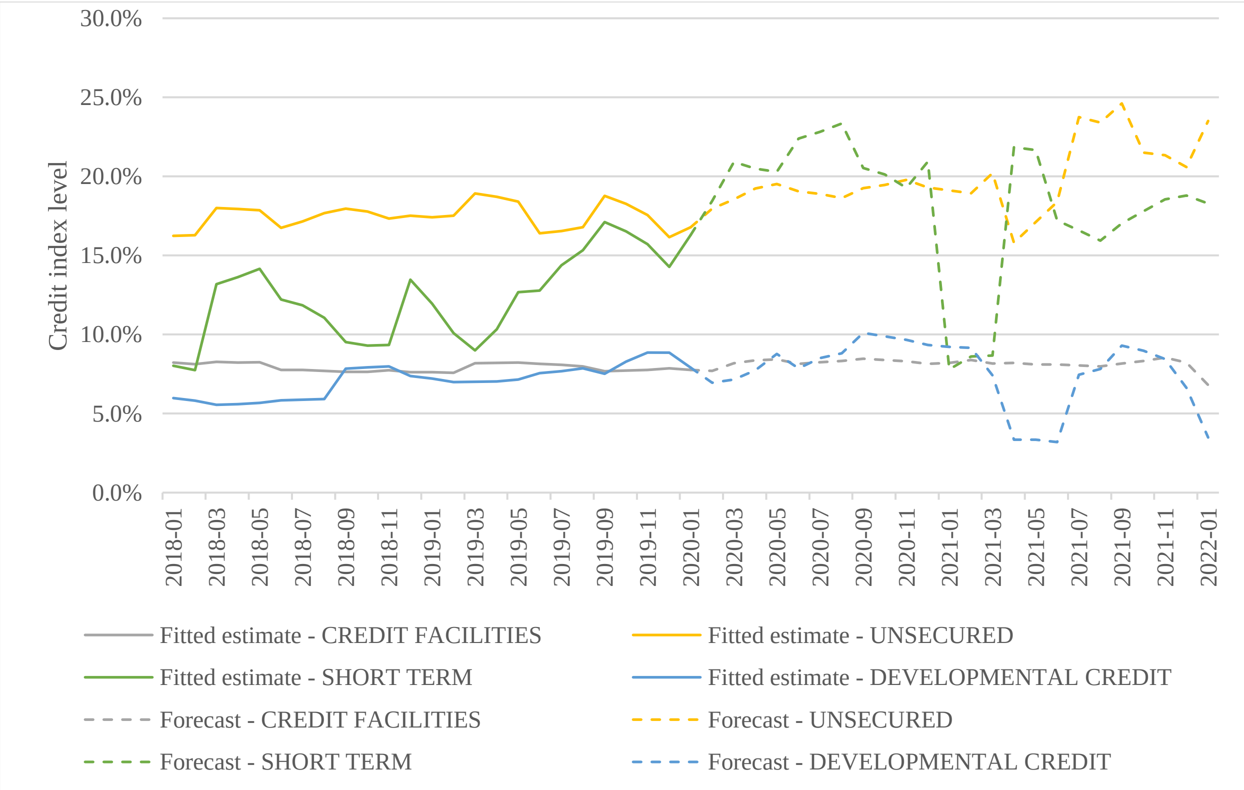

Figure 68: Forecasted credit risk index of unsecured loans, credit facilities, short term loans and developmental credit

These credit indices represent the increase in credit risk due to the stressed macroeconomic scenario.

To estimate credit impairments the volume of loans per category needs to be combined with the forecasted credit risk indices to produce a combined credit risk index for each bank. Based on the average risk level and sensitivity to the index an impairment coverage ratio is estimated. Note that the long run average impairment level is increased in line with each bank's specific increase in impairment from IAS39 to IFRS9 to be reflective of current levels of impairment. This impairment calculation is done in line with the method of section 3.3 . The combined impact on all five banks are as follows:

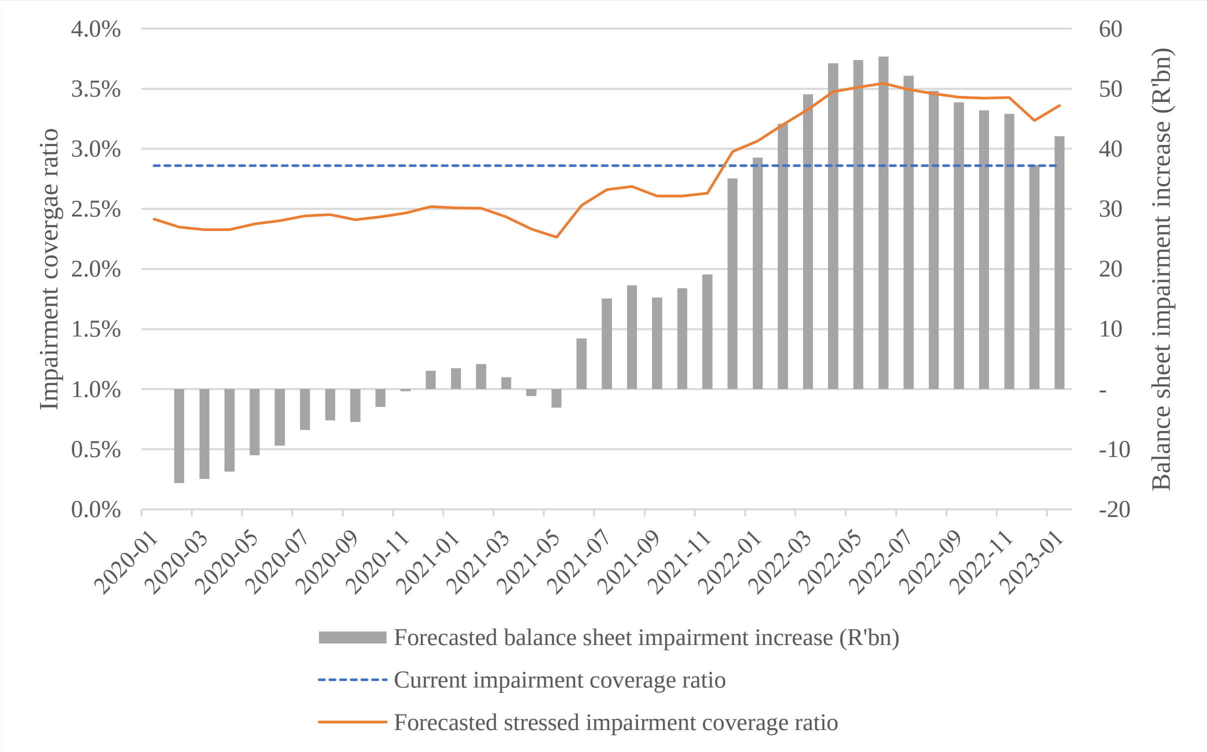

Figure 69: Forecasted increase in impairment under stress

For the above graph it can be seen that a repeat of conditions associated with the 2008 global financial crisis would lead to a R55 billion peak increase in balance sheet impairments for the largest five banks by June 2022.

6.4 *Forecasted bank deposit volumes*

From a liability perspective bank deposits need to be forecasted. The volume of bank, retail corporate, financial institution and government and SOE deposits needs to be forecast. This is done by running the forecasted macroeconomic factors through the market deposit volume forecast model from section 4.2.4 . Running the indicative forecast through the market deposit volume projection module produces the following market deposit volumes per deposit category:

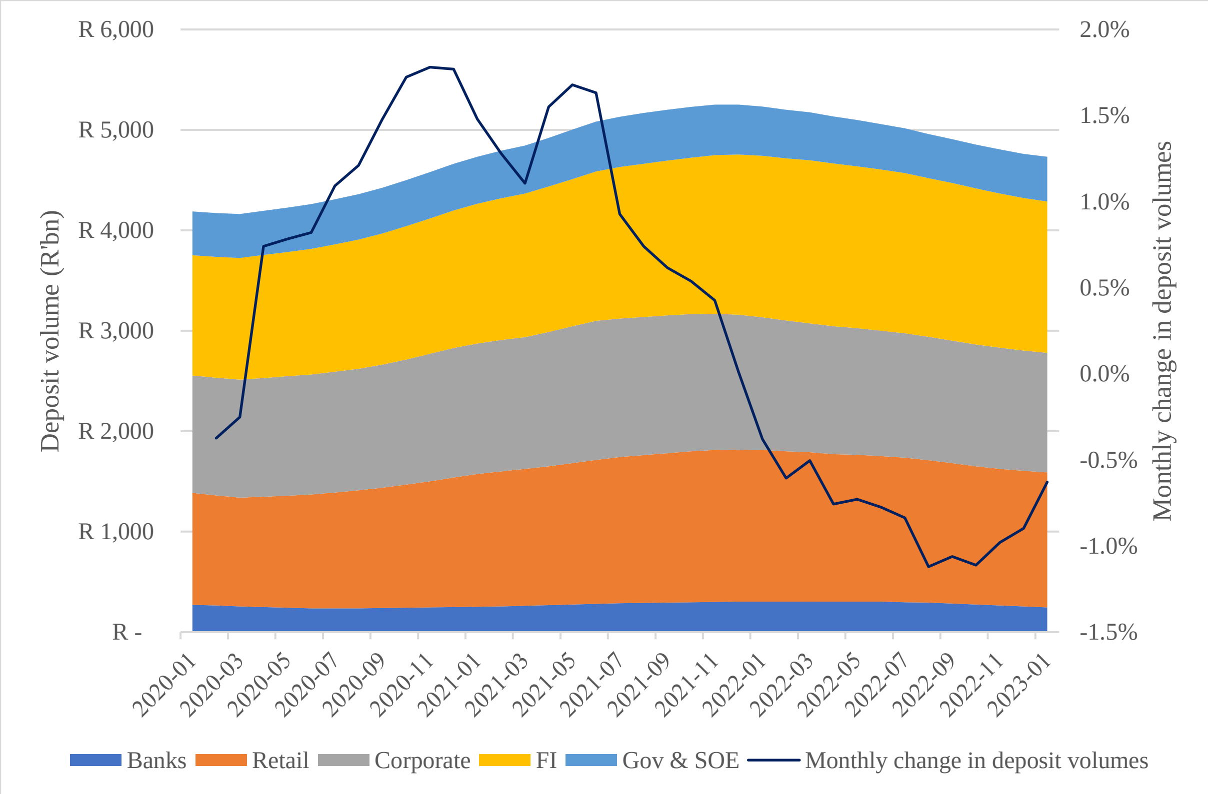

Figure 70: Forecasted overall change in market deposit volumes and market deposit volumes per deposit category

Once the market deposit volumes have been forecast, the market share of each bank can be simulated based on the method in section 4.3 . This will allow the variability for each bank to be considered.

6.5 *Simulation of bank specific deposit moves*

Once the total market volume of deposits has been forecasted, the bank specific deposit volume fluctuations due to changes in market share can be simulated. Market share is not driven by macroeconomic conditions and is therefore simulated based on the time series relationships described in section 4.3 . The simulation is done by generating random numbers between 0 and 1 that is then used to calculate the normal standard term for each bank deposit category for each point in time. The error terms are then used to forecast the market share for each deposit category for 100 simulations. The results per bank is presented below:

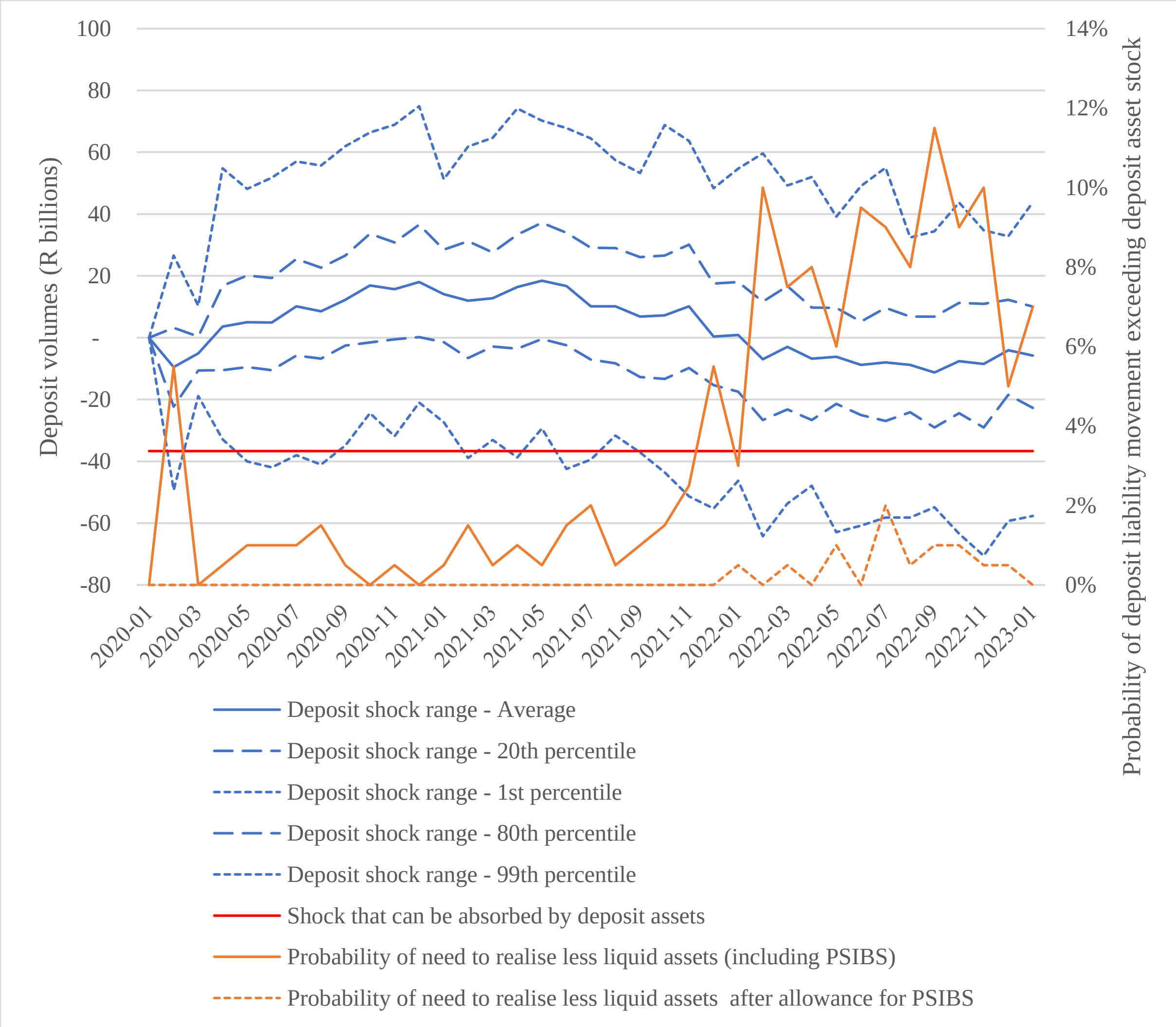

Figure 71: Simulated range of deposit changes that reflects the overall market movement and potential market share movements and the corresponding deposits assets available to cover sudden reduction in deposit liabilities for Absa

Figure 71 shows that there is a fair probability (12%) that public sector interest bearing securities need to be realised by Absa during a period of stress. The probability that less liquid assets also need to be realised is however, small (2%). Even the size of the shortfall of R34bn before public sector interest bearing securities is taken into account is small compared to the overall bank equity level of R90bn.

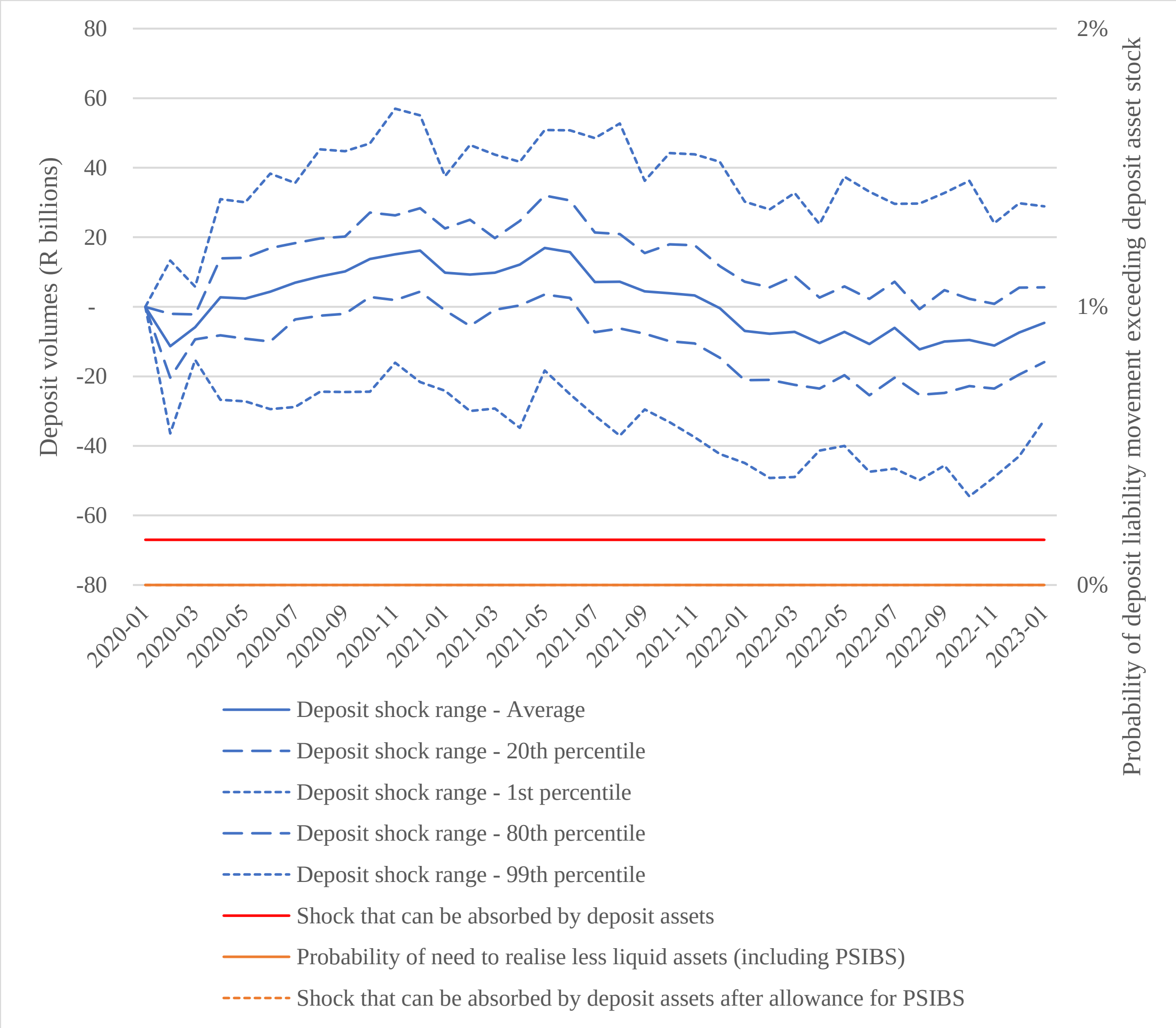

Figure 72: Simulated range of deposit changes that reflects the overall market movement and potential market share movements and the corresponding deposits assets available to cover sudden reduction in deposit liabilities for FirstRand

Figure 72 shows that none of the simulations showed that FirstRand need to realise public sector interest bearing securities or other less liquid securities during a period of stress. This is due to the large volume of bank and SARB deposit assets held by FirstRand.

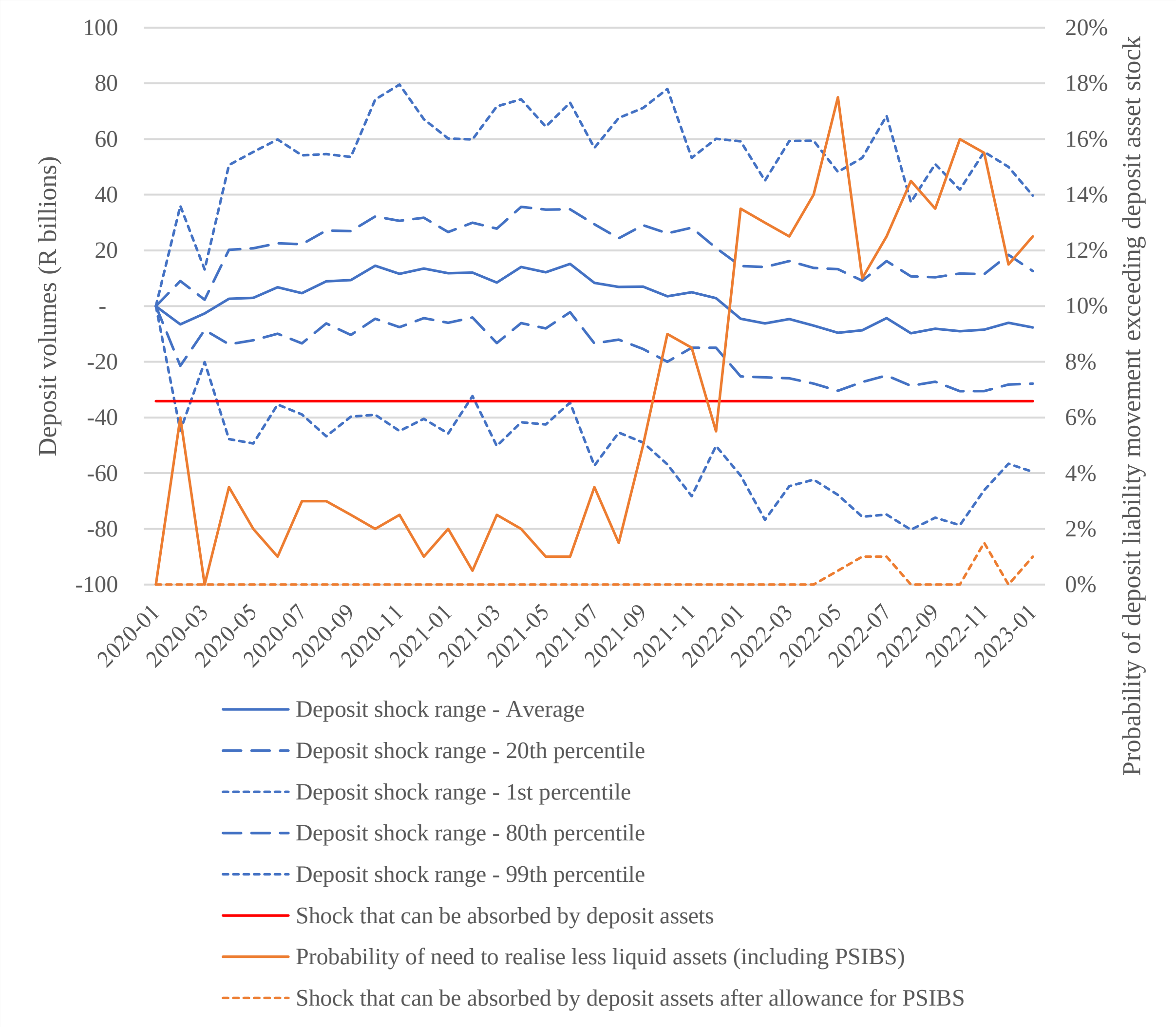

Figure 73: Simulated range of deposit changes that reflects the overall market movement and potential market share movements and the corresponding deposits assets available to cover sudden reduction in deposit liabilities for Nedbank

Figure 73 shows that there is a fair probability (18%) that public sector interest bearing securities need to be realised by Nedbank during a period of stress. The probability that less liquid assets also need to be realised is however, small (2%). Even the size of the shortfall of R46bn, before public sector interest bearing securities is taken into account, is small compared to the overall bank equity of R81bn.

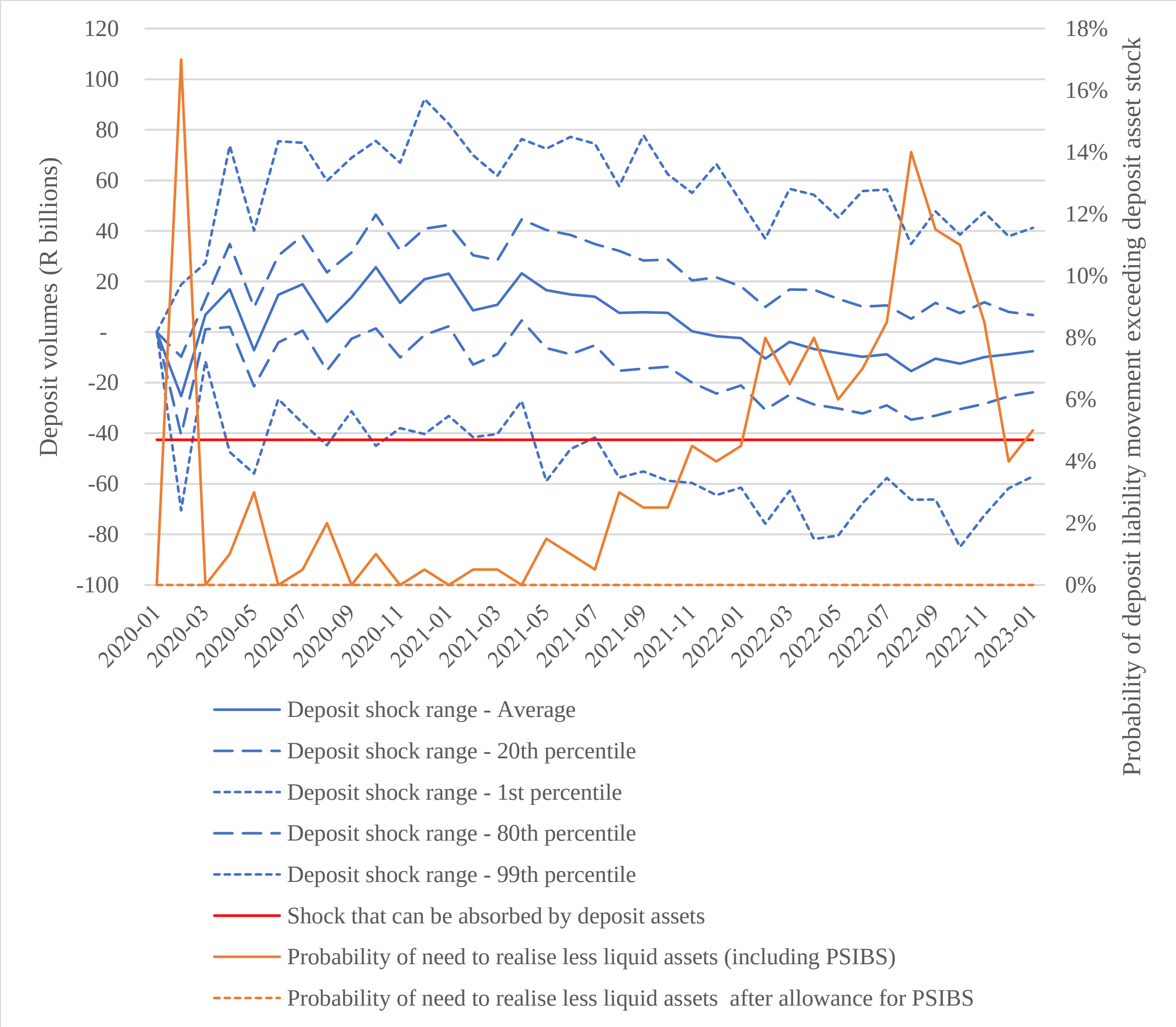

Figure 74: Simulated range of deposit changes that reflects the overall market movement and potential market share movements and the corresponding deposits assets available to cover sudden reduction in deposit liabilities for Standard Bank

Figure 74 shows that there is a fair probability (17%) that public sector interest bearing securities need to be realised by Standard Bank during a period of stress. There is however, no simulation where less liquid assets also needed to be realised. Even the size of the shortfall of R42bn, before public sector interest bearing securities is taken into account, is small compared to the overall bank equity of R103bn.

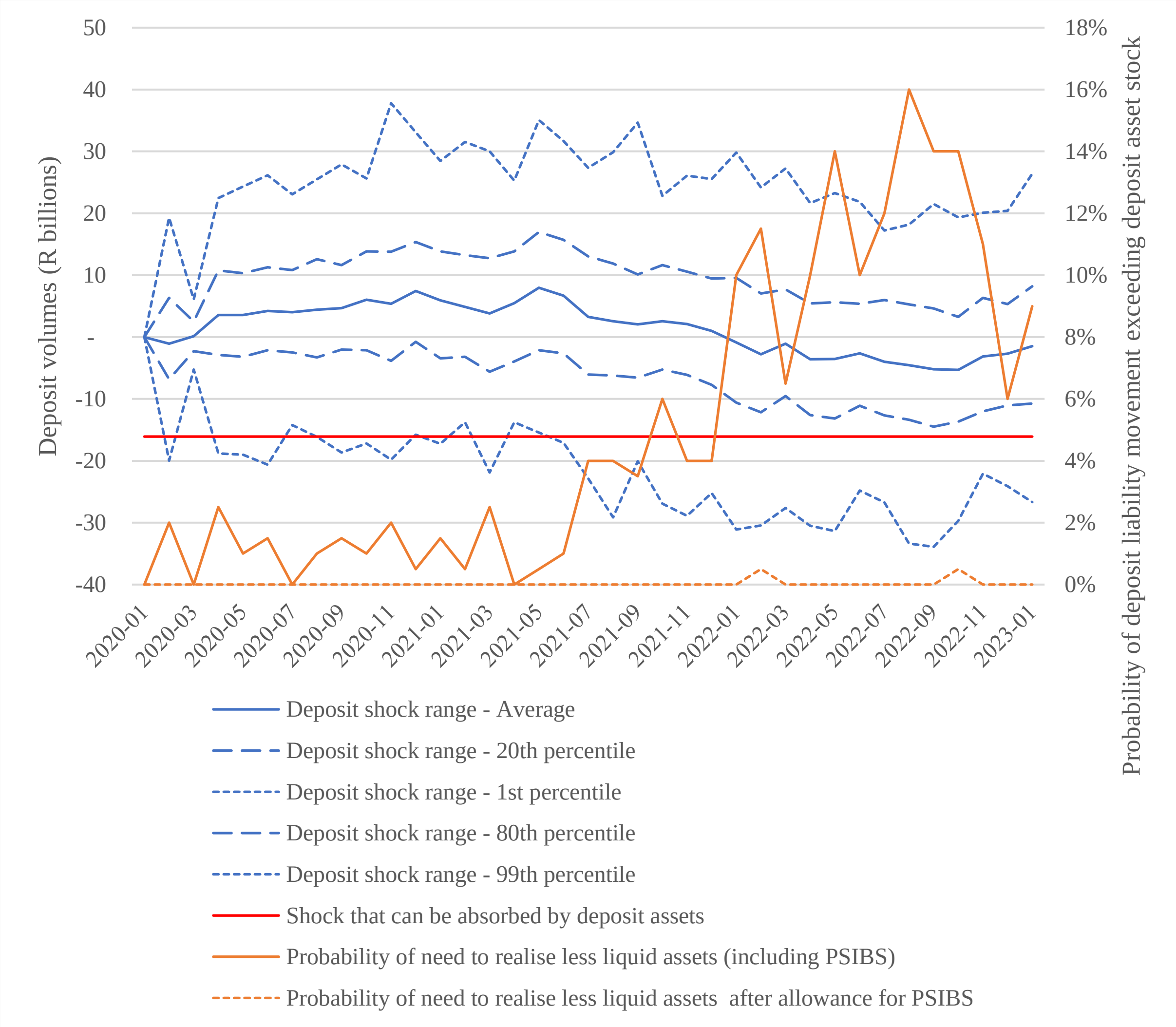

Figure 75: Simulated range of deposit changes that reflects the overall market movement and potential market share movements and the corresponding deposits assets available to cover sudden reduction in deposit liabilities for Investec

Figure 75 shows that there is a fair probability (16%) that public sector interest bearing securities need to be realised by Investec during a period of stress. The probability that less liquid assets also need to be realised is however, small (1%). Even the size of the shortfall of R18bn, before public sector interest bearing securities is taken into account, is small compared to the overall bank equity of R38bn.

6.6 *Simulation of bank specific equity movements*

Although movements in credit impairments is the one of the primary drivers of bank losses during stressed periods, other movements in the bank equity levels can also occur. Movements in bank equity levels is therefore also simulated by combining expected changes in credit impairments with other movements in bank equity levels described in section 5. The simulation is done by generating random numbers between 0 and 1 that is then used to select equity movements from the empirical equity movement distribution. This is then combined with the expected movements in credit impairment to forecast the bank equity level for 100 simulations. The level of equity can in turn be compared to the minimum core equity tier 1 ("CET1") capital requirement of 7.5% with bank specific add-ons of roughly 1% [51]-[55] of RWA. The RWA is estimated for future months by assuming the credit risk RWA moves in proportion to the total volume of loans. This is a conservative assumption since increased credit risk impairments are likely to lead to reduced capital requirements since the gap between capital tail risk estimates and current risk estimates represented by credit impairments are narrower. The reduction in RWA under stress is a future enhancement that can be added to this model structure the results per bank is presented below.

Figure 76 and Figure 77 shows the resilience of Absa from a capital perspective. Minimum CET1 capital requirements are not breached in any of the simulations under stress.

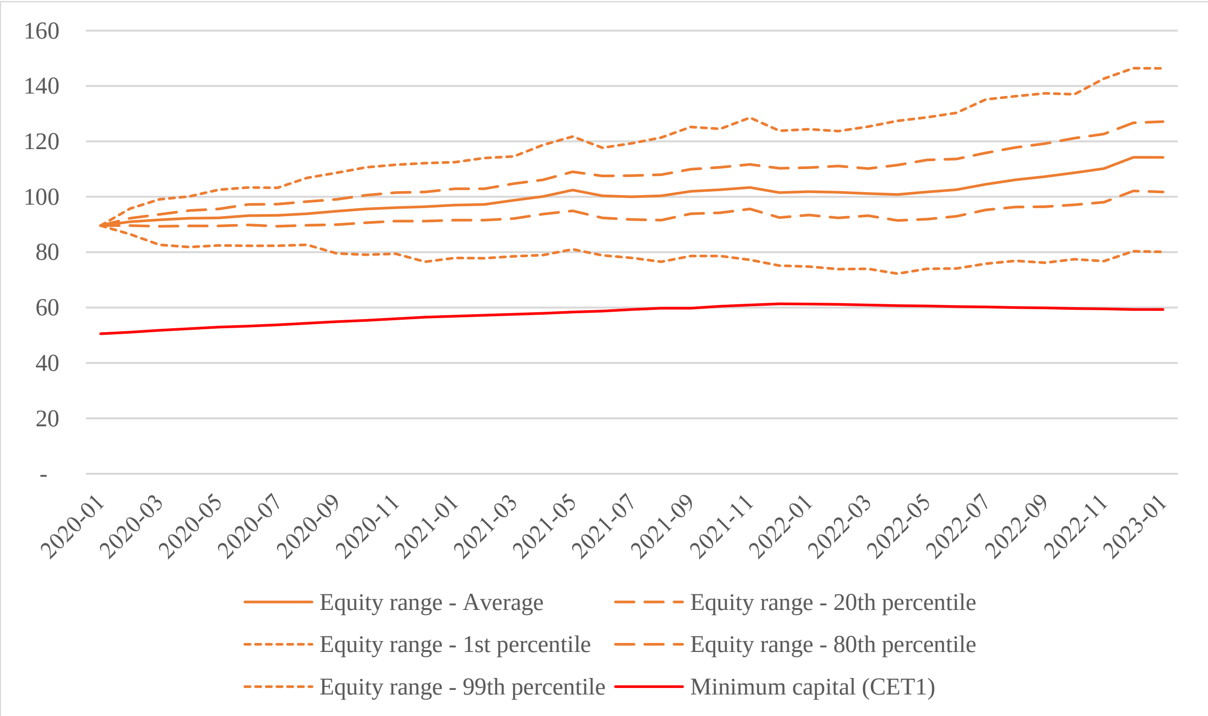

Figure 76: Simulated range of equity levels and the minimum CET1 level that needs to be covered by equity for Absa

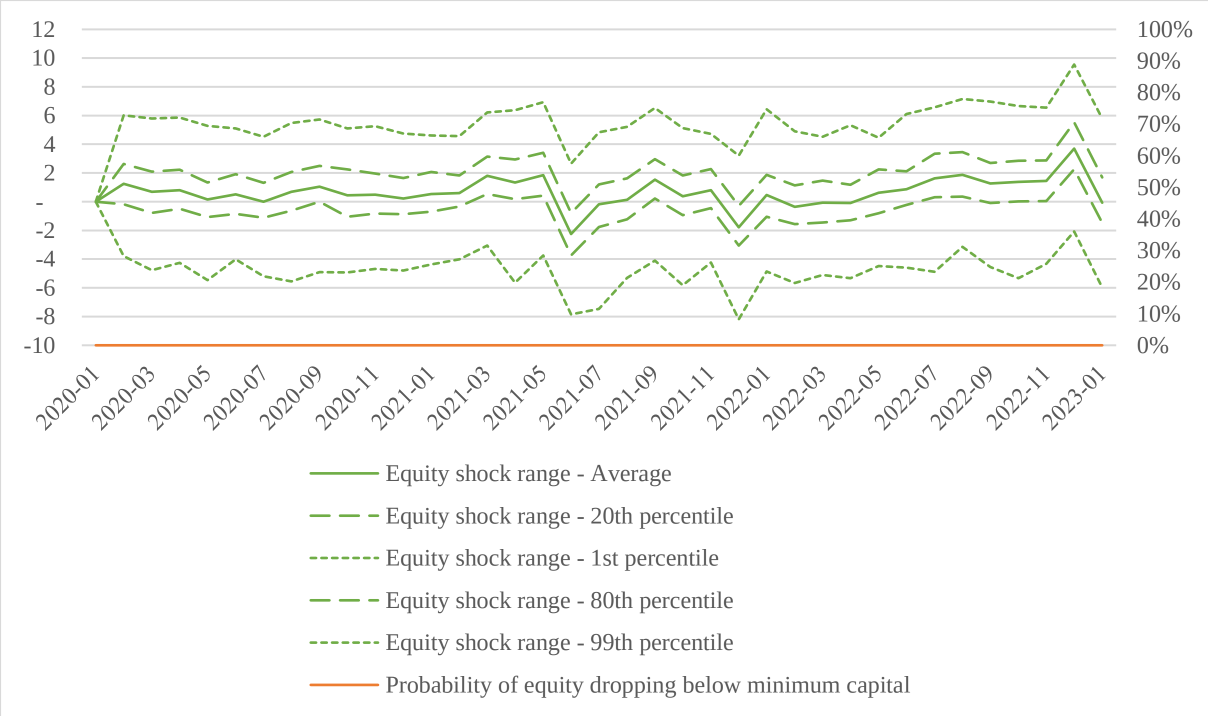

Figure 77: Simulated range of equity movements and the corresponding probability that equity drops below the minimum CET1 level for each future month for Absa

Figure 78 and Figure 79 shows the resilience of FirstRand from a capital perspective. Minimum CET1 capital requirements are not breached in any of the simulations under stress.

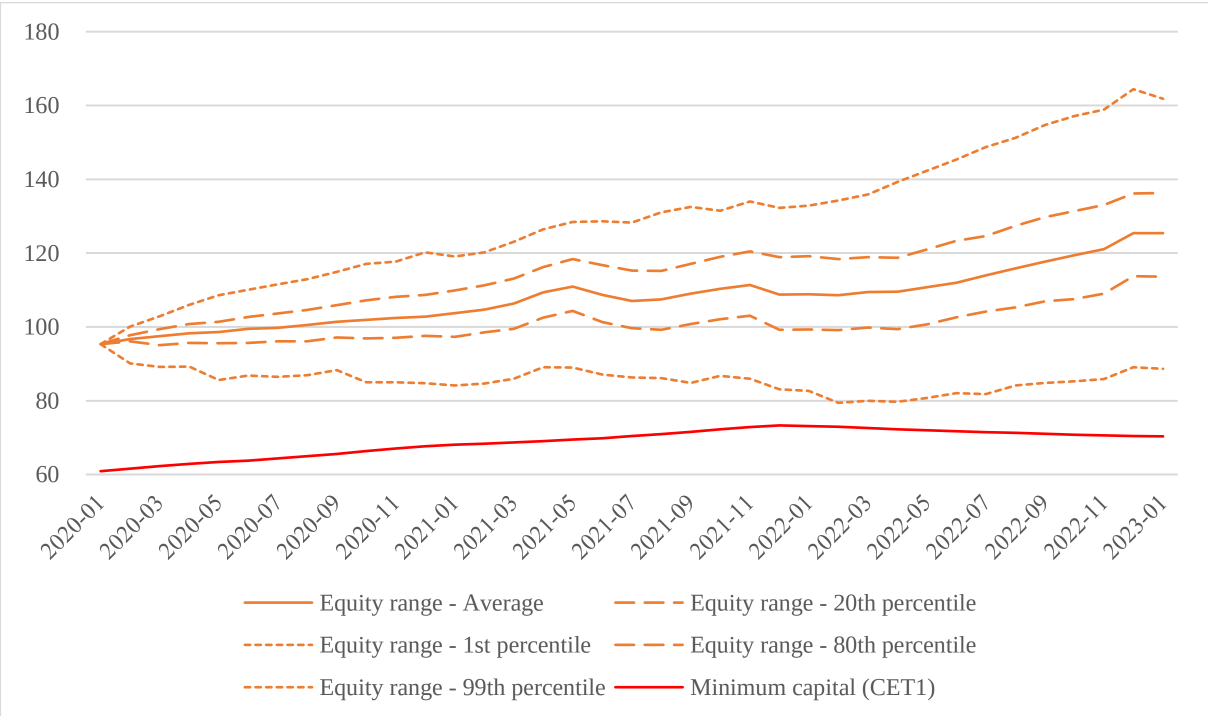

Figure 78: Simulated range of equity levels and the minimum CET1 level that needs to be covered by equity for FirstRand

Figure 80 and Figure 81 shows the resilience of Nedbank from a capital perspective. Minimum CET1 capital requirements are not breached in any of the simulations under stress.

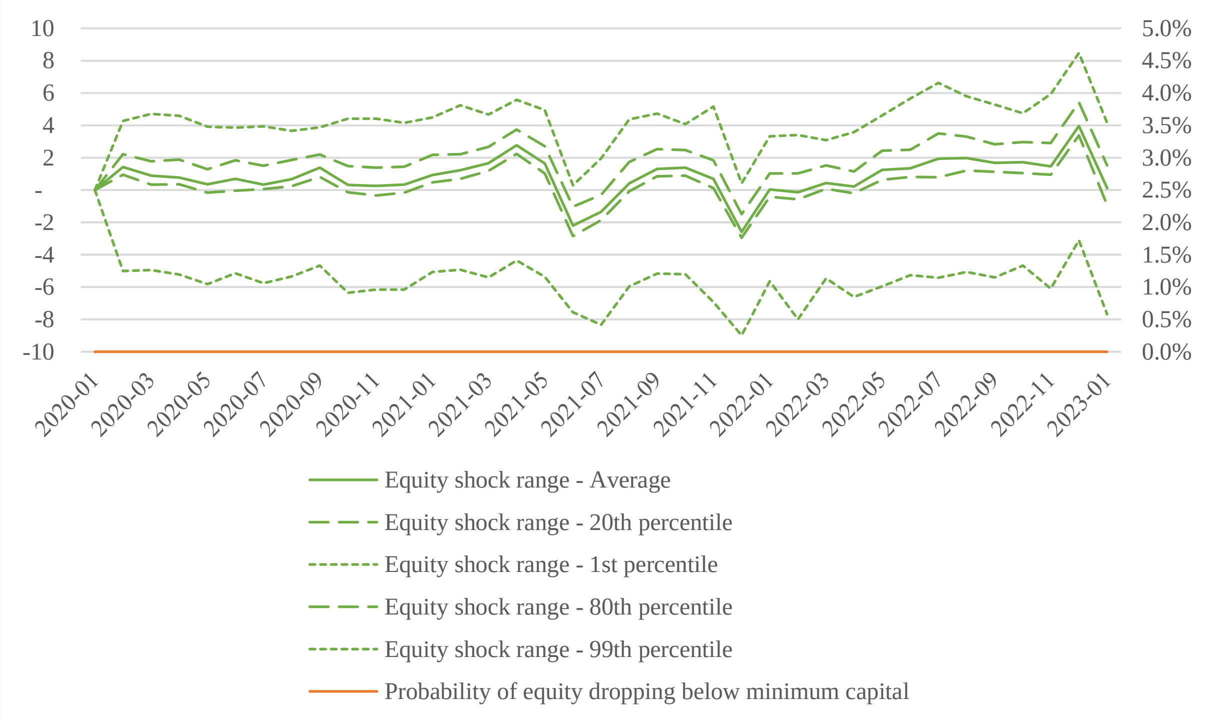

Figure 79: Simulated range of equity movements and the corresponding probability that equity drops below the minimum CET1 level for each future month for FirstRand

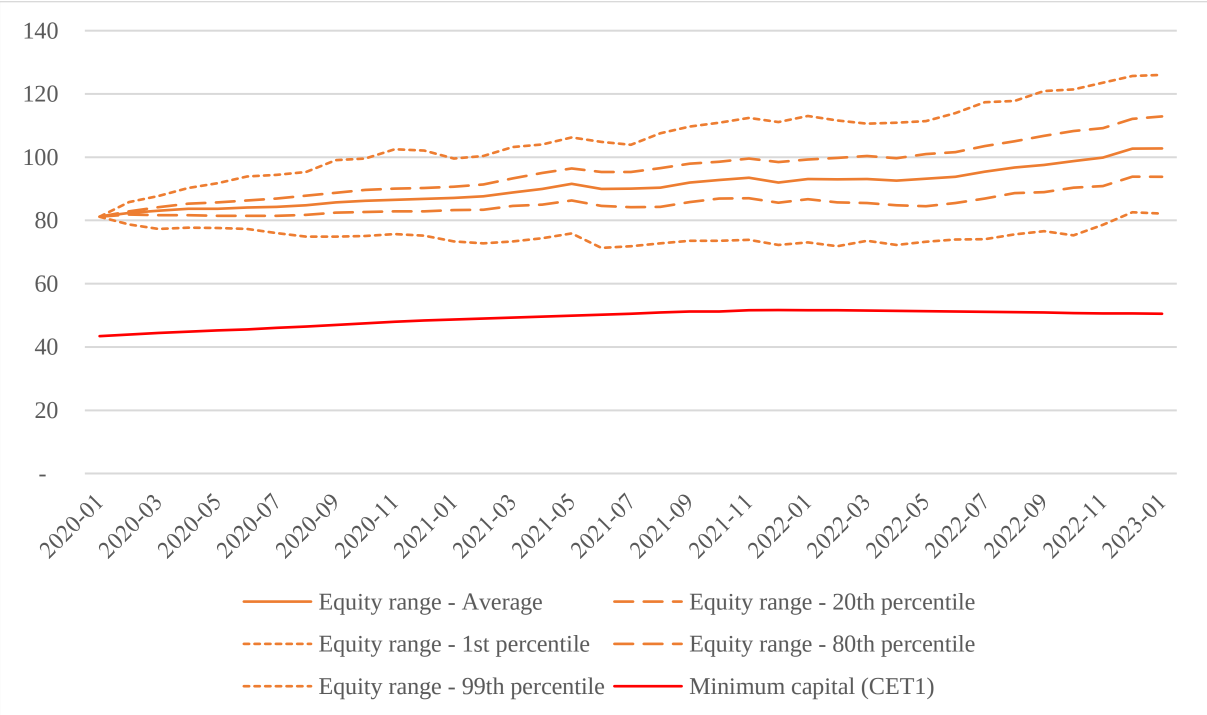

Figure 80: Simulated range of equity levels and the minimum CET1 level that needs to be covered by equity for Nedbank

Figure 82 and Figure 83 shows the resilience of Standard Bank from a capital perspective. Minimum CET1 capital requirements are not breached in any of the simulations under stress.

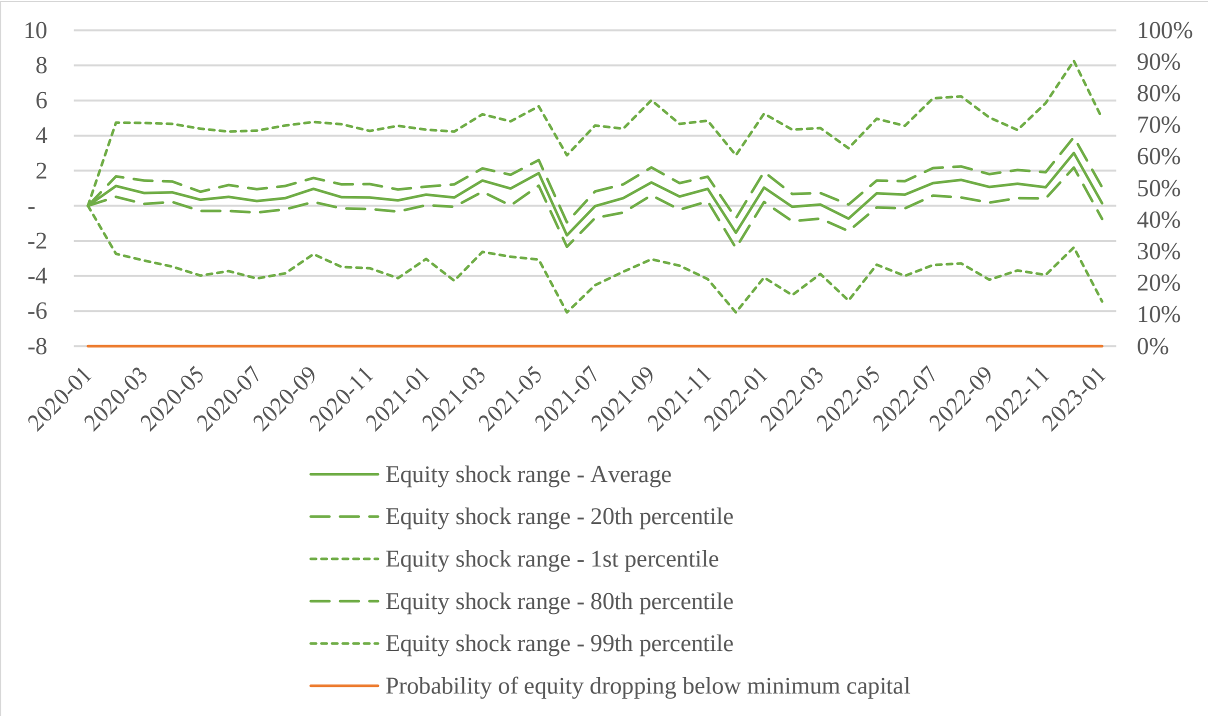

Figure 81: Simulated range of equity movements and the corresponding probability that equity drops below the minimum CET1 level for each future month for Nedbank

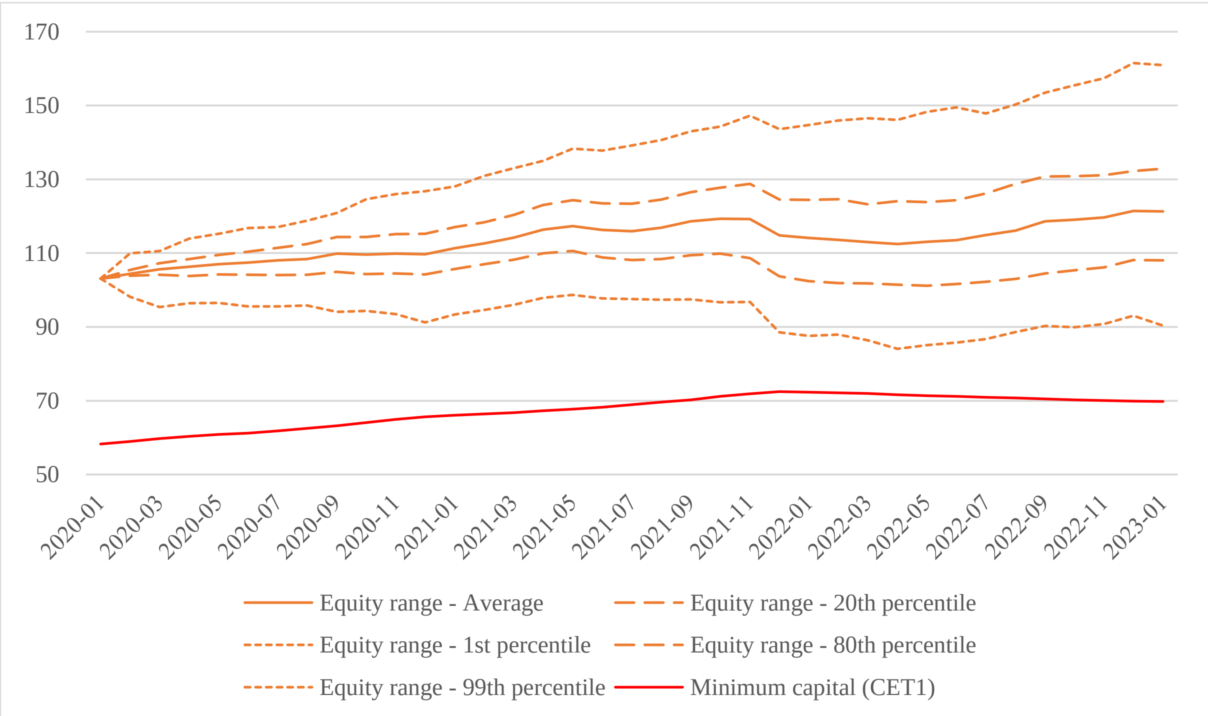

Figure 82: Simulated range of equity levels and the minimum CET1 level that needs to be covered by equity for Standard Bank

Figure 84 and Figure 85 shows the resilience of Investec from a capital perspective. Minimum CET1 capital requirements are not breached in any of the simulations under stress.

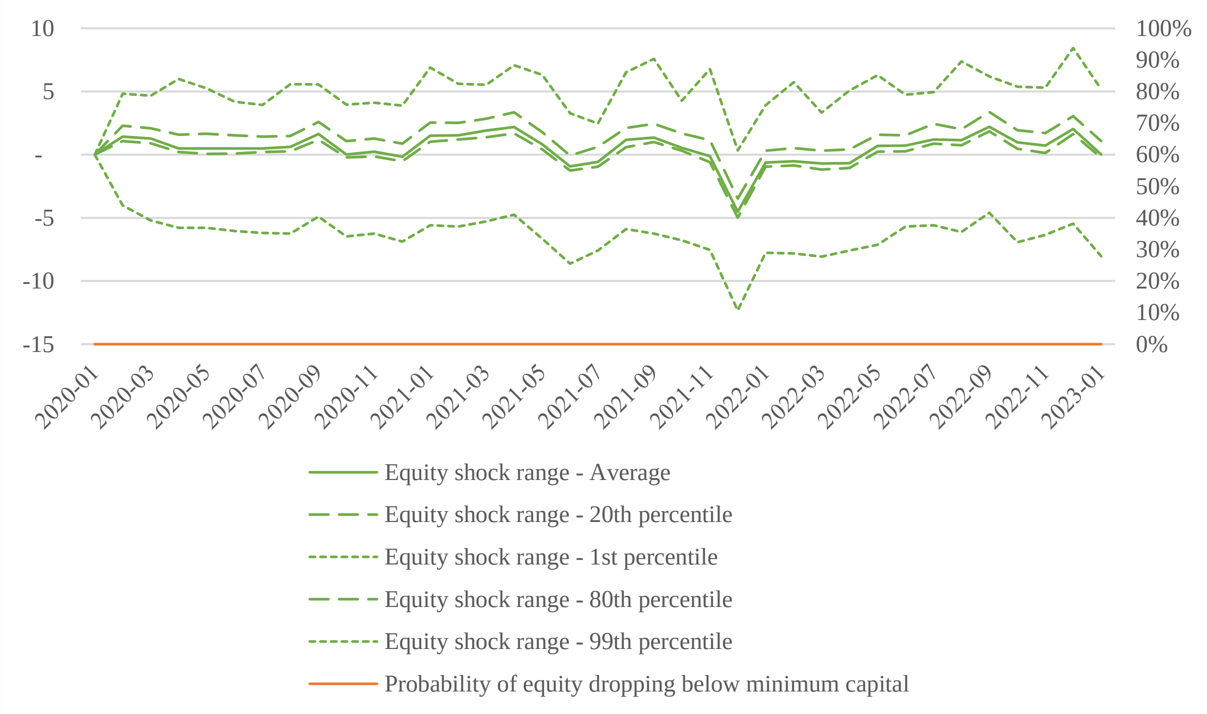

Figure 83: Simulated range of equity movements and the corresponding probability that equity drops below the minimum CET1 level for each future month for Standard Bank

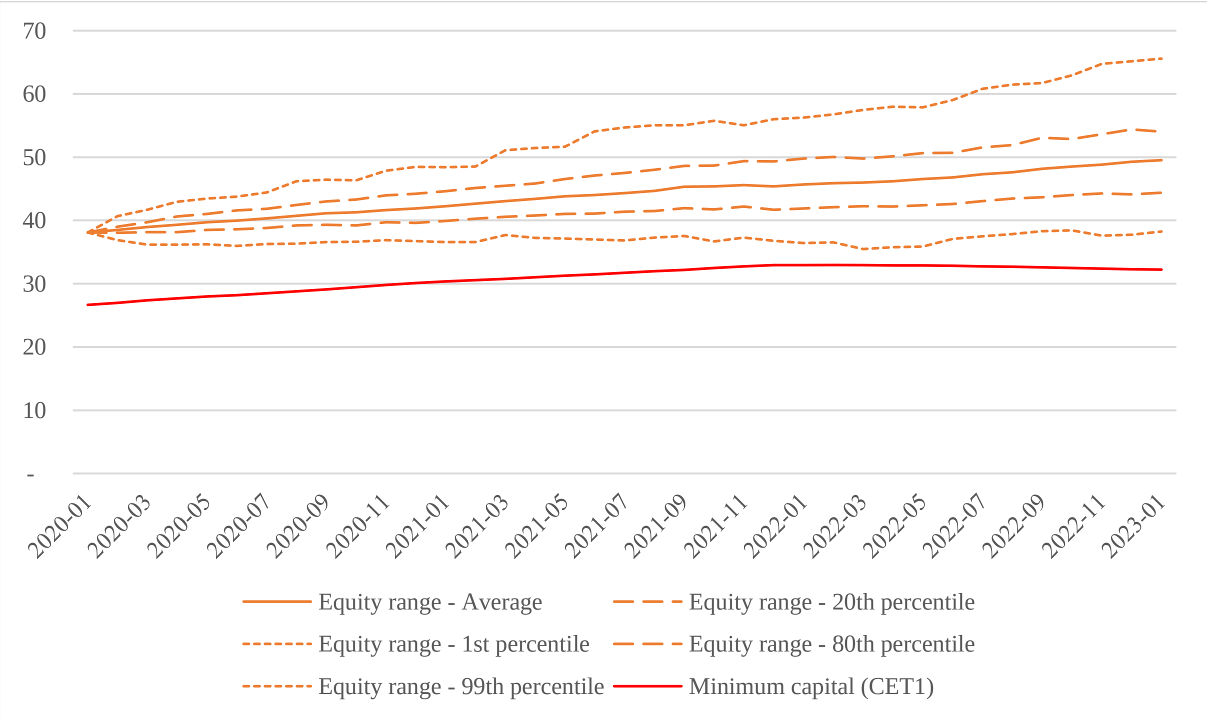

Figure 84: Simulated range of equity levels and the minimum CET1 level that needs to be covered by equity for Investec

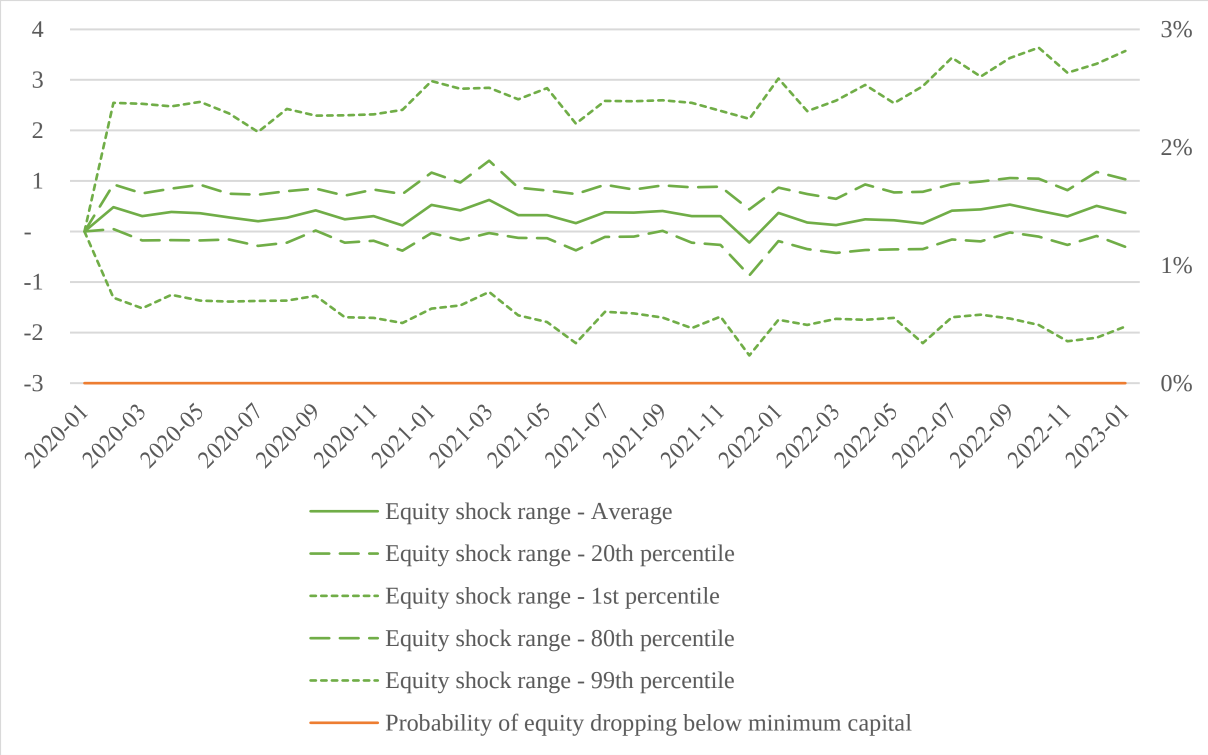

Figure 85: Simulated range of equity movements and the corresponding probability that equity drops below the minimum CET1 level for each future month for Investec

From Figure 76 to Figure 85 it can be seen that none of the banks breach CET1 requirements under a scenario similar to the 2008 global financial crisis.

Chapter 7

7. Conclusion

The financial cycle is characterised by various crises that occur due to a variety of reasons. The severe consequences and complex and interrelated nature of the financial systems have driven the development and refinement of various macro-prudential tools used by regulators. Stress testing is one of these tools that have been refined with significant development happening since the 2008 global financial crisis. Each crisis will, however, have its own unique features which will allow stress testing to evolve and be refined over time.

The USA and UK have sophisticated stress testing requirements that include top-down models that are used to asses systemic risk and check detailed bank level stress tests submitted by individual banks. Both jurisdictions use detailed balance sheet modelling where individual balance sheet components are modelled in a way that represents the underlying risks and available data.

An investigation into stress testing in South Africa has not revealed a similar top-down model being used by the SARB. The development of a top-down stress test model that that draws from a range of principles, including the USA and UK models, will therefore assist in the refinement of stress testing in South Africa. The market is dominated by five large banks that cover 94% of loans and 92% of deposits as at April 2019. The majority of lending is also concentrated in a limited number of large products such as mortgage loans [35].

7.1 Key modelling components

Bank balance sheets are dominated by loans and advances that make up 61% of all assets and deposits that make up 77% of the liabilities (refer to Figure 1) for the five largest full service banks in South Africa. Loans and advances and deposits also correspond to credit and liquidity risk. Stress testing considers bank resilience under severe stress so the consideration of credit and liquidity risk is key since economic conditions will directly drive credit losses and bank deposit levels. While idiosyncratic events such as fraud or large trading losses can also cause bank failures, the primary cause of such events is the choices of individuals and banks rather than economic conditions and was therefore not considered beyond the use of simulated equity shocks in this study. The five banks being considered have however, experienced large historic movements in equity in the past (see Figure 59 and Figure 60) so allowance is made through the simulation of equity movements.

This research and development of a top-down stress test model shows that top-down modelling of key balance sheet elements such as loans and advances, credit risk impairments, deposit volumes and general movements in equity levels can be used to model the resilience of banks under stress. It is possible to develop a top-down model that focuses on a manageable number of balance sheet lines while still producing realistic results for the entire banking system. The model is also set up in an automated manner to allow updates of bank balance sheets in an efficient manner. The top-down nature of the model also allows repeatable and efficient running of macroeconomic scenarios.

7.2 Macroeconomic drivers of credit risk

The modelling shows that interest rates are a key driver of the overall level of credit risk in the banking system. This includes the prime lending rate and government bond yields over various periods such as 0 to 3 years, 3 to 5 years, 5 to 10 years and more than 10 years. High inflation and high household debt to disposable income are also significant contributors to the level of credit risk. Key drivers per lending category however, varies. For retail secured and mortgage lending categories interest rates and household debt to disposable income is the most important drivers of credit risk. For retail unsecured credit the level of credit extension, inflation rates, GDP growth and household disposable income are key. For corporates the level of interest rates and growth in the stock market are the key macroeconomic indicators. The level of sovereign credit risk is driven by inflation, disposable income of households and the ratio of gross savings to GDP. Consideration of the macroeconomic conditions during the 2008 global financial crises, however, also shows that not all macroeconomic variables are equally stressed when credit impairment levels peak. It is the combination of moderate to severe stresses in multiple variables (see Figure 34 to Figure 36) that correspond to a period of severe stress in credit risk. This also implies that an isolated stress in a single variable such as a stock market crash may not lead to a stress in credit risk for banks if the other drivers or indicators of credit risk are not stressed.

7.3 Drivers of bank liquidity risk

Historic data and modelling of bank deposits show that the overall volume of bank deposits and the market share of each bank needs to be considered as both drive the liquidity risk of banks. A bank can therefore experience liquidity strain due to a reduction in market deposits or reduction in deposit market share that can be more volatile than movements in the market volume of bank deposits (see Figure 49 to Figure 53).

The modelling shows that the key macroeconomic factors that drive the volume of bank deposits include total credit extended to the private sector, CPI, ALSI level, GDP, household disposable income, the national government surplus/deficit, gross savings to GDP and household debt to disposable income. The key drivers for individual deposit customer types are, however, different. Retail deposits are positively affected by gross savings to GDP and credit extended to the private sector and negatively affected by business confidence and the national government surpluses. Government and SOE deposits on the other hand is positively affected by business and consumer confidence and negatively affected by CPI and household debt to disposable income. Financial institution deposits are positively affected by disposable income of household and credit extended to the private sector and disposable income of households and negatively impacted by CPI and national government surpluses. Corporate deposits are positively impacted by GDP and disposable income of households and negatively by inflation and household debt to disposable income. Bank deposits are positively impacted by the level of the ALSI and disposable income of households and negatively impacted by business confidence and a national government surplus. It should be noted that the overall impact of business confidence is low, and that high business confidence seems to show a flow of deposits from retail clients and banks into corporates and the government. A smaller national government deficit or surplus seems to lead to lower overall deposits which could be the consequence of increased tax collection that drives the surplus.

7.4 Assessing bank resilience

Combining the key modelling components allow the resilience of banks under severe macroeconomic stress to be considered. Credit risk as represented by credit impairments, liquidity risk as represented by the availability of liquid assets to cover reductions in deposit volumes and simulated movements in equity needed to cover minimum capital requirements all need to be considered to assess the resilience of banks.

The combined modelling shows that the banks under consideration are resilient to large macroeconomic stress. The modelling also shows that a bank failure will likely be driven by a combination of factors rather than a single element in isolation. For example, a general equity stress event must be combined with a credit risk impairment stress to threaten the capital adequacy (as represented by CET1) of these banks. None of the banks breached their conservatively estimated CET1 requirement in the severe stress scenario being considered. The modelling however, showed that banks would be more vulnerable to liquidity risk. The combination of a drop in overall bank deposit volumes with a drop in bank market share could require the sale of less liquid assets or assistance from the South African Reserve Bank as a lender of last resort. The simulations showed that the probability that banks needed to rely on assets other than bank and central bank deposits to cover reduced deposits volumes could be as high as 18% during a period of severe stress. The availability of liquid public sector interest bearing securities however, covered most of this risk meant that further sales of less liquid assets or borrowing would only be needed in a maximum of 2% of simulations during a period of severe stress. This does, however, highlight that a sovereign debt crisis where public sector interest bearing securities become illiquid and lose value, would dramatically increase the liquidity risk of banks as well.

7.5 *Final conclusions*

The top-down stress testing model developed on publicly available information is able to capture the key drivers of bank risk that includes credit risk, liquidity risk and other movements in equity levels. Different loan products and deposit categories are also affected by different macroeconomic factors. A bank with multiple funding sources and loan products will therefore have a natural level of diversification. The modelling illustrates that the five large banks under consideration are resilient to large macroeconomic shocks and that a combination of stresses would be needed to lead to a failure in one of these banks.

7.6 *Areas of future research and model limitations*

The model that was developed focussed on the largest South African banks and the key risks. The model can be calibrated to the other South African banks to cover an even greater proportion of the market. The model can also be expanded to cover more banks, a broader range of risks and also add more granularity and complexity to the risks being modelled. The RAMSI model used by the BoE outlines some of the areas that can be expanded upon such as explicit forecasting of the bank balance sheet elements. Links to shadow banking can also be made.

Although the risk of a sovereign debt crisis it remote it dramatically increases the risk of a banking crisis when it occurs. The modelling can therefore be expanded to consider the risk of a sovereign debt crisis.

The data that underpins this study only covers the start of the COVID-19 pandemic. The exact economic impacts of the pandemic were unknown in 2020 and the subsequent credit losses may not fully emerge until the end of 2021 or 2022. An indicative COVID-19 macroeconomic scenario was however, run through the model. The results showed that the biggest banks under consideration would remain resilient even though large credit losses would be suffered[1]. Once the impact of COVID-19 is known the model performance can be tested on this period. The model can also be refined since the 2008 was the only severe stress for which sufficient data was available to develop the model. The use of machine learning techniques and a broader range of macroeconomic factors could also be used to enhance the model and capture more complex relationships between risks and macroeconomic variables.

The study focussed on the link between macroeconomic factors and stress experienced by banks. The key indicators or drivers of stress can also be used to help inform resolution strategies that can be followed by regulators. The model can also be expanded to run a variety of scenarios generated by a macroeconomic scenario model. The impact of changes bank structure such as leverage can also be investigated by expanding on this model.

The model was developed using publicly available information. This means that the loan and deposit specific information that includes default rates were not available. While periods of stress is reflected specific nuances of the bank portfolios may not be fully captured. The techniques outlined in this study can however, be applied to more granular bank specific data where it is available.

Historic data only included one severe stress in the form of the 2008 global financial crisis. The COVID-19 pandemic highlighted that macroeconomic stress can manifest in many different ways. The data from the COVID-19 pandemic can therefore be used as a backtest and incorporated into the calibration in future.

[1] https://www.pwc.co.za/en/press-room/covid-19-stress-testing-indicates-resilience-of-largest-sa-banks.html

Bank impairments and especially credit risk impairments calculated before 2018 under the IAS39 standard would only fully reflect the stress when defaults started increasing. In contrast the current impairments under the IFRS9 standard would increase as soon as the macroeconomic forecasts reflect the expected level of stress. The speed at which credit risk impairments react to stress has therefore changed although the overall level of stress should be similar. More data on the behaviour of IFRS9 impairments under stress can therefore be collected and used to refine the lags and timing of stress in the model.

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Appendix A

The figures below illustrate the historic overall impairment and the fitted impairment per bank from 2001 to 2016.

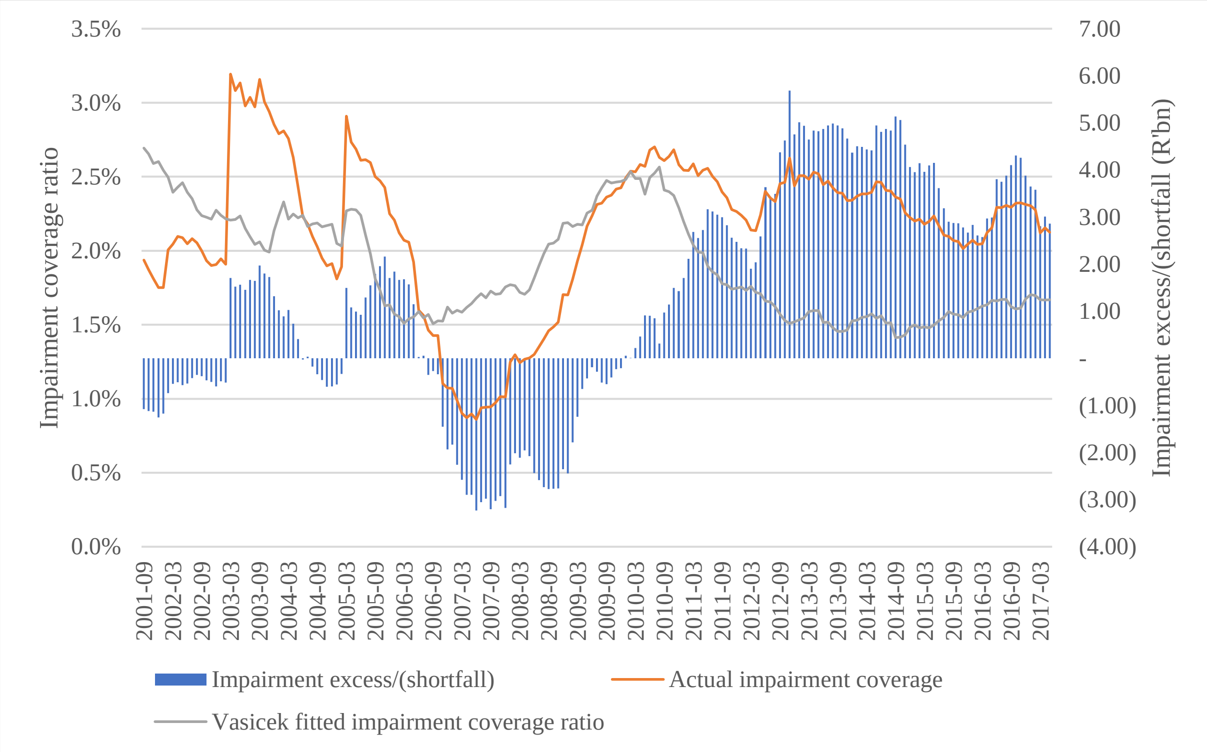

Figure 86: Actual Absa impairment coverage ratio compared to the fitted impairment coverage ratio with an indication of the Rand difference in impairment

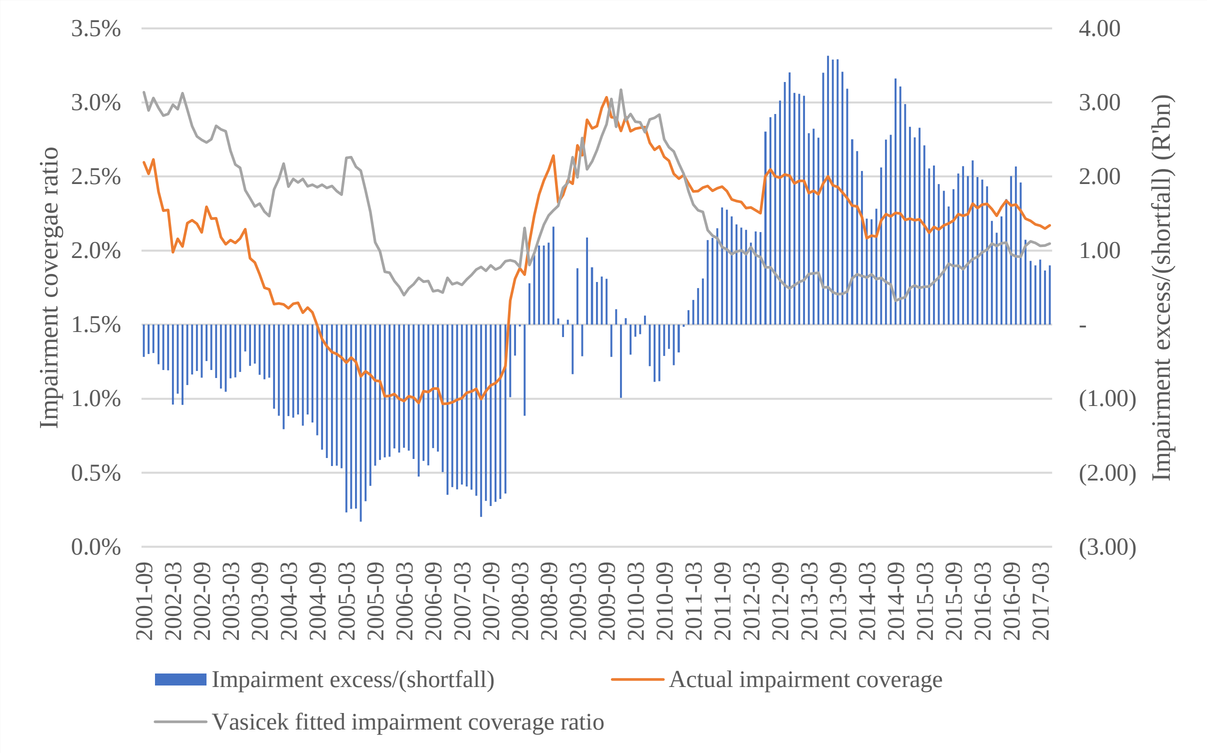

Figure 87: Actual FirstRand impairment coverage ratio compared to the fitted impairment coverage ratio with an indication of the Rand difference in impairment

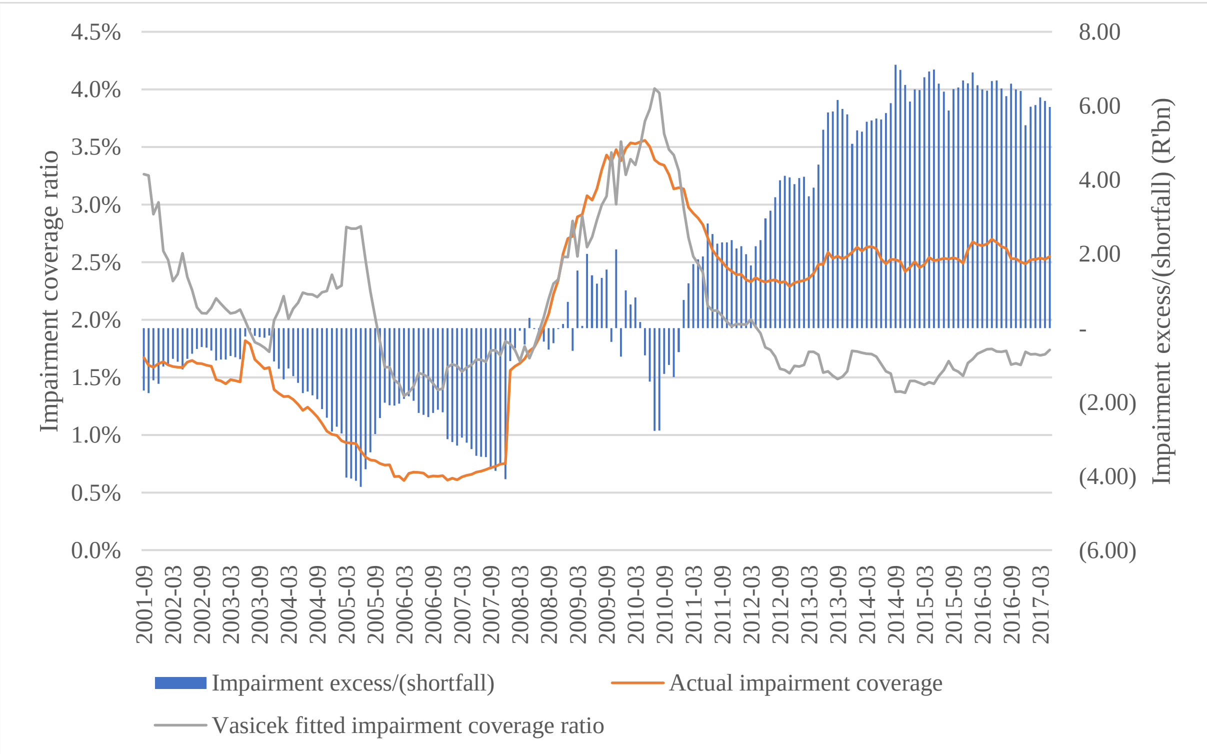

Figure 88: Actual Standard Bank impairment coverage ratio compared to the fitted impairment coverage ratio with an indication of the Rand difference in impairment

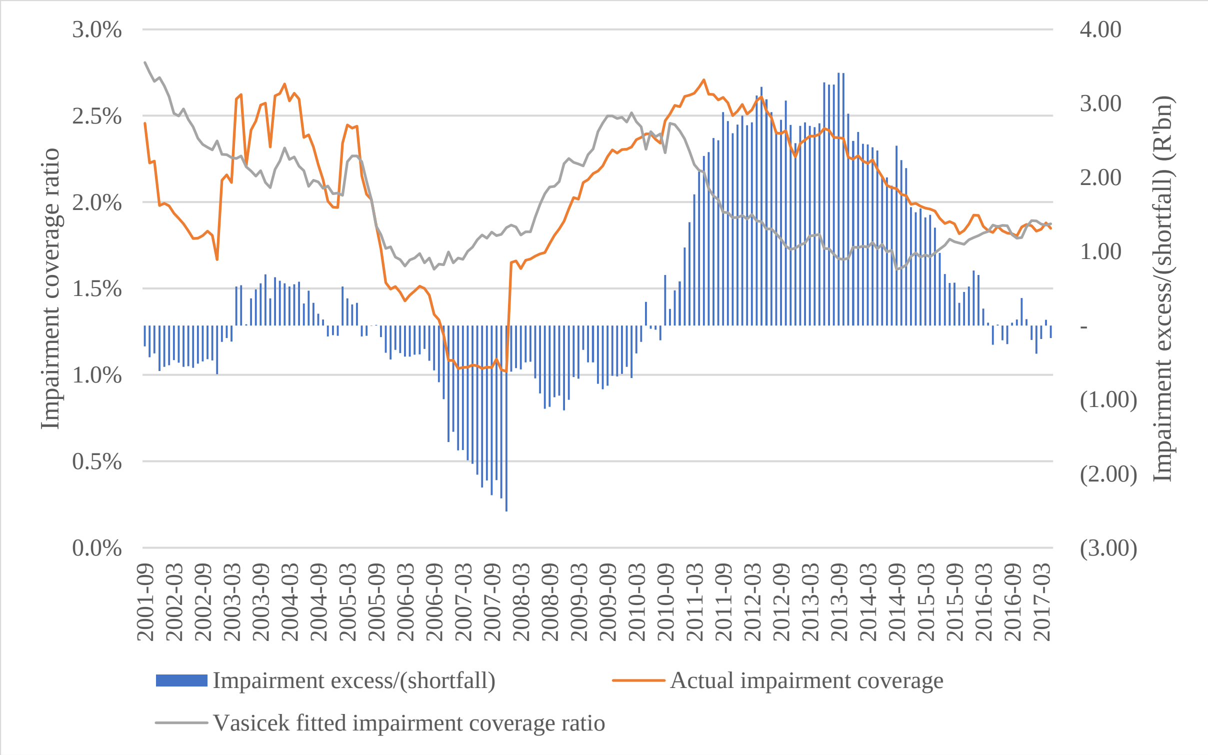

Figure 89: Actual Nedbank impairment coverage ratio compared to the fitted impairment coverage ratio with an indication of the Rand difference in impairment

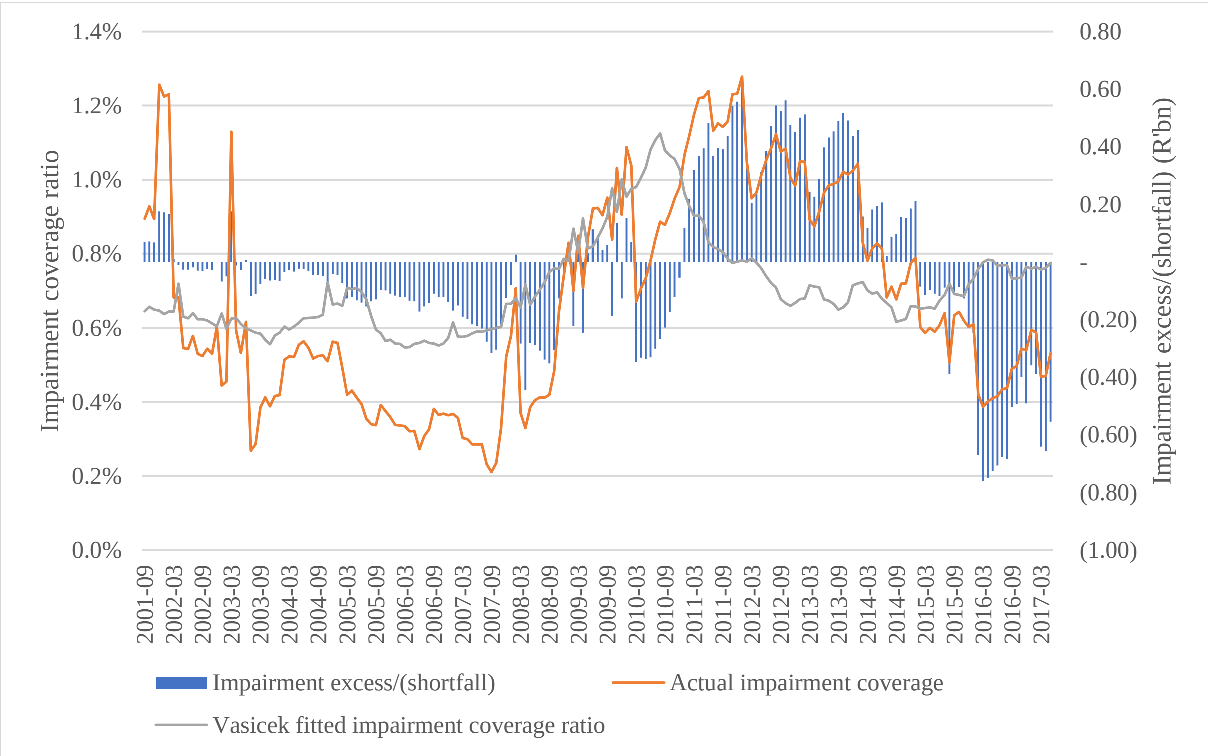

Figure 90: Actual Investec impairment coverage ratio compared to the fitted impairment coverage ratio with an indication of the Rand difference in impairment

Appendix B

The relationship of public sector interest bearing securities and the difference between deposits and loans granted is shown for each bank below.

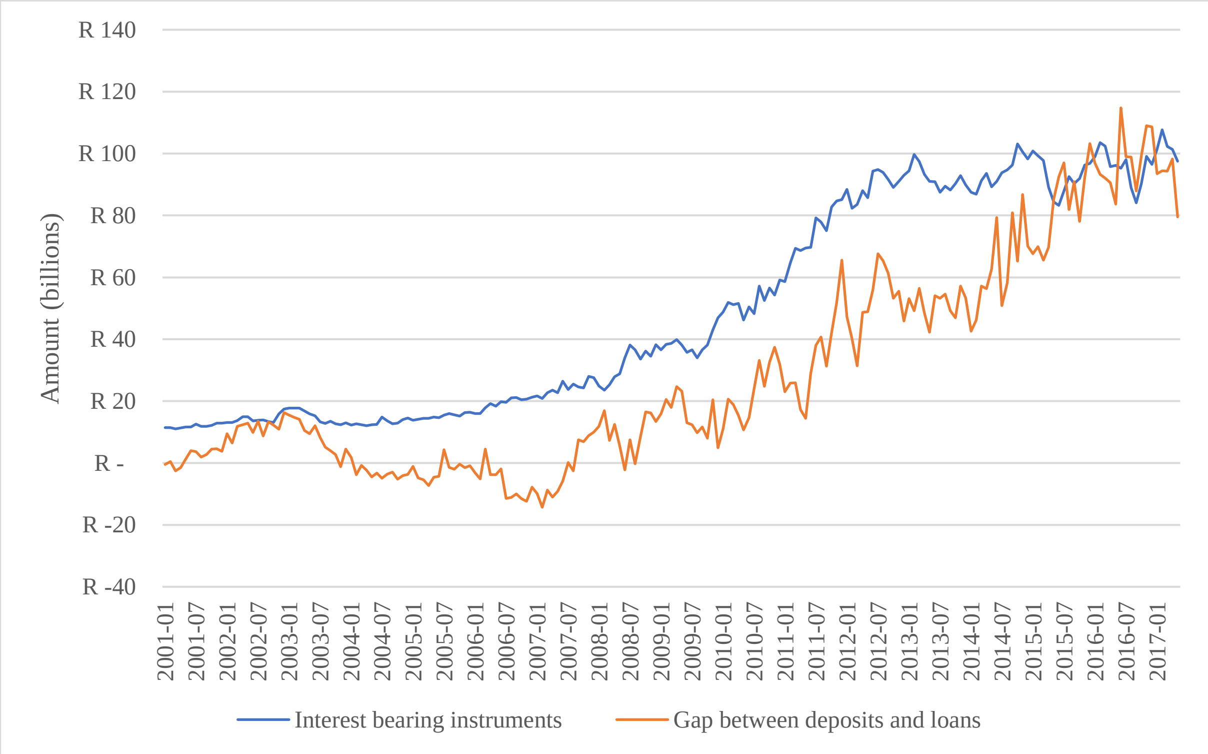

Figure 91: Absa public-sector interest-bearing securities compared to the difference between total bank deposits and loans granted over time

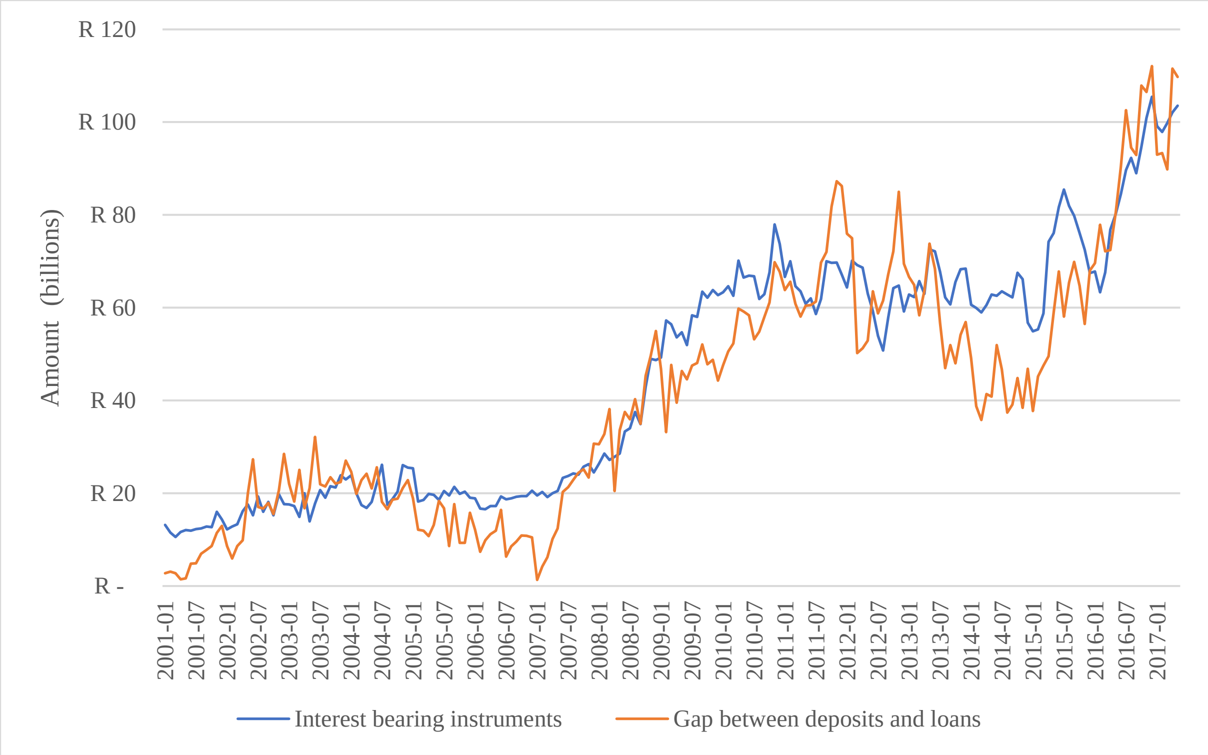

Figure 92: FirstRand public-sector interest-bearing securities compared to the difference between total bank deposits and loans granted over time

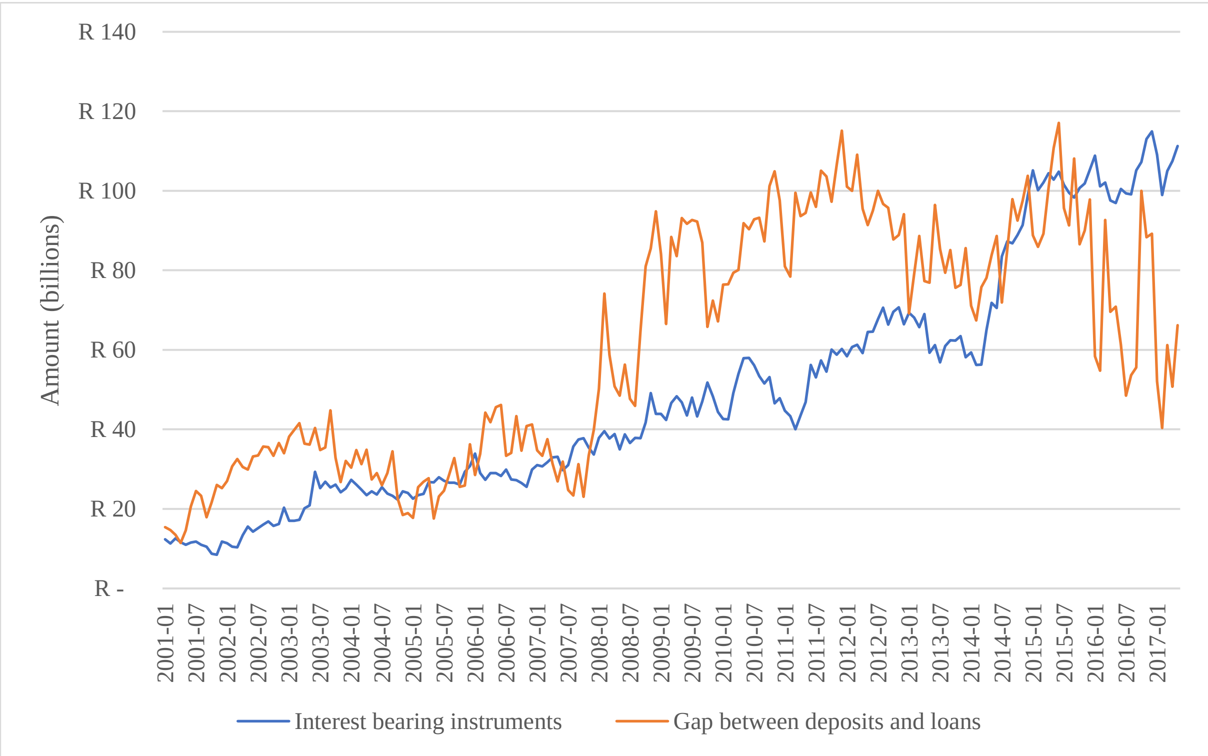

Figure 93: Standard Bank public-sector interest-bearing securities compared to the difference between total bank deposits and loans granted over time

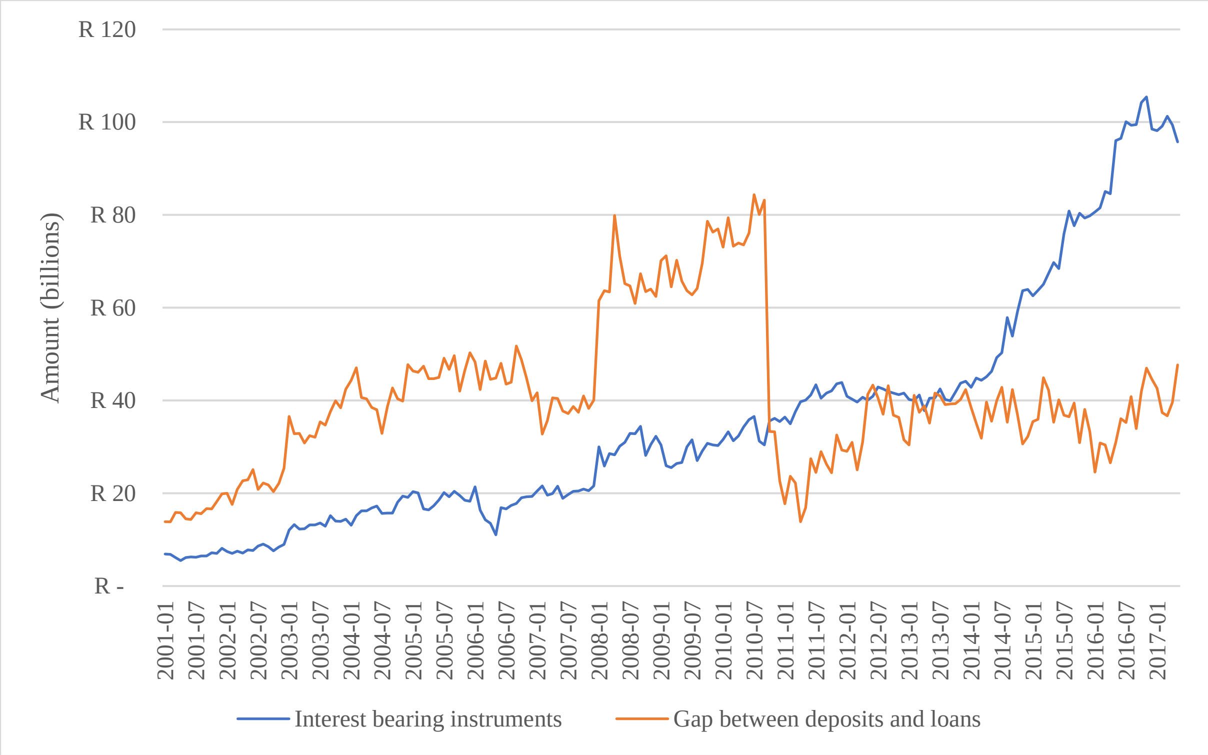

Figure 94: Nedbank public-sector interest-bearing securities compared to the difference between total bank deposits and loans granted over time

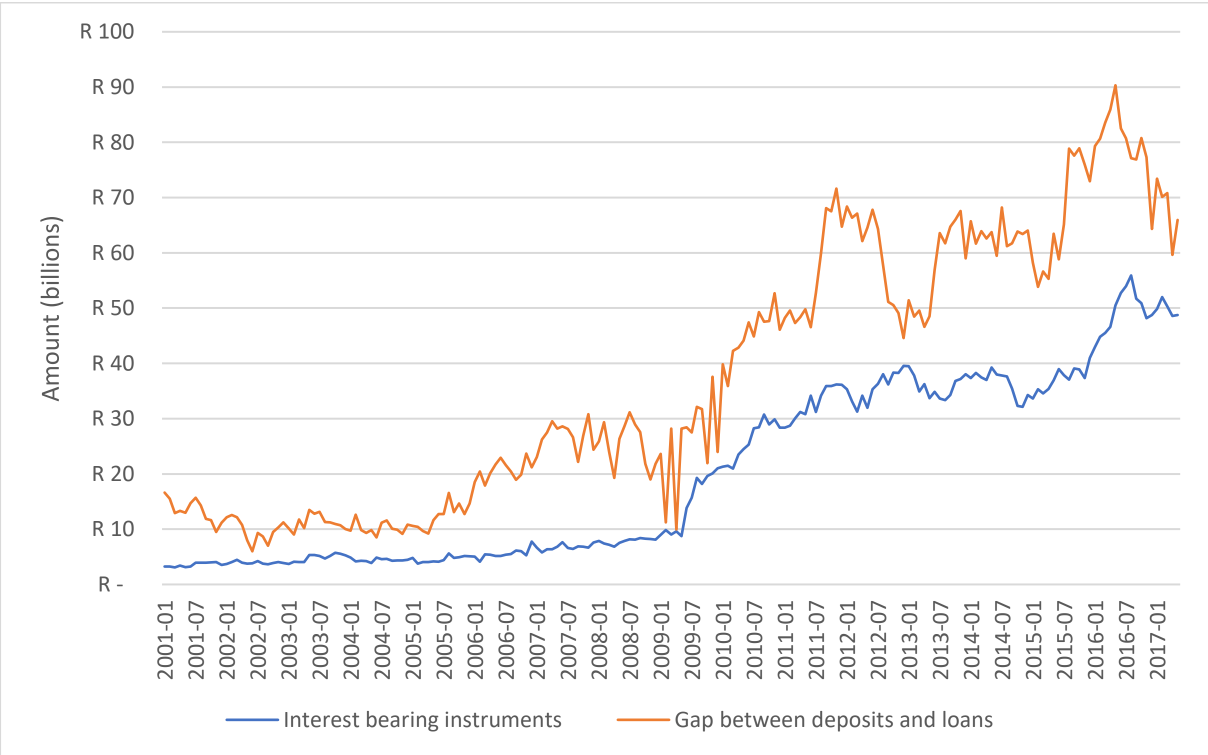

Figure 95: Investec public-sector interest-bearing securities compared to the difference between total bank deposits and loans granted over time

Appendix C

Backtesting the level of public sector interest bearing securities predicted by the difference between deposits and loans granted against the actual level of public sector interest bearing securities is shown for each bank below:

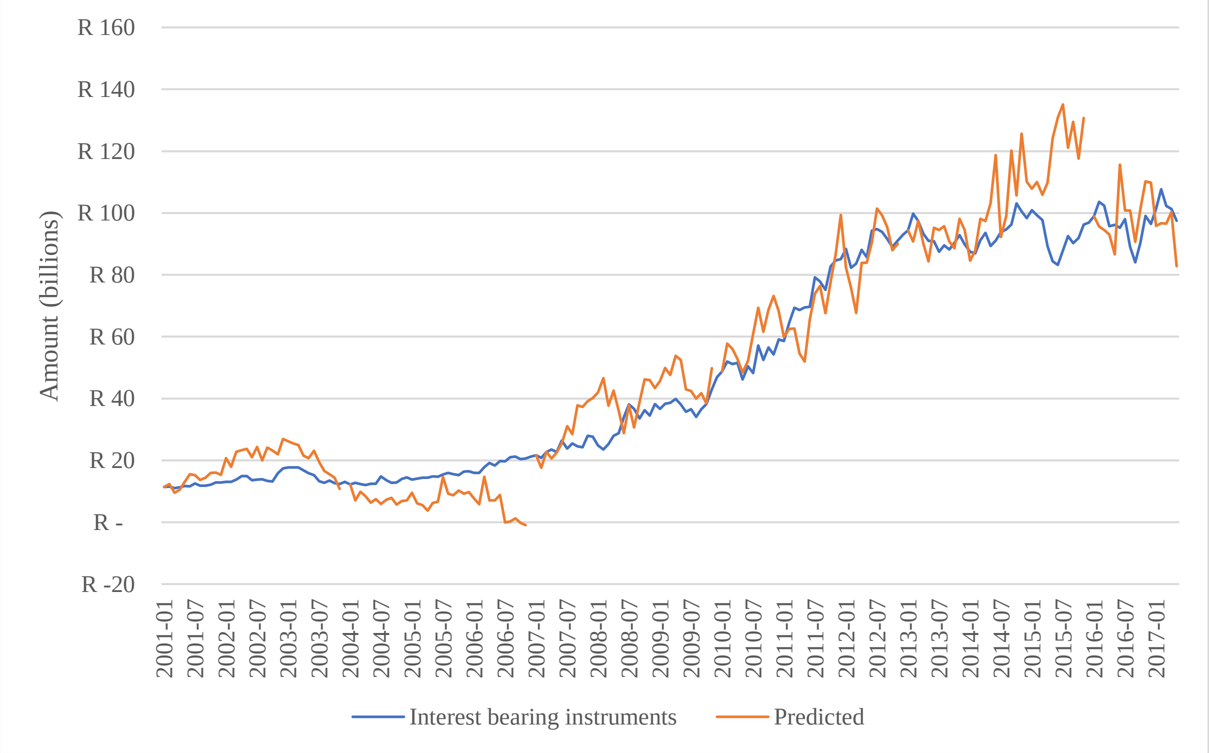

Figure 96: Backtest of Absa public sector interest bearing security values as predicted by changes in the difference between deposits and loans

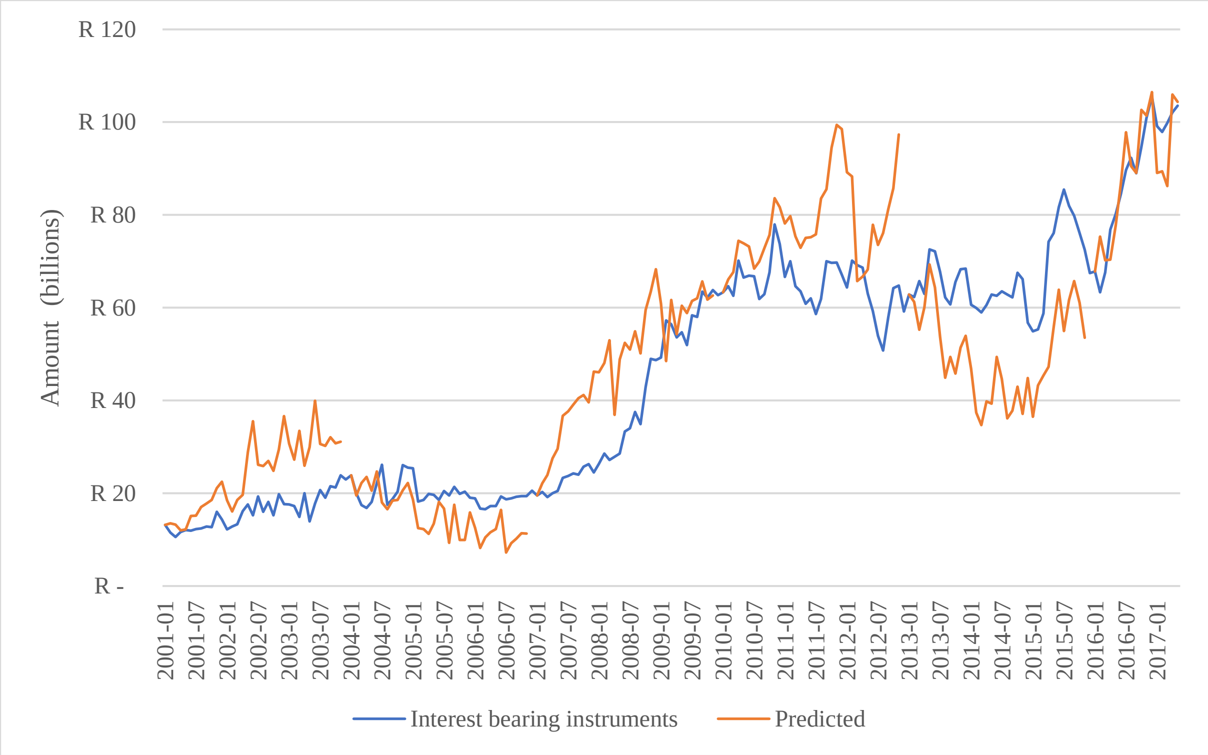

Figure 97: Backtest of FirstRand public sector interest bearing security values as predicted by changes in the difference between deposits and loans

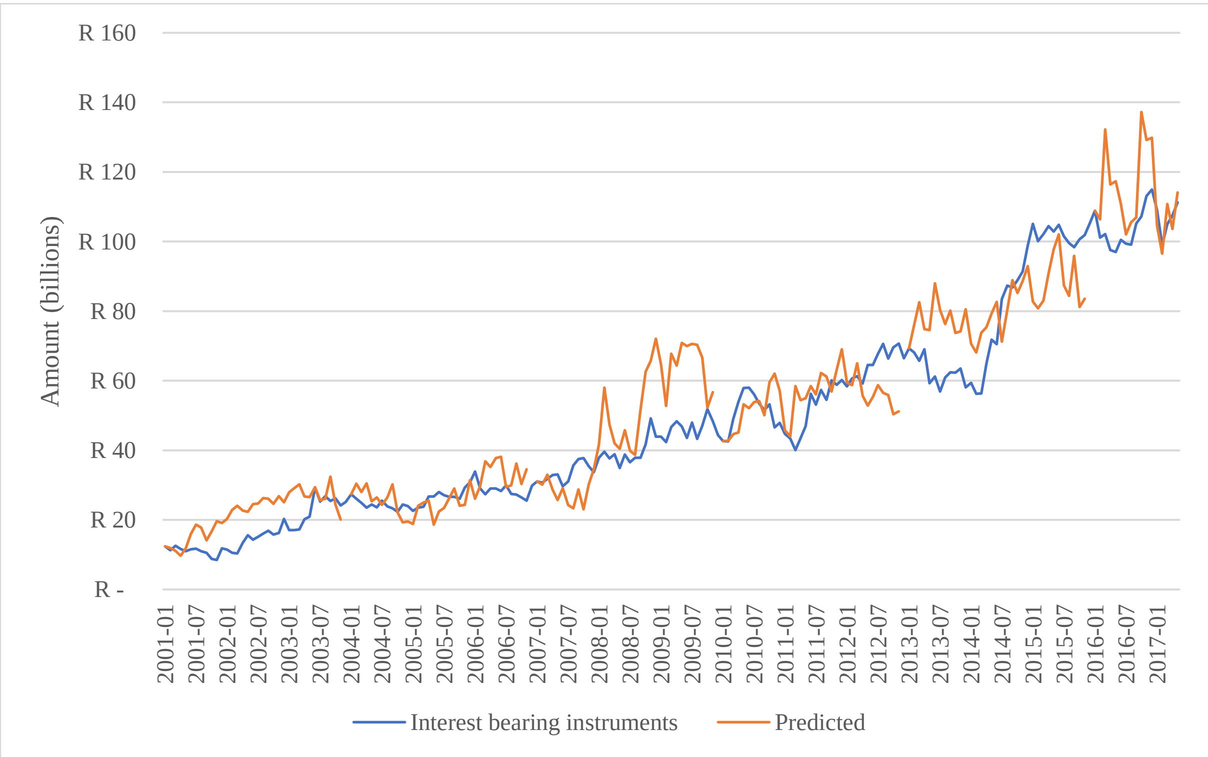

Figure 98: Backtest of Standard Bank public sector interest bearing security values as predicted by changes in the difference between deposits and loans

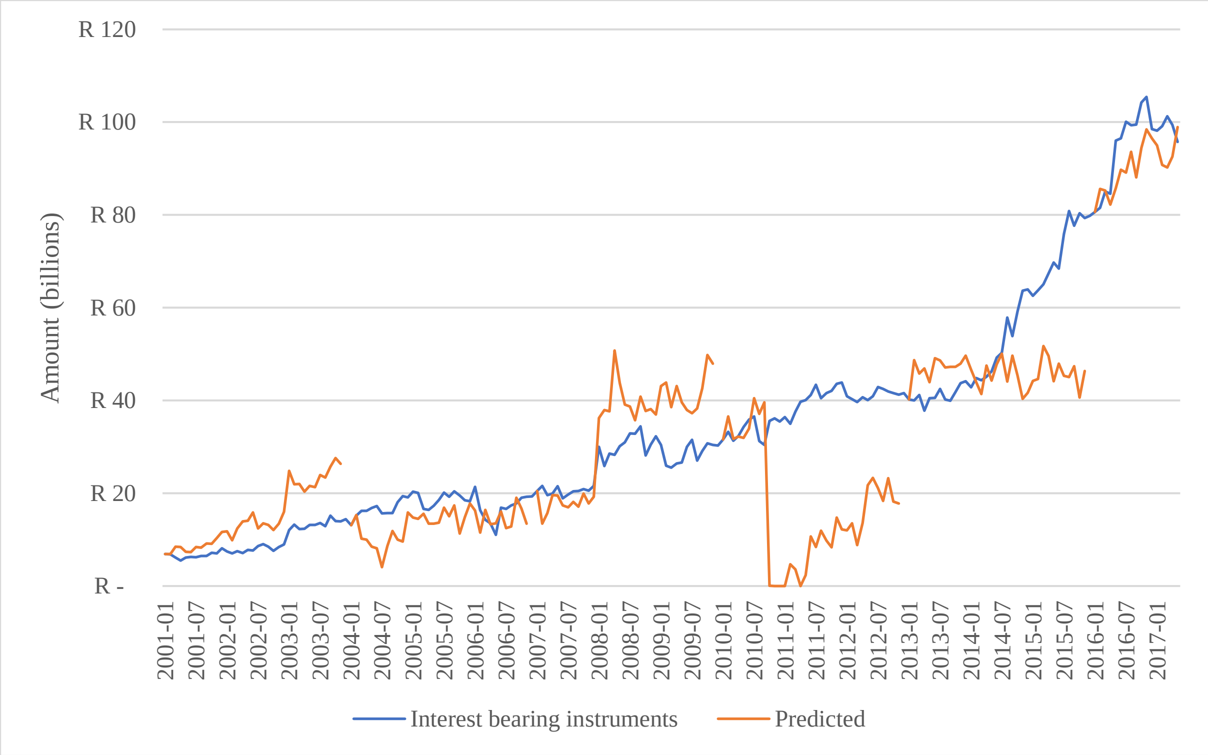

Figure 99: Backtest of Nedbank public sector interest bearing security values as predicted by changes in the difference between deposits and loans

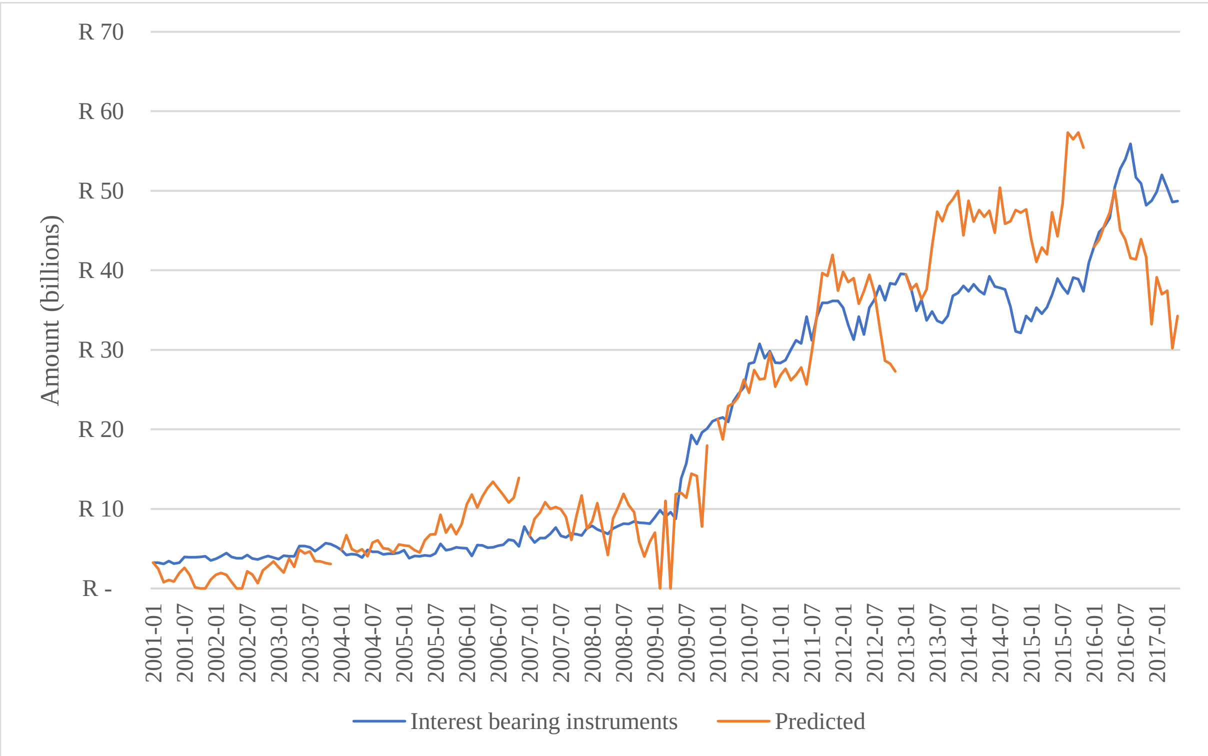

Figure 100: Backtest of Investec public sector interest bearing security values as predicted by changes in the difference between deposits and loans

Appendix D

Backtesting the predicted growth in loan volumes and annualised quarterly growth rate per category is shown for each loan category below:

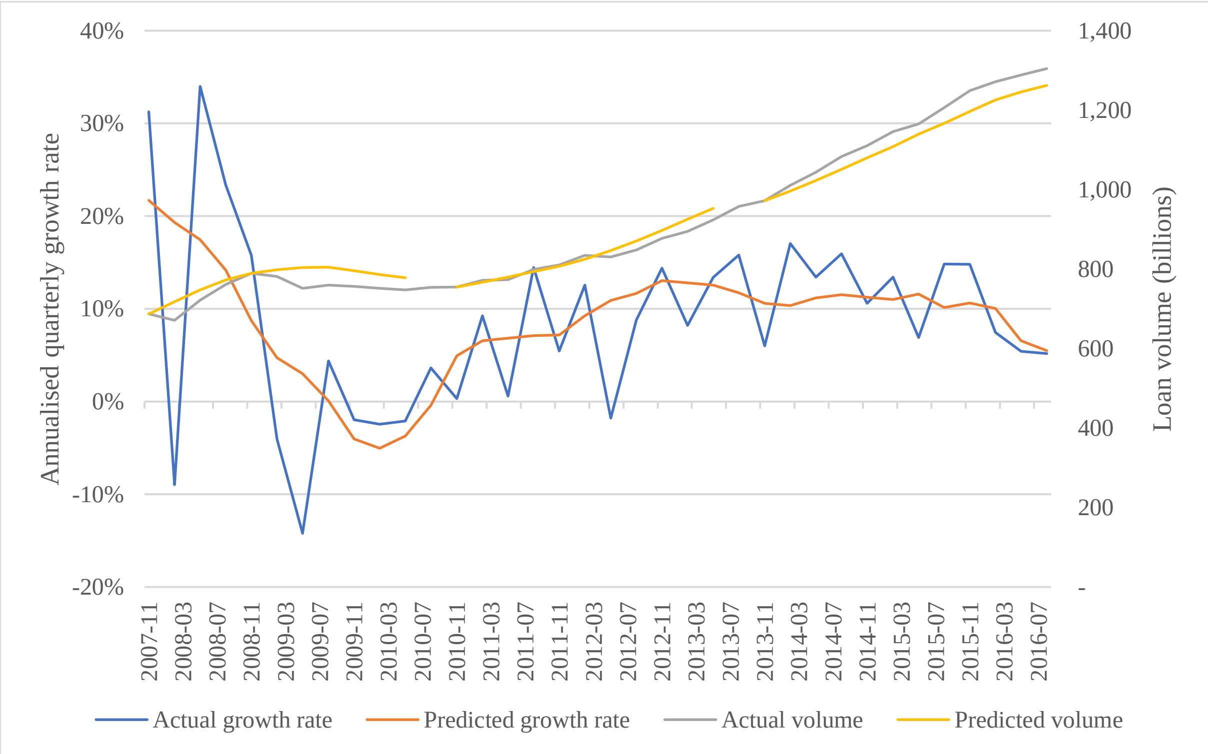

Figure 101: Fitted quarterly company loan growth rates including 30 month forecast of loan volumes using fitted growth rates

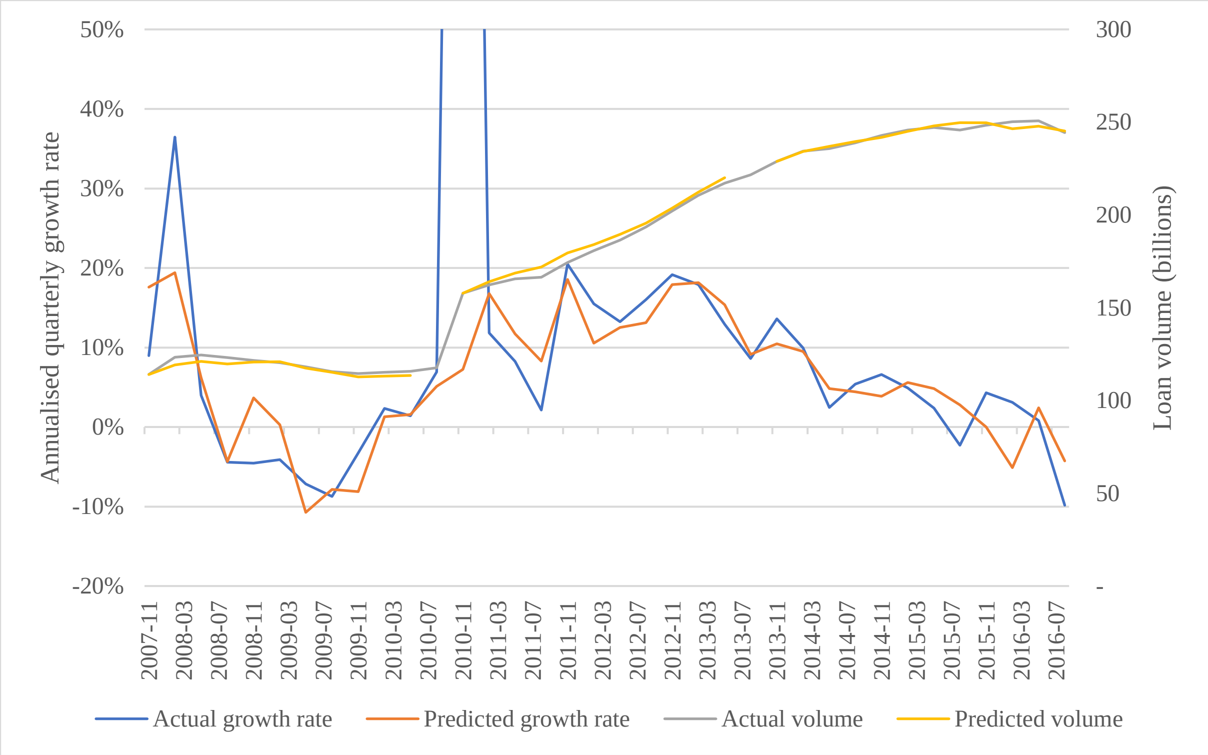

Figure 102: Fitted quarterly secured retail loan growth rates including 30 month forecast of loan volumes using fitted growth rates

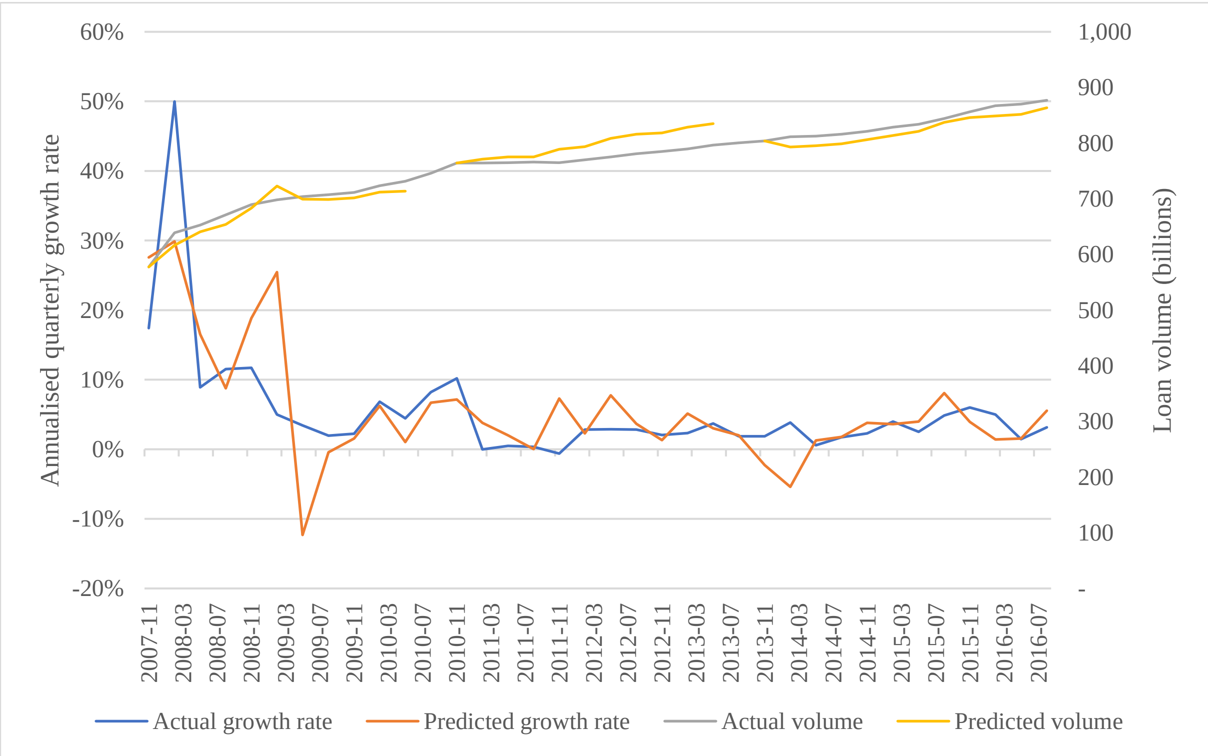

Figure 103: Fitted quarterly mortgage loan growth rates including 30 month forecast of loan volumes using fitted growth rates

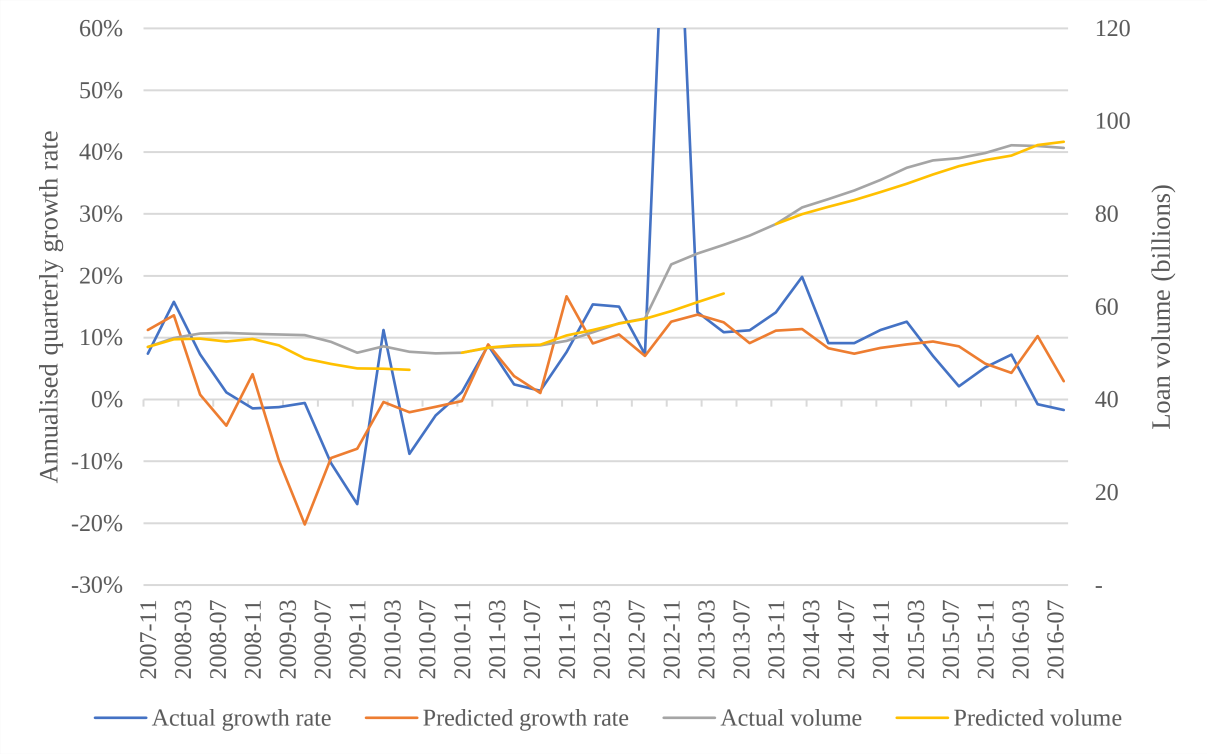

Figure 104: Fitted quarterly credit facility growth rates including 30 month forecast of loan volumes using fitted growth rates

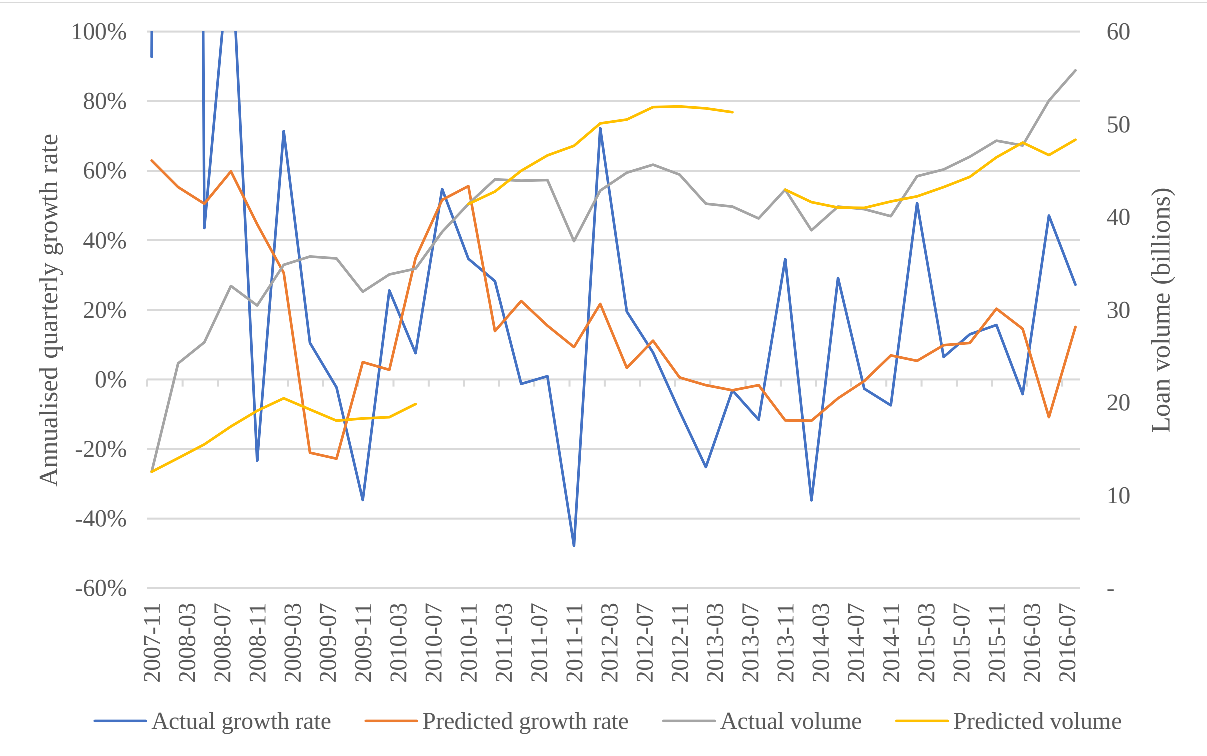

Figure 105: Fitted quarterly government loan growth rates including 30 month forecast of loan volumes using fitted growth rates

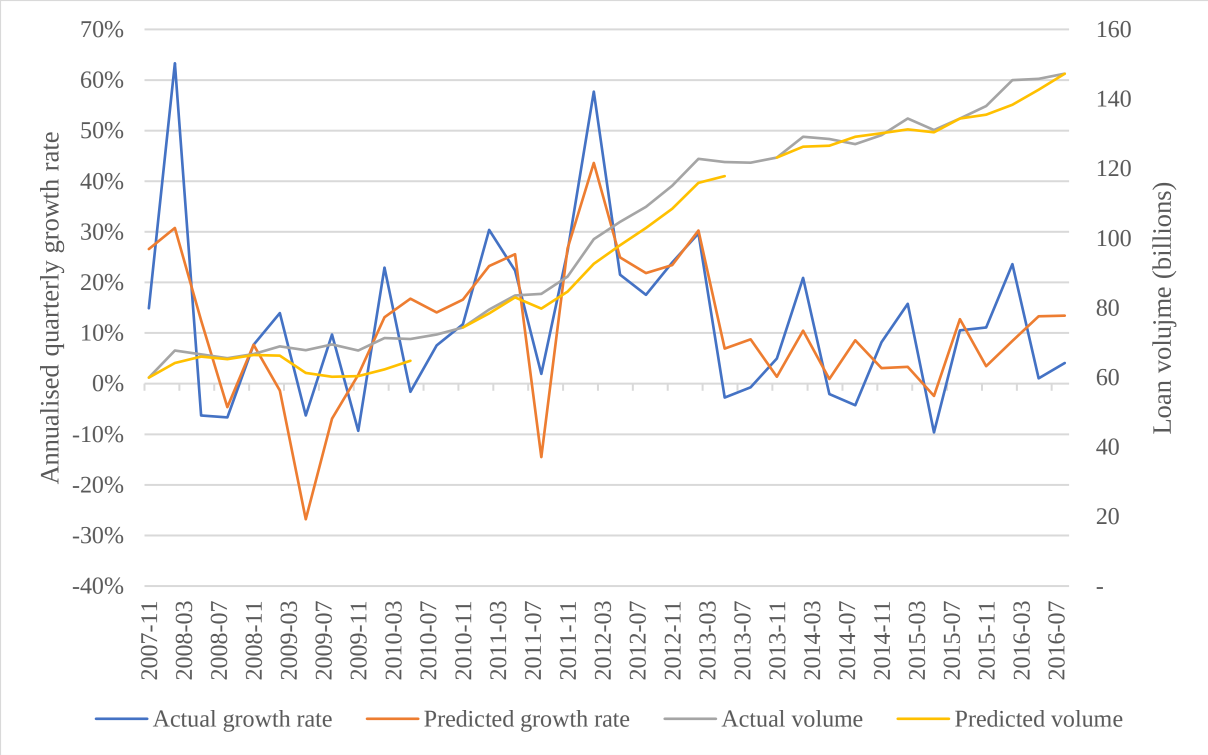

Figure 106: Fitted quarterly credit facilities, unsecured loans, short term loans & developmental credit growth rates including 30 month forecast of loan volumes using fitted growth rates