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Essays in Macroeconomics: An Analysis of the South African Financial System

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of the requirements for the degree of
Doctor of Economics (Ph.D.)

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Glossary

AE	Advanced Economies
ANFCI	Adjusted National Financial Conditions Index
BCBS	Basel Committee on Banking Supervision
CAPM	Capital Asset Pricing Model
CAR	Capital Adequacy Ratio
DFM	Dynamic Factor Model
DMA	Dynamic Model Averaging
DMS	Dynamic Model Selection
EM	Expectation Maximisation
EME	Emerging Market Economy
EWMA	Exponential Weighted Moving Average
FAVAR	Factor-Augmented Vector Auto-Regressive
FCI	Financial Conditions Index
FPI	Financial Price Index
FX	Foreign Exchange
G7	Group of Seven
GaR	Growth-at-Risk
GDP	Gross Domestic Product
GFC	Global Financial Crisis
HQLA	High-Quality Liquid Assets
IMF	International Monetary Fund
IRF	Impulse Response Function
JIBOR	Johannesburg Interbank Offered Rate
JSE	Johannesburg Stock Exchange
LCR	Liquidity Coverage Ratio
NEER	Nominal Effective Exchange Rate
NFCI	National Financial Conditions Index
NIM	Net Interest Margin
NPL	Non-Performing Loan
NSFR	Net Stable Funding Ratio
PCA	Principal Component Analysis
RMSFE	Relative Means Squared Forecast Errors
SA	South Africa
SARB	South African Reserve Bank
TVP-FAVAR	Time-Varying Parameter Factor-Augmented Vector Auto-Regressive
UK	United Kingdom
US	United States
VAR	Vector Auto-Regressive
VIX	Volatility Index

Abstract

This thesis consists of three empirical essays analyzing the financial systems in South Africa. Chapter 1 constructs a financial conditions index (FCI) for South Africa, over the period January 2000 to April 2017, that can be used to predict risks in the financial market emanating from both the domestic market and the global market. It uses a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model, proposed by Koop and Korobilis (2014) that allows the FCI to vary with time. Further, the results show that the TVP-FAVAR model outperforms the constant-loadings factor-augmented vector autoregressive (FAVAR) model and the traditional vector autoregressive (VAR) model in the out-of-sample forecasting of the inflation rate and the real gross domestic product (GDP) growth rate. The FCI leads the measure of GDP indicating that the FCI can be used as an early warning indicator of a financial crisis. The chapter shows that tighter financial conditions contract the real economy and are deflationary at the same time.

Chapter 2 analyzes how the relationship between bank capital and liquidity affects bank lending. It uses a non-linear fixed affected model that interacts banks' capital ratios with their liquidity levels, proposed by Kim and Sohn (2017), on 25 South African banks over the period January 2008 to July 2020. In addition, it runs the marginal effects of bank capital on lending at the mean of liquidity to interpret the interaction between bank capital ratios and liquidity levels. The results indicate that, at average liquidity levels, banks with higher capital ratios increase the volume of commercial loans and decrease

the amount of retail loans, implying that banks prefer to lend to firms than to households. As banks strengthen their solvency position, they are better situated to increase the capacity of their “risker" loan portfolio by raising their volume of enterprise loans. This then comes with the consequence of reducing household credit.

Chapter 3 examines the bank-sovereign nexus in South Africa. It uses a Markov regime-switching model over the period January 2008 to October 2020 to analyze how changes in bank exposure to the sovereign impact the sovereign's risk position and how financial institutions' increased exposure to the sovereign impacts bank lending rates and volumes. The results indicate that during periods of economic stress, as banks increase their holding of government debt, the domestic sovereign finds it too costly to default as a default heightens the chances of a banking sector crisis. It also finds that higher bank exposure to the sovereign is linked with higher bank lending rates and lower loan volumes, again during periods of economic distress. Higher sovereign debt exposures tighten banks' capital constraints which impairs their lending abilities.

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The opinions expressed and conclusions arrived at are those of the author and are not necessarily to be attributed to the South African Reserve Bank, the World Bank Group, or Trinity College Dublin.

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Introduction

The global financial crisis (GFC) was a period of extreme stress in global financial markets and banking systems between 2007 and 2009. During the GFC, a downturn in the US housing market was a catalyst for a financial crisis that spread from the United States to the rest of the world through linkages in the global financial system. In addition, many banks around the world incurred large losses and relied on government support to avoid bankruptcy. Emerging markets and developing nations were hard hit by the GFC. One such country is South Africa. As the second largest African economy, the most industrialized, technologically advanced, and diversified economy in Africa overall; the impact of the GFC on the South African economy was large. The economy went into recession in 2008 and 2009 for the first time in 19 years, inflation reached its highest level of approximately 10 percent (breaching the monetary policy target of 4 to 6 percent), and the unemployment rate soared to 25 percent.

Prior to the GFC, a misconception emerged that macroeconomic stability automatically leads to financial stability. However, the GFC proved this is not the case. A crisis in the banking sector became systemic and quickly threw the entire financial system into distress, and in turn, the macroeconomy. The first chapter studies this transmission channel in South Africa by constructing a financial conditions index (FCI) that has the ability to monitor each sector of the financial sector and establish a link between the financial sector and the real economy. By doing so, this chapter is able to predict a possible crisis in the financial sector before it affects the economy. The chapter estimates a time-varying FCI for South Africa using 39 monthly financial time-series variables over the period January 2000 to April 2017. The FCI spans six sectors of the financial market; namely the credit, funding, real estate, foreign exchange, equity, and the global financial market. The empirical strategy applied is a time-varying factor-augmented vector autoregressive (TVP-FAVAR) model following Koop and Korobilis (2014). The approach attaches different weights to each sector of the financial market, making it easy to identify a sector that is under stress. The main results indicate the ability of the FCI to capture global and idiosyncratic financial risks that affect the financial market in South Africa during the period of analysis. The FCI predicts well episodes of financial distress and leads the constructed measure of GDP growth by at least four months, further suggesting its use as an early warning signal. Chapter 1 is a co-authored article that has been published in Empirical Economics Journal in March 2020.

The GFC highlighted the importance of maintaining financial stability within the banking sector. Under normal conditions, banks perform liquidity transformation by funding long-term assets with short-term liabilities. However, during the GFC the short-term liabilities that were invested in illiquid assets were claimed at short notice, which in turn spurred a crisis in the banking sector. Following the GFC, the Basel Committee on Banking Supervision released a set of capital and liquidity measures that strengthened equality and sustained sound liquidity risk management, known as Basel III. The framework under Basel III strengthened the existing capital regulations and introduced a new set of liquidity indicators that would ensure banks have sufficient levels of stable funding. To comply with these measures, banks had to build up their capital measures and improve the liquidity of their assets by modifying their balance sheet structures. This would have a possible effect on banks' core function, its ability to provide credit. Chapter 2 examines how the complex relationship between bank capital and lending affects its lending volumes. It uses monthly data covering a panel of 25 South African banks over the period January 2008 to July 2020 to estimate a non-linear fixed effects regression in which bank capital and liquidity interacted, as proposed by Kim and Sohn (2017). In addition, it uses the marginal effects of bank capital on lending at average liquidity levels to interpret the results. The results indicate that, at average liquidity levels, banks with higher capital ratios increase the volume of commercial loans and decrease the amount of retail loans, implying that banks prefer to lend to firms than to households. As banks strengthen their solvency position, they are better situated to increase the capacity of their “risker" loan portfolio by raising their volume of enterprise loans. This then comes with the consequence of reducing household credit.

During periods of distress like the GFC and the European sovereign debt crisis, domestic sovereigns tend to increase the amount of public debt held. This becomes a concern when the banking sector is highly exposed to the domestic sovereign by holding a large share of domestic sovereign credit. The problem occurs when stress in the sovereign creates and amplifies stress in the banking sector, and vice versa. For example, the deterioration of sovereign creditworthiness reduces the market value of banks' holding of government bonds. This, in turn, may reduce the solvency and lending activity of banks. The link between banks and the sovereign received renewed attention during the Covid-19 pandemic as public sector debt in emerging markets rose from 52 percent prior to the pandemic to 67 percent in 2021 as governments had to increase fiscal support to households and the non-financial sector (IMF, 2022). Banks also increased the amount of public debt they held during the same period. Chapter 3 examines the bank-sovereign nexus in South Africa - a growing link between the domestic sovereign and the banking sector, particularly during crisis periods. It focuses on the top five commercial banks in South Africa (who have the highest share of total assets in the banking sector) as their exposure to the sovereign has increased considerably over the last ten years. The chapter estimates a Markov regime-switching dynamic regression model using monthly data over the period January 2008 to November 2020. The main results indicate that during periods of economic distress, as banks hold more government debt, sovereign credit risk reduces. It becomes too costly for the sovereign to default as a default could trigger a credit crunch in the banking sector. Additionally, banks increase their lending rates and lower their loan volumes when they hold more sovereign credit during crisis periods as higher sovereign borrowing costs diminish their balance sheets.

1 Estimating a Time-Varying Financial Conditions Index for South Africa*

Abstract

This chapter uses 39 monthly time series of the financial market observed from January 2000 to April 2017 to estimate a financial conditions index (FCI) for South Africa. The empirical technique used is a dynamic factor model with time-varying factor loadings proposed by Koop and Korobilis (2014) based on the principal component analysis and the Kalman smoother. In addition, we estimate a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model, which includes, in addition to the FCI, two observed macroeconomic variables. The results show the ability of the estimated FCI to predict risks in the financial market emanating from both the domestic market and the global market. Furthermore, the TVP-FAVAR model outperforms

*This chapter is a published article in the Empirical Economics Journal that is co-authored with Dr. Alain Kabundi who is affiliated with the International Monetary Fund and was written while he was affiliated with the South African Reserve Bank. My contributions to this chapter include estimating the empirical model and drafting the results, writing the literature review, and co-writing the introduction and results sections. The FCI constructed in this chapter is currently being used by the South African Reserve Bank (SARB) as a tool to monitor movements within the financial sector. It is also published annually as a box in the SARB's financial stability report the constant-loadings factor-augmented vector autoregressive (FAVAR) model and the traditional vector autoregressive (VAR) model in the out-of-sample forecasting of the inflation rate and the real gross domestic product (GDP) growth rate. Finally, tighter financial conditions contract the real economy and are deflationary at the same time. Importantly, the responses of macroeconomic variables are asymmetric and vary over time.

1.1 Introduction

Since the Global Financial Crisis (GFC) of 2007-2008, there has been an emergence of interest in macro-financial linkage. The deep and lasting effects of the crisis on the real economy is the essential element explaining this interest in academia and policy circles. Many countries are still struggling with low output, households are still deleveraging in some parts of the world, and supply of credit has been increasing slowly even after expansionary monetary policy.

Prior to the GFC, a misconception that was broadly shared among practitioners, academics, and policy makers was that macroeconomic stability automatically leads to financial stability. The latter was perceived as the natural consequence of the first. The other fallacy commonly believed before the GFC was cleaning up the mess after the bubble has burst instead of pricking it because of the inherent difficulty in predicting economic behaviour. As the eminent Nobel Prize-winning economist, Samuelson (1966, p. 92), put it: “Wall Street indices predicted nine out of the last five recessions." But the depth of the GFC, together with its impact on the global economy, which is still present in some countries, proved this hypothesis wrong.

The main issue with the financial market is its size and complexity. For example, a crisis in the banking sector does not necessarily spill over to another sector, like equity. It is also worth emphasising that not all financial crises become systemic. However, crises like the GFC are systemic and affect the entire financial system, which in turn affects the entire economy. It is therefore necessary to monitor each sector of the financial market as well as the system as a whole to predict possible crisis before they spillover into the macroeconomy. It is equally important to establish the linkage between financial sector and the economy, especially in crisis periods.

The literature on macro-financial linkages is still in its infancy in South Africa, where the work of Gumata et al. (2012), Thompson et al. (2015), and Balcilar et al. (2016) are exceptions. Against this backdrop, this chapter assesses the effects of financial stress on real and nominal variables in South Africa. Moreover, the chapter determines the predictability of these variables with financial variables, especially during crisis periods. To achieve this, the chapter estimates a time-varying financial conditions index (FCI) for South Africa using 39 monthly financial time series observed from January 2000 to April 2017. Along the lines of Oet et al. (2012), we construct an index which encompasses the 6 main sectors of the financial system, namely the credit, funding, real estate, foreign exchange, equity, and the global financial market. One of the advantages of this approach is that it uses different weights associated with different sectors of the financial market, such that it is relatively easy to identify a sector that is under stress. Hence, the index may serve as a warning signal of a possible crisis which is still in its early stage when the index is persistently above a certain predetermined threshold. This will allow policy makers to maintain macroeconomic stability during periods of financial instability. The empirical method used is the time-varying factor model of Koop and Korobilis (2014), which uses the two-step estimation procedure based on the principal component analysis and the Kalman smoother. To assess how good the estimated FCI is in predicting macroeconomic variables, we estimate a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model which includes, besides the FCI, the annual headline inflation rate and a measure of real activity based on the nowcasting of gross domestic product (GDP) growth proposed by Kabundi et al. (2016). It is possible with this framework to assess the impact of an FCI shock on macroeconomic variables at different points in time of our sample.

The results show strong correlation between the financial sector and the macroeconomy in South Africa. Specifically, the constructed FCI captures instances of global and idiosyncratic financial risks which affect the financial market in South Africa during the period under investigation. For example, the maximum value reached by the FCI during the crisis of 2001 which came from the foreign exchange market was less than the level attained at the GFC of 2007-2008. The results also show evidence of a tranquil period from 2003 to 2006 and from 2009 to the end of the sample. This suggests that the FCI predict quite well episodes of financial stress. Additionally, the results depict strong correlation between the FCI and macroeconomic variables. Particularly, the extracted FCI comove with headline inflation, with a correlation coefficient of 67 percent. Moreover, the results indicate that our extracted FCI tends to lead the constructed GDP growth rate by at least four months, once again indicating that stress in the financial market can be perceived as a warning signal of possible future weaknesses in the real economy. The results also depict evidence of time-varying loadings for a few selected variables.

The out-of-sample forecasting performance of the TVP-FAVAR model outperforms the traditional vector autoregressive (VAR) model with two observed variables for all the forecasting horizons for both macroeconomic variables. Similarly, the TVP-FAVAR outperforms the constant-loadings FAVAR of Gumata et al. (2012) in the out-of-sample forecasting for all the forecasting horizons except for the first three months where the latter model does well. The performance is comparable with the 12-month horizon for GDP growth. The results based on impulse response functions (IRFs) show that tighter financial conditions affect both GDP growth and the inflation rate negatively. The effects die out with a longer forecasting horizon. Interestingly, the GDP growth depicts relatively weaker effects before the exchange rate crisis of 2001. But the effects increase with the crisis and then fade away gradually. For inflation, the effects seem stronger in 2001 compared to the GFC period. Both variables show weaker reaction towards the end of the same period, which coincides with an environment of loose financial conditions both globally and domestically.

The results seem to suggest the presence of asymmetric relationship between the FCI and GDP growth. In particular, financial conditions provide a warning signal of negative non-normal shocks to the economy. This is consistent with recent finding of Adrian et al. (2019) for the US. Instead of assessing the predictability of the average future growth, these authors uncover the entire distribution of future GDP growth with a quantile regression. The current paper uses the same framework and confirm the asymmetry observed in the forecasting exercise and time-varying IRFs.

The remainder of the chapter is organised as follows. Section 2 provides a brief literature review on the financial stress index or the FCI. In Section 3, we describe the time-varying parameters of the FAVAR model and the nowcasting approach used to estimate the monthly measure of real activity. Section 4 describes the data used, the construction of some financial variables, and the transformation. The empirical results are discussed in Section 5. The section includes a pseudo out-of-sample forecasting performance of our model relative to the traditional VAR and the constant-loadings FAVAR. We also show the advantage gained in using the time-varying loadings instead of the constant-loadings approach. We discuss the response of the macroeconomic variables to tighter financial conditions. In addition, we discuss the asymmetric behavior of GDP growth from a tightening financial conditions. Section 6 concludes the chapter.

1.2 Literature Review

The global financial crisis (GFC) was a clear indication of macro-financial linkages[1]. However, crises such as the GFC are not the first of its kind. Kindleberger and Aliber (2000) and Reinhart and Rogoff (2009) have shown that financial crisis occur throughout economic history and affecting a range of countries. When a crisis becomes systemic it can have lasting, dampening effects on macroeconomic growth. However, not all financial crises are systemic. Some crises, like a currency crisis, affect only one sector of the financial market (such as the foreign exchange market in the case of the currency crisis) but can still spillover into, and hamper, economic growth. Once financial instability hinders economic growth, both the financial and real sector enter into a vicious cycle with feedback loops that further exacerbates systemic stress. It is therefore important to monitor the financial market and establish the linkage between financial sector and the economy, especially in crises periods.

The empirical literature on the effects of financial crisis on the real economy is vast. Bernanke (1983) examines the effects of the Great Depression of the 1930s on aggregate output and finds that it resulted in higher costs and reduced availability of credit, depressing aggregate demand, while Bernanke et al. (1991) focus on the impact of the 1990 US credit crunch. Diamond and Dybvig (1983) show that bank runs are a feature of financial crises and gravely hamper real economic activity. More recently, Barkbu et al. (2012) examines the multilateral response of financial crisis spanning over 4 decades and finds that emergency lending has grown but reliance on debt restructuring has declined, while Schularick and Taylor (2012) examine the behaviour of money, credit, and macroeconomic indicators for a panel of 14 developed countries over the period 1870 - 2008, and finds credit growth is a predictor of financial crisis. Using the cross-section of banks' equity returns (CATFIN),

[1]See Claessens and Kose (2017) for a detailed literature review on macro-financial linkages.

Allen et al. (2012) derive a measure of aggregate systemic risk to forecast macroeconomic downturns for a panel of U.S., European, and Asian banks. They find that systemic risk in the banking sector hinders the real economy through the bank-lending channel.

It is evident that financial stress can cause real economic damage. It is therefore important to account for financial instability in macroeconomic models. Mendoza (2002) does this by focusing on binding borrower constraints, while Dubey et al. (2005) focus on borrower default. Lorenzoni (2008) focus on limited commitment in financial contracts and asset prices determined in the spot market, Brunnermeier and Sannikov (2014) look at endogenous financial risk and asset price correlations, while He and Krishnamurthy (2019) present a macroeconomic model with a financial intermediary sector subject to an equity capital constraint.

Another such measure integrating the financial market with the real economy is Financial conditions indices (FCIs), which focus on instances when financial markets are under strain, which in turn make them unstable and vulnerable to shocks. By construction, FCIs are a mapping of financial conditions onto macroeconomic conditions. They serve primarily as a channel through which monetary policy affects the real economy. More than just movement in the policy rate, Brave and Butters (2011) argue that FCIs represent stress in the financial market while Arregui et al. (2018) describe FCIs as “reflecting how easy it is to obtain finance".

Hatzius et al. (2010), Koop and Korobilis (2014), and the International Monetary Fund IMF (2017b) demonstrate that FCIs are a reliable predictor of economic activity. They are constructed from a wide range of financial variables that aim to capture the cost of funding in the economy. The strength of FCIs lies in its ability to summarise information from numerous financial variables into a single latent variable. Empirically, measures of FCIs can be more helpful in predicting future economic activity than indicators of current and past real economic activity.

The central banks of many countries, especially those of advanced economies (AEs), use the FCI as a leading indicator and early warning signal of stress in the financial market. For instance, the KOF barometer, produced by the ETH Zurich, measures the business cycle of Switzerland by utilising a panel of over 400 financial variables. The KOF barometer extracts a principal component from the dataset and identifies the common variance of the variables. In the U.S., many Federal Reserve Banks have their own measure of the FCI. The most popular ones are from the Chicago Fed, the Cleveland Fed, the Kansas City Fed, and the St Louis Fed. Hakkio and Keeton (2009) construct an FCI for the Kansas City Fed from the first principal component of 11 monthly financial indicators. The Chicago Federal Reserve Financial Conditions Index (NFCI) was developed by Brave and Butters (2011) using a dynamic factor model (DFM). They follow closely Hatzius et al. (2010) and also propose a purged version of the NFCI known as the Adjusted National Financial Conditions Index (ANFCI) which studies asymmetric responses to shocks from financial conditions and show that both indicators are a a leading predictor of financial stress of up to one year.

Since the GFC, an extensive literature on macro-financial linkages and financial conditions arose, in particular for Advanced Economies (AEs). However, the literature for South Africa remains at its infancy. Even though consensus has emerged regarding their ability to predict the real economy, empirically, the approach to measure FCIs has been contested. For example, Gauthier et al. (2004) construct FCIs for Canada using three approaches: weights derived from an IS-Phillips curve; weights from a vector autoregressive's (VAR) impulse-response functions; and employing the PCA approach. These authors find that the weighted sum approach produces better FCIs than the PCA approach. Goodhart and Hofmann (2001) estimate FCIs for the Group of Seven (G7) countries using a reduced-form VAR model that includes short-rates, exchange rates, house prices and share prices, whilst Swiston

(2008) estimates an FCI for the United States by obtaining weights from the impulse responses from a reduced-VAR.

Evidence for South Africa is limited. Gumata et al. (2012) construct an FCI from 11 nominal indicators by applying two alternative approaches, the PCA and the Kalman filter with constant loadings and homoscedastic errors, over the period 1991Q1-2011Q4. The authors demonstrate that their indicator has predictive information for near-term GDP growth and that it outperforms the South African Reserve Bank's (SARB) leading indicator. Thompson et al. (2015) re-evaluate the FCI derived by Gumata et al. (2012) by applying a recursive PCA with constant loadings to 16 monthly financial variables and 3 macroeconomic variables (output, inflation, and interest rates, where industrial production is used as a proxy for output) over the period 1966-2011. Their variables cover asset prices, interest rate spreads, stock market yields and volatilities and money aggregates. The causality tests reveal that their FCI is a good out-of-sample prediction of industrial production growth but a weak forecasting tool for inflation and interest rates. Additionally, they find their rolling-window FCI a good predictor of real-time economic activity. Closely related to our approach is the analysis by Balcilar et al. (2016) who extract the FCI using the Koop and Korobilis (2014) approach. They then include it in a nonlinear logistic smooth transition VAR (LSTVAR) model to account for the asymmetric effects on the real economy caused by change in volatility. Their results indicate that inflation and interest rates react more forcefully to financial shocks in the upswing phase, whereas manufacturing output growth tends to respond more to financial shocks during recessionary periods.

In addition, a few authors include South Africa in various cross-country analysis of FCIs. The IMF's *Global Financial Stability Report* of April 2017 examines the importance of common components of domestic financial conditions for selected AEs and EMEs, including South Africa (IMF, 2017a). The purpose of this report is to explore the country characteristics that influence the extent to which domestic financial conditions move with global factors and the ability of monetary policy to influence domestic FCIs. Following Koop and Korobilis (2014), this report uses a DFM to construct three factors, namely the global financial factor, the emerging market factor, and the euro area factor. They use the US FCI as a proxy for global FCI after finding that the constructed global factor closely follows the movement in the US FCI and a standard measure of global risk, the VIX. They find that countries are still able to manage their domestic FCIs even in the presence of adverse global financial conditions. Global financial conditions, in turn, explain 20 to 40 percent of the variation in domestic financial conditions. Lastly, Bicchetti and Neto (2017) construct FCIs for 11 EMEs and developing countries, including South Africa, over the period from January 1995 to March 2017 as well as from 1991Q1 to 2017Q1; they opt to use a DFM to construct the indicator in real time. The authors find that the constructed indicators are good predictors of periods of stress and that they are able to lead GDP growth.

This chapter follows closely the approach proposed by Koop and Korobilis (2014). These authors construct an FCI for the US using a TVP-FAVAR approach. Banerjee et al. (2008) and Bates et al. (2013), prove that the TVP-FAVAR outperforms the traditional VAR in the out-of-sample forecasting of macroeconomic variables. Their FCI is estimated using 20 quarterly financial variables. They further develop a dynamic model selection (DMS) and dynamic model averaging (DMA) in selecting the best models and averaging out the out-of-sample forecast. This approach seems superior in predicting macroeconomic variables. Finally, the estimated FCI leads real variables and inflation, and it follows the same pattern as existing FCIs from different Federal Reserve Banks.

In addition to estimating the FCI, forecasting GDP growth and inflation, and assessing the response of GDP growth and inflation to tighter financial conditions, the chapter runs a quantile regression to uncover the asymmetry which exists between financial conditions and GDP growth rate. Note that this analysis is closely relates to the concept of growth-at-risk (GaR) (IMF, 2017b). There is a growing interest since the GFC in predicting the entire distribution of GDP growth above point forecasts that are commonly used in the forecasting literature (see for example, Giglio et al. (2016), Adrian et al. (2019), Loria et al. (2019), Miglietta and Venditti (2019), and Chavleishvili and Manganelli (2019)).

1.3 The time-varying parameters of the FAVAR model

Following Koop and Korobilis (2014), we estimate a TVP-FAVAR model with a measurement equation represented as follows:

$$y_t = \lambda_t f_t + \beta_t z_t + v_t \tag{1.1}$$

where y_t is an $n \times 1$ vector of financial variables,f_t is $k \times 1$ a vector of latent common factors which captures a large co-variation between financial variables included in y_t, z_t is a $l \times 1$ vector of observed macroeconomic variables, $v_t \sim N(0, V_t)$ is a vector of idiosyncratic components with time-varying co-variances V_t, λ_t is $n \times k$ a matrix of time-varying factor loadings, β_t and is a $n \times l$ matrix of coefficients of observed variables. Since y_t covers the 6 key markets of the financial system in South Africa – namely the equity, funding, foreign exchange, credit, real estate, and global financial market – the extracted factor, f_t, is the FCI for South Africa. The model is flexible enough to account for structural breaks in the loadings.

Applying a time-varying parameter approach allows all parameters to take a different value at each time t. This is an important implication of the model as it is reasonable to believe there is time variation in the loadings and covariances of factor models that use both financial and macroeconomic data, as the relationship between the financial market and the macroeconomy can change over time. For instance, in 2008 during the financial crisis, the sub-prime housing market played a dominant role in affecting the macroeconomy, whereas in different circumstances, financial variables may have varying responses to changes in monetary policy (e.g. monetary policy works differently with interest rates near the zero bound) which would change the impact on real activity.

The state equation follows a VAR (p) process, including common factors and observed macroeconomic variables, represented as follows:

$$\begin{bmatrix} z_t \\ f_t \end{bmatrix} = \Theta_t(L) \begin{bmatrix} z_{t-1} \\ f_{t-1} \end{bmatrix} + \psi_t \tag{1.2}$$

where $\psi_t \sim N(0, \Psi_t)$ is a vector of disturbances with time-varying covariances Ψ_t and $\Theta_t(L) = I - \Theta_{t,1}L - \cdots - \Theta_{t,p}L^p$ is a time-varying matrix polynomial of order p. As Equation 1.2 links the financial system with macroeconomic variables, the FCI can be used to forecast macroeconomic variables, included in z_t.

Using a multivariate system allows us to use it to forecast macroeconomic variables using the FCI. This means all the variables in the model are jointly modeled, allowing us to better describe their co-movements. Further, the FCI is purged of the effect of macroeconomic conditions meaning the extracted FCI solely shows information associated with the financial sector.

Assume that the time-varying parameters $\gamma_t = (\lambda_t', \beta_t')'$ and $\delta_t = (vec(\Theta_{t,1})', \ldots, vec(\Theta_{t,p})')'$ follow multivariate random walks of the form:

$$\begin{aligned} \gamma_t &= \gamma_{t-1} + \varepsilon_t \\ \delta_t &= \delta_{t-1} + \omega_t \end{aligned} \tag{1.3}$$

where $\varepsilon_t \sim N(0, \Xi_t)$ and $\omega_t \sim N(0, W_t)$ are uncorrelated error terms with time-varying co-variances Ξ_t and W_t respectively. Koop and Korobilis (2014) clearly demonstrate that this TVP-FAVAR with time-varying loadings represented by equations 1.1, 1.2, and 1.3 is general enough, such that the VAR with the observed macroeconomic variables ($f_t = 0$), the constant-factor loading FAVAR ($\Xi_t = W_t = 0$), and the homoscedastic FAVAR ($V_t = V$ and

$\Psi_t = \Psi$) are its special cases. Hence, the FCI estimated by Gumata et al. (2012) – using the FAVAR with constant loadings, constant coefficients of the VAR, and homoscedastic errors – is nested in the current framework.

We follow closely the two-step estimation procedure based on the PCA and the Kalman smoother proposed by Koop and Korobilis (2014) instead of the computationally expensive technique commonly used in the literature, as in Primiceri (2005) and Del Negro and Otrok (2008). It is worth mentioning that the approach of Koop and Korobilis (2014) is based on the two-step method of Doz et al. (2011). For stochastic volatilities (V_t, Ψ_t, Ξ_t, and W_t), we use a recursive simulation-free variance matrix discounting proposed by Quintana and West (1988). Specifically, we use the exponential weighted moving average (EWMA) estimators, in line with Primiceri (2005) and Cogley and Sargent (2005), for V_t and Ψ_t, whereas the forgetting factor technique of Koop and Korobilis (2012, 2013) is used to estimate Ξ_t and W_t. The two-step estimation procedure involves obtaining an estimate of the common factors f_t and updating the parameters $\kappa_t = (\gamma_t, \delta_t)$ in the first step, while the second step involves updating the common factors given the estimate of parameters κ_t based on information only up to $t-1$. More precisely, we first estimate the principal component of the unobserved common factors, f_t, based on initial parameters λ_0, δ_0, f_0, V_0, and Ψ_0, using the PCA and obtaining estimates for κ_t. We then estimate V_t, Ψ_t, Ξ_t, and W_t conditional on κ_{t-1} and the common factor f_t using the variance discounting approach. Next, we use the Kalman smoother to update the estimate of the time-varying coefficients κ_t conditional on V_t, Ψ_t, Ξ_t, W_t, and the common factor f_t. Finally, we use a Kalman filter to update our estimate of the unobserved factor f_t conditional on the updated κ_t and V_t, Ψ_t, Ξ_t, and W_t. Thus, the estimation process involves the use of two different linear Kalman smoothers for κ_t and f_t.

Note that the vector of the observed macroeconomic variables, z_t, contains the annual inflation rate and the economic growth rate. We use the monthly information consistent with financial variables. However, the real GDP, which is the proxy of economic activity, is only available at a quarterly frequency. We follow the recent study of Kabundi et al. (2016), which estimates the nowcasting of real GDP growth, to construct a monthly series of the real GDP growth from a panel of monthly and quarterly economic indicators. We estimate GDP by using a dynamic factor model that allows us to use a Kalman filter to estimate unobserved variables in a system of equations given an information set. The Kalman filter allows us to minimize the mean squared error estimator.

We start by extracting common factors for monthly indicators that summarize co-movements from the latest available information set as follows:

$$x_t = \mu_1 + \Lambda f_t^m + \xi_t \tag{1.4}$$

where x_t is a $n_1 \times 1$ vector of monthly series used in Kabundi et al. (2016). Like in Equation 1.1, all variables are transformed to induce stationarity. f_t^m is a $r \times 1$ vector of common factors, Λ is a $n_1 \times r$ matrix of factor loadings for the monthly variables, and ξ_t is a $n_1 \times 1$ vector of idiosyncratic components. The factors are estimated as a VAR process of order p:

$$f_t^m = C + A_1 f_{t-1}^m + \cdots + A_p f_{t-p}^m + u_t \tag{1.5}$$

where $A_1, \ldots, A_p$ are a $r \times r$ matrix of autoregressive coefficients, and u_t is an *iid* process such that $u_t \sim N(0, \sigma_u^2)$. The idiosyncratic component follows an autoregressive process of order 1, represented as:

$$\xi_t = \rho_1 \xi_{t-1} + \eta_t \tag{1.6}$$

where $\rho_1 < 1$ and $\eta_t \sim N(0, \sigma_\eta^2)$.

Our estimation of monthly GDP growth entails solving the problem of missing data, where the quarterly value of GDP is treated as the third-month data of the respective quarter. It means the quarterly level of GDP is the sum of its unobserved monthly contribution. As in Mariano and Murasawa (2003), Evans (2005), Giannone et al. (2008), and Bańbura et al. (2011), we have:

$$G_t^q = \frac{1}{3}\left(G_t^m + G_{t-1}^m + G_{t-2}^m\right) \tag{1.7}$$

where $t = 3, 6, 9, \ldots$, G_t^q is the level of quarterly GDP, and G_t^m is the level of monthly GDP. Taking the three-period difference yields:

Let $y_t^q = G_t^q - G_{t-3}^q$ and $y_t = \frac{1}{3}G_t^m + G_{t-1}^m)$, then 1.7 becomes:

$$y_t^q = y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4} \tag{1.8}$$

We use Equation 1.8 to link the observed monthly values of GDP to the unobserved values. This yields the following expression:

$$y_t^q = \left\{ \begin{array}{ll} G_t^q - G_{t-3}^q & \quad \text{for } t = 3, 6, 9, \ldots \end{array} \right.$$

Like Mariano and Murasawa (2003) and Bańbura et al. (2011), we assume the unobserved monthly growth rate, y_t, can be represented by the same factor as the monthly real variables in Equation (4), such that:

$$y_t = \mu_2 + \Gamma f_t^m + \zeta_t \tag{1.9}$$

and

$$\zeta_t = \rho_2 \zeta_{t-1} + \varphi_t \tag{1.10}$$

where $\rho_2 < 1$ and $\varphi_t \sim N(0, \sigma_\varphi^2)$.

Suppose $y_t^+ = (x_t', y_t^q)$ and $\mu^+ = (\mu_1', \mu_2)$. We use the following state-space representation:

$$\begin{aligned} y_t^+ &= \mu^+ + Z(\theta) s_t + e_t \\ s_t &= T(\theta) s_{t-1} + w_t \end{aligned} \tag{1.11}$$

where $w_t \sim N(0, \Sigma(\theta))$, $s_t = (f_t', f_{t-1}', f_{t-2}', f_{t-3}', f_{t-4}', \xi_{1,t}, \ldots, \xi_{n,t}, \zeta_t, \zeta_{t-1}, \zeta_{t-2}, \zeta_{t-3}, \zeta_{t-4})'$, all parameters μ^+, Λ, Γ, A_1, σ_u^2, ρ_1, ρ_2, $\sigma_{\eta,1}, \ldots, \sigma_{\eta,n}$, σ_φ are included in θ, which is estimated by the Expectation-Maximisation (EM) algorithm like Doz et al. (2012), Bańbura and Modugno (2014), and Bańbura et al. (2011).

1.4 Data and data transformation

This chapter uses monthly data for South Africa from the period January 2000 to April 2017, collected from Bloomberg and the SARB. The dataset comprises 39 financial variables and 2 macroeconomic variables, namely the GDP growth rate and the year-on-year headline inflation rate. The financial variables are grouped according to the major markets of the financial system in South Africa, namely the equity, funding, foreign exchange, credit, real estate, and global financial market. The equity market considers price indices that measure the movement in stock markets, while the funding market covers interest rate spreads. The credit market includes a range of government bond spreads, which are a measure of credit risk, while the foreign exchange market considers exchange rate variables. The real estate market includes house prices (following the impact of the global financial crisis), while the global market includes international financial indicators (such as the US Vix) that would impact an emerging market like South Africa. The list of variables, their sources, and the treatment are included in the Appendix. We use the natural logarithms for all the variables, except those in rate. We use spreads for most of short- and long-term interest rates, expressed as a difference from the 91-days Treasury bills. Particularly, the South African TED spread, which is simply the difference between the JIBOR and the 91-days Treasury bill rate, provides evidence on liquidity risk in interbank lending.[2] We transform all the series accordingly to induce stationarity.

The foreign exchange (FX) market crash describes uncertainty or liquidity demand when the FX market crashes and indicates the extent to which the nominal effective exchange rate (NEER) has collapsed over the past 12 months. We calculate it as follows:

$$FXcrash_t = \frac{x_t}{\max\left[x_t \in (x_{t-i} | i = 1, \ldots, 12)\right]} \tag{1.12}$$

[2]The US TED spread is the difference between the LIBOR and the 90-days Treasury bill rate.

where x_t is the trade-weighted NEER and $\max\left[x_t \in (x_{t-i}|i = 1, \ldots, 12)\right]$ is the maximum NEER observed over the previous year.

Equivalently, the stock market crash describes expectations about the state of banks and indicates the extent to which the All-Share Index has collapsed over the past 12 months. Like the FX crash, it yields the following expression:

$$Stockcrash_t = \frac{x_t}{\max\left[x_t \in (x_{t-i}|i = 1, \ldots, 12)\right]} \tag{1.13}$$

where x_t is the All-Share Index of JSE Limited (JSE).

Other variables we calculate are the financial beta (β_{fin}) and the banking beta (β_{bank}), which represent the relationships between each of these sectors with the overall index, in this case, the JSE All-Share Index. More precisely, the financial beta captures the co-variance between the Financial Price Index and the JSE All-Share Index over the variance of the Financials Price Index, derived from the capital asset pricing model (CAPM). Mathematically, we have:

$$\beta_{fin} = \frac{cov\left(r_{fin,t}|_{t-1}^{t}, r_{JSE,t}|_{t-1}^{t}\right)}{var\left(r_{JSE,t}|_{t-1}^{t}\right)} \tag{1.14}$$

where $r_{fin,t}|_{t-1}^{t}$ is the return of the financial price index from the previous year and $r_{JSE,t}|_{t-1}^{t}$ is the market return of the previous year, represented here by the JSE All-Share Index.

Similarly, β_{bank} describes the risk in the banking sector. It yields the following expression:

$$\beta_{bank} = \frac{cov\left(r_{bank,t}|_{t-1}^{t}, r_{JSE,t}|_{t-1}^{t}\right)}{var\left(r_{JSE,t}|_{t-1}^{t}\right)} \tag{1.15}$$

Finally, all the series are standardised by subtracting the mean and dividing by their respective standard deviations before estimating the FCI, which implies that the FCI itself is standardised.

1.5 Empirical results

1.5.1 Extracted FCI and macroeconomic activity

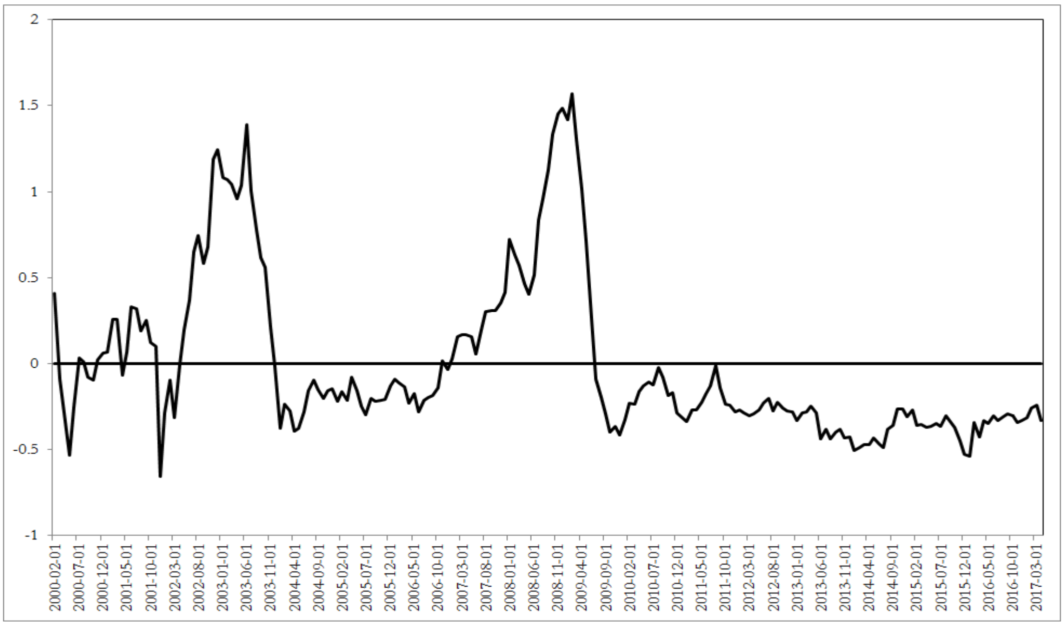
We use a single-factor model based on the IC and PC criteria of Bai and Ng (2002). It is consistent with the literature, such as Koop and Korobilis (2014).

Figure 1.1 shows the extracted FCI based on the PCA and the Kalman smoother. Since the FCI is standardized, 0, which is the mean of the FCI, can be interpreted as the financial system at the average level of risk. We use it as the threshold, such that values above 0 exceed the average and hence send a signal of a plausible crisis in the financial market. Positive values that are close to 0 represent the low probability of a crisis, whereas values strictly greater than 0 indicates an imminent crisis in the financial market. Additionally, as we follow the methodology of Koop and Korobilis (2014) the FCI is purged of any contemporaneous macroeconomic impact. Put differently, by including both the unobserved factor and macroeconomic activity (nowcast GDP growth and inflation) in the VAR specification, we remove any impact current macroeconomic activity has on the financial market. By doing so, we ensure our FCI captures only movements in the financial market[3].

With that in mind, Figure 1.1 is a graphical representation of our FCI. The FCI was above 0 from 2000 to 2001, from 2002 to 2003, and from 2006 to 2009. The increase in the FCI in 2000 was caused by the depreciation of the domestic currency, originating from stress in the global financial market owing to the burst of the Dotcom bubble. While the South African rand depreciated, the country experienced high levels of imports (at 26 percent of GDP) and a reduction in export volumes which contributed to a slowing down

[3]For robustness, we purge the FCI of economic activity using industrial production growth as a proxy for GDP. The two FCIs trend together throughout the sample. Moreover, we find a very high correlation coefficient of 99.22 percent between the two FCIs. A graphical representation comparing the two FCIs can be found in the appendix

Figure 1.1: FCI



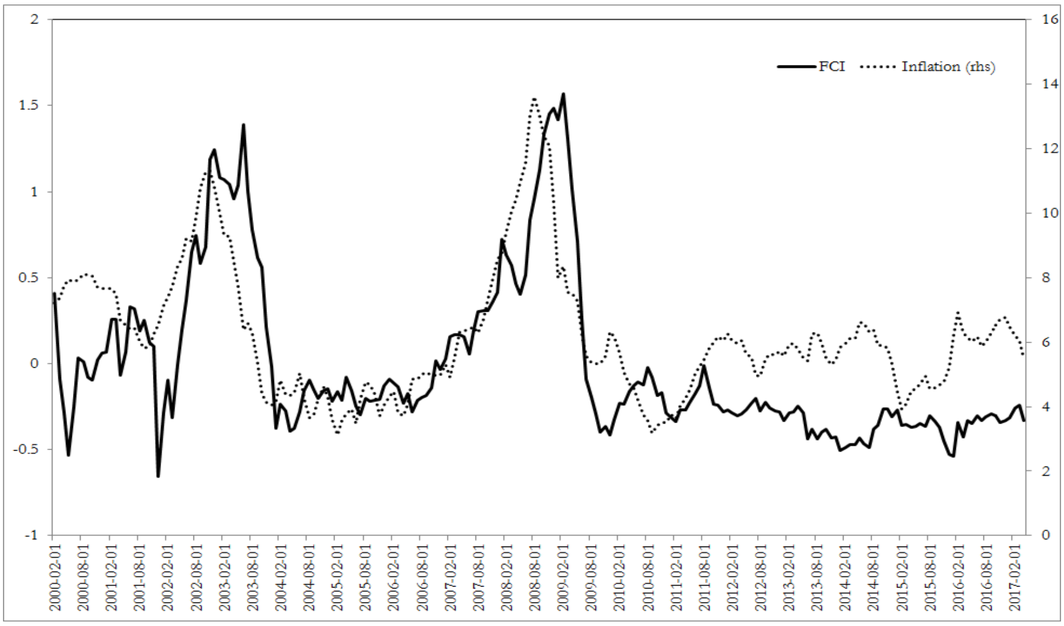
This is a graphical representation of our FCI. As the FCI is standardized, values above 0 indicate stress in the financial market while those below represent ease of financial tensions.

in domestic economic growth. It also experienced a decline in bond yields despite having significant negative net foreign assets prior to the crash. The second period, which was somewhat idiosyncratic to South Africa, coincided with the massive depreciation of the rand in the second half of 2001. The South African rand depreciated by 26 percent in nominal terms against the U.S. dollar, but short-term interest rates remained stable, long-term bond yields increased by about 100 basis points, and sovereign U.S. dollar-denominated bond spreads narrowed by about 40 basis points. The last breach of the threshold captured the stress from the most recent GFC, which started in 2006, way before the 2008 crash in the US and the 2009 crash in South Africa.

The upward movement observed from late 2006 until the end of 2008 was mainly due to risk emanating from the credit side of the FCI as it was a period of an unprecedented rise in credit growth which created a bubble in the real estate sector. It is worth mentioning that this surge in credit and the risk it created in the financial market was not specific to South Africa; it was observed globally. Then in August 2008, the GFC originating in the US exerted downward pressure on the FCI after inducing a recession in the real sector; all 6 financial-market sectors portrayed a marked decline. The stock market plummeted. The rand depreciated at first, then appreciated later on. Financial intermediaries cut their funding because of a lack of demand. Since then, the FCI has been stable, below the 0 threshold, with a few instances of an increase in financial stress. More precisely, the spikes in the FCI close to the 0 mark from 2009 to 2010 and in 2011 were caused by, respectively, the fear of a double-dip recession in the US and the European debt crisis.

The remaining events, with relatively high risk, are specific to South Africa. In August 2014, the debacle of African Bank generated risk in the financial market based on a fear of contagion to other banks. The FCI exhibits a small uplift at the end of the sample, which was caused by the depreciation of the rand coming from the removal of the then Finance Minister Nhlanhla Nene. Stress remains slightly elevated, with the most recent political turmoil culminating in the removal of the then Finance Minister Pravin Gordhan.

Figure 1.2: Relationship between FCI and Headline Inflation



This graph shows the relationship between the FCI and headline inflation, where inflation is on the right hand side axis.

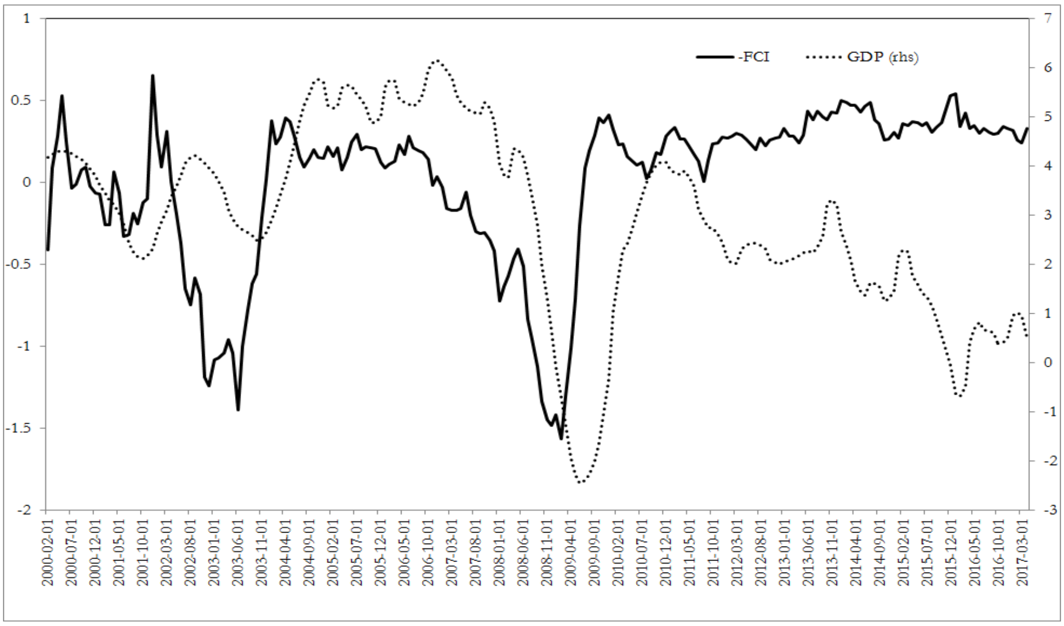
Figure 1.2 shows the correlation between the extracted FCI and headline inflation. It is clear the two series trend together throughout the sample, but headline inflation appears more volatile than the FCI. Evidence of co-movement between the two series is exemplified by a correlation coefficient of 67%. The increases in both the FCI and inflation in 2000 were caused by a depreciation of the rand together with contractionary monetary policy. A further depreciation of the rand in 2001 pushed inflation even higher, from 5.88% in October 2001 to 11.33% in November 2002. This also created stress in the FX market, with the FX crash variable attaining its lowest level ever. The SARB reacted to inflationary pressure by increasing the policy rate. The FCI reached its peak a month later, then decreased and increased again before a sharp drop in June 2003. Interestingly, the highest level it attained was lower than its highest level during the GFC. In addition, the market risk increased considerably, contracting the stock market.

It is worth mentioning that the currency shock of 2001 was mainly idiosyncratic, but it exerted stress of a magnitude that was only slightly lower than the one witnessed during the GFC, which was the worst financial crisis since the Great Depression of the 1920s.

The two series trend downwards and remain stable from 2003 to 2006. This period is perceived as a relatively tranquil episode in the financial market. But in the wake of the GFC, the two series exhibit a synchronized upward movement. The gradual rise in inflation from 2006 to 2008 was caused by a rise in demand combined with an increase in oil and food prices and a depreciation of the rand. Importantly, inflation declined first as a result of the GFC, and the FCI followed 6 months later. Notice also that the GFC spilled over into South Africa through rapid and sharp movements in the exchange rate, yields of different maturities, and the stock market. It, therefore, makes sense to observe a delayed reaction of the FCI compared with inflation. The two series have been stable ever since, with inflation portraying more volatility.

Similarly, Figure 1.3 represents the relationship between the FCI and the

Figure 1.3: Relationship between negative FCI and GDP growth

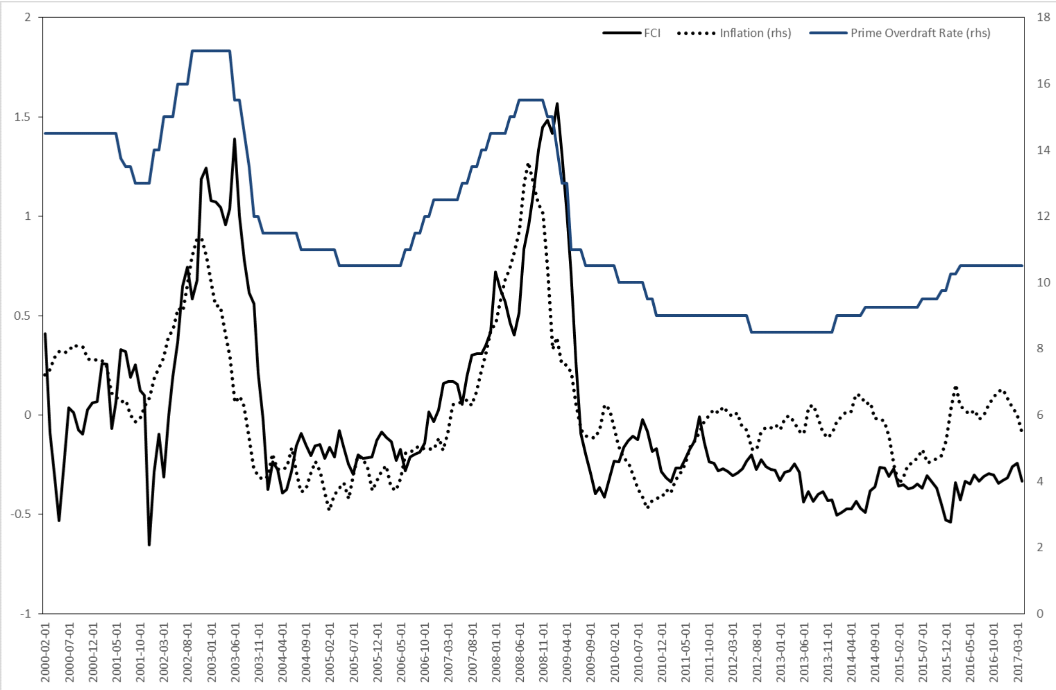


This graph shows the relationship between the inverse of the FCI and the nowcast GDP growth. GDP growth is on the right hand side axis.

constructed monthly GDP growth rate. Note that we use the negative value of the FCI for a better comparison. In general, the two series co-move, except in the aftermath of the GFC. During this period, the FCI is primarily driven by inflationary pressure owing to the exchange rate, oil, and food price movements. The relationship is not contemporaneous like with the inflation case in Figure 1.2. Instead, the FCI tends to lead the GDP growth rate by at least four months.

In general, stress in the financial market can be perceived as a warning signal of possible future weaknesses in the real economy. It helps to predict dynamics in the business cycle, especially the turning points. For example, the FCI in Figure 1.3 passed the threshold in May 2002 – approximately 6 months before the economic growth rate reached its peak. And its downward trend commenced in April 2006, followed by a decline in economic activity in February 2007. Finally, the FCI reached a trough in February 2009, four months before the real economy did.

Figure 1.4: Relationship between FCI, Inflation, and the Prime Overdraft Rate



This graph shows the relationship between the FCI, headline inflation, and the prime overdraft rate. Headline inflation and the prime overdraft rate is on the right-hand side axis.

It is interesting to observe that the FCI lags inflation (as seen in Figure 1.2) yet leads GDP growth (as seen in Figure 1.3). Moreover, we note the high correlation between inflation and the FCI. The FCI can be seen as a reaction function responding to changes in the policy rate that spillover into the financial market. This takes place through the interest rate channel. For example, assume we observe an increase in consumer prices increasing the inflation rate, and the SARB responds by tightening monetary policy and increasing the policy rate to anchor inflation. This increase in the policy rate leads to an increase in short-term real interest rates that induces an increase in financial market activity, such as the exchange rate, a decrease in the stock market, and a reduction in investment activity. FCI, in turn, reacts to a tightening in the financial sector and starts to rise. In turn, this reduces economic activity such that GDP growth decreases. It is not uncommon for FCI to react to movements in inflation. Purcell (2022) show that Goldman

Sach's FCI leads US inflation rates, particularly after the 2008 global financial crisis, where the variables representing its FCI (a weighted average of riskless interest rates, the exchange rate, equity valuations, and credit spreads) were impacted by quantitative easing. It is common practice to gauge financial conditions by looking at nominal or real interest rates, credit spreads, equity valuations, and the exchange rate. Therefore, it is reasonable for monetary policy action that affects the movement of these financial market variables to change financial conditions. The relationship between the FCI, inflation, and the prime overdraft rate can be seen in Figure 1.4. We use the prime overdraft rate as a proxy for the policy rate. It is evident that the 3 series co-move. Moreover, the prime overdraft rate lags inflation by approximately 2 months but leads the FCI by 3 - 4 months.

1.5.2 Time-varying factor loadings

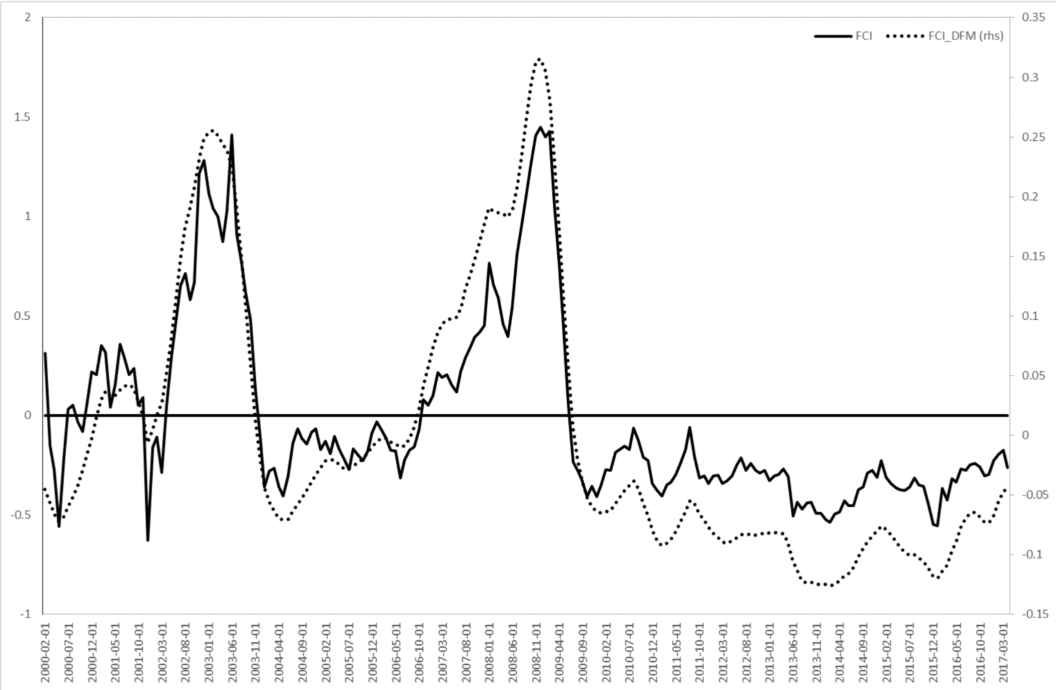
An advantage of using a time-varying FAVAR model is that the model allows the factor loading to change with time. It is worth mentioning that the time-varying weights follow a random walk and therefore change slowly but are more persistent, meaning the FCI is a better historical representation of financial movements. Put differently, at short time horizons, our FCI with time-varying weights and constant parameters FCI are the same. However, at longer horizons, differences between the time-varying and constant parameters FCI are noticeable. We demonstrate this in Figure 5, which shows the relationship between an FCI with time-varying weights against one with constant parameters. Following Matheson (2012), the constant parameters FCI is constructed using a dynamic factor model of the following:

$$X_t = \lambda F_t + e_t$$

$$F_t = \beta F_{t-1} + u_t$$

where X_t is a vector of financial variables and F_t is an unobserved factor, i.e. the constant parameters FCI (shown as FCI_DFM in Figure 1.5). Once again, as seen in Figure 1.5, a noticeable difference can be observed between our FCI and the FCI_DFM over the entire period, particularly after the GFC in which the two FCIs deviate. Koop and Korobilis (2014) show that the FCI for the US with time-varying loadings is quite similar to that with constant coefficients but differs more substantially during some peaks and troughs.

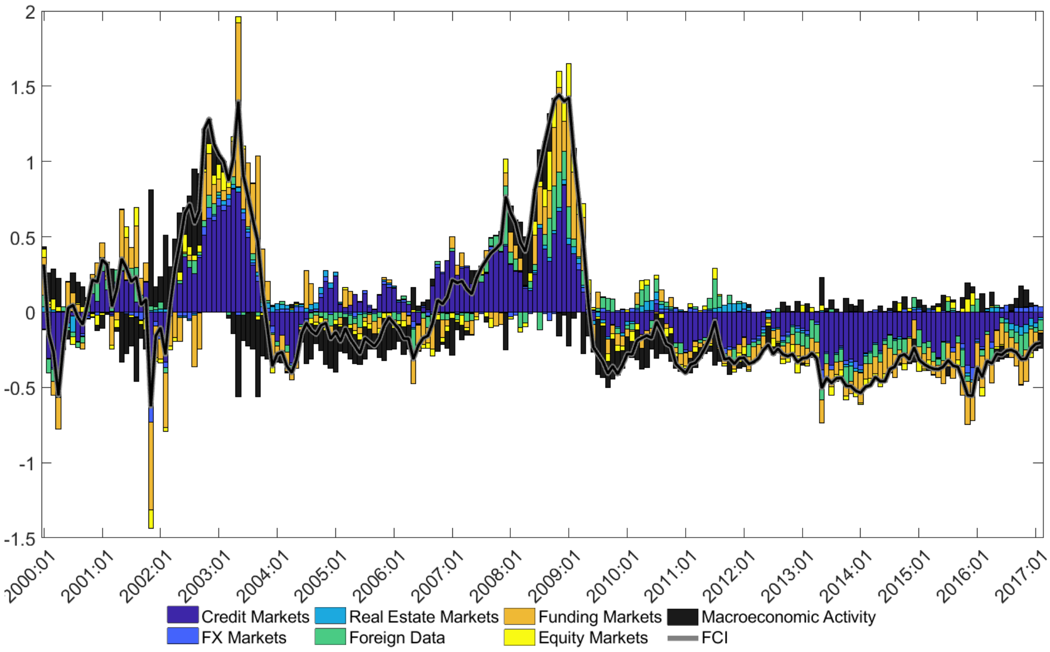
Figure 1.5: Long-term relationship between time-varying and constant parameters FCI



This graph shows the relationship between the FCI with time-varying weights against one with constant parameters.

As the time-varying weights change with time, it is useful to examine the drivers of our FCI. We do this by observing the financial sector's contribution to our FCI. The contribution of all 6 financial sectors is represented in Figure 1.6, as well as the contribution owing to purging the FCI of macroeconomic activity (labeled Macroeconomic Activity). The increase in the FCI during the depreciation of the rand from 2001, as well as the build-up to the GFC in 2006, is primarily driven by the credit market and, to a lesser extent, the funding market (and the FX market during the period of massive depreciation). Both periods include global shocks to the domestic market (i.e. the burst of the Dot.com bubble in 2001 and the leadup to the GFC), which led to stress

Figure 1.6: FCI and contributions by financial sector



in foreign debt and, subsequently, increased credit risk. Similarly, the credit market (and, to a lesser extent, the funding and foreign markets) is a main driver in easing financial tensions following the GFC (credit spreads represent approximately 30 percent of the index).

In Figure 1.7 we look deeper into the FCI contributions by examining the 2-factor loadings with the highest average over the sample period in the credit, funding, FX, and foreign markets. It is clear that factor loadings are not constant. Hence, using constant loadings like Gumata et al. (2012) is too restrictive.

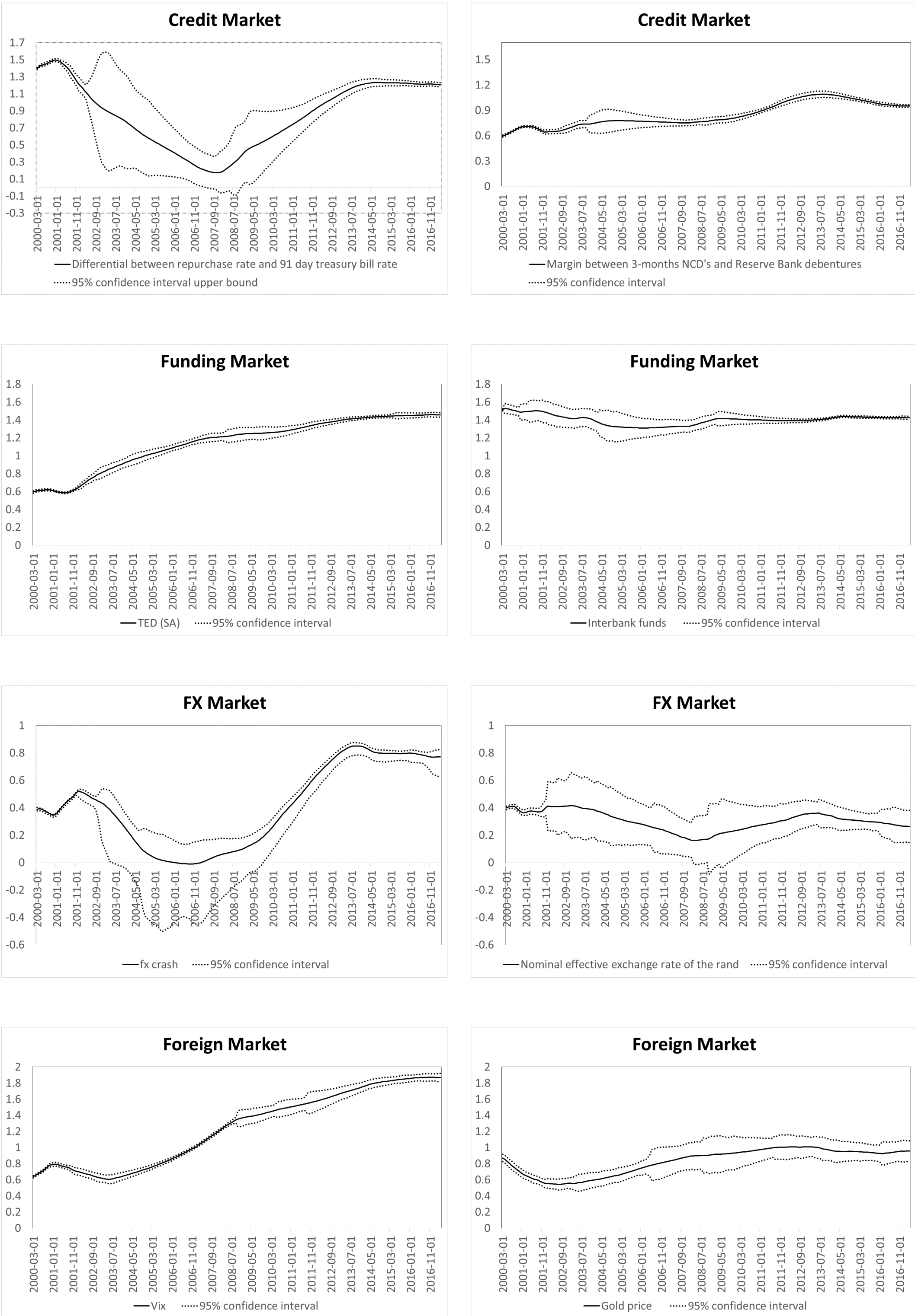
The first two graphs show the 2-factor loadings with the highest average over the sample period in the credit market. The differential between the repurchase rate and the 91-day treasury bill rate scored the highest values during the U.S. stock market crash of 2001 and then drastically decreased, obtaining its lowest value during the GFC. The margin between the 3-month NCD and the Reserve Bank debentures shows a more steady pattern. It increases slowly before the GFC, takes a slight dip during the GFC, and rebounds back to its pre-GFC level before gradually decreasing during Nene-gate in 2016 (in which the President removed then Minister of Finance Nhlanla Nene from his position in office). The next two graphs represent the loadings in the Funding Market. The South African TED spreads are trending upward, albeit with different slopes, indicating increased liquidity risk in interbank lending. In contrast, interbank funds slightly reduce over the South African exchange rate crisis of 2002 but rebounded after and remained constant throughout the rest of the sample.

The bottom middle graphs represents the FX market. The loadings of the FX crash depict V-shaped pattern, which captures both the South African exchange rate crisis of 2002 (where the FX crash started to sharply fall) and the GFC. It strengthened following the GFC and remained constant towards the end of the period. Similarly, the nominal effective exchange rate gradually decreases over during the exchange rate crisis, hits its lowest level during the GFC, and then gradually improves. Finally, the final graphs present the foreign market. The weight of the VIX trends upward from the beginning to the end of the sample while the Gold price decreases at the start of the sample. The VIX takes a slight dip following the U.S. stock market crash and then trends upwards, indicating an increase in stock market volatility. In contrast, the gold price reaches its lowest level following the terrorist attack in 2001 and then gradually increases and remains constant.

1.5.3 Forecasting ability

To evaluate the predictability of the FCI, we compare the out-of-sample prediction of the economic growth rate and the inflation rate using the TVP-FAVAR. We use a two-variable vector VAR model, which includes the economic growth rate and the inflation rate, as a benchmark model. The main difference between the VAR and the TVP-FAVAR models is that the latter contains the estimate FCI in addition to the two macroeconomic variables. Furthermore, we use the FAVAR model with constant loadings –

Figure 1.7: Selected Factor Loadings of Variables in Different Markets



like Gumata et al. (2012) – as an alternative model. Table 1 exhibits the relative mean squared forecast errors (RMSFEs) of the out-of-sample forecasts from January 2005 to April 2017. The RMSFE in Table 1.1 represents the forecasting ability of the TVP-FAVAR (or the FAVAR in columns 4 and 5) relative to a simple VAR model. Values above 1 suggest the VAR model outperforms the TVP-FAVAR (or FAVAR). Conversely, values below 1 suggest the TVP-FAVAR (or FAVAR) outperforms the VAR model, and a value of 1 indicates equal performance.

In general, the TVP-FAVAR, depicted in columns 2 and 3 of Table 1, outperforms the VAR for both variables for all the forecast horizons. The results are roughly the same when we use the constant-loading FAVAR.[4] Like the TVP-FAVAR, the forecast of GDP growth outperforms the small VAR over the entire forecasting horizon. Additionally, after performing Diebold-Mariano test of forecasting accuracy, these results are all statistically significant at 10 percent.

Finally, when we compare the RMSFEs of the TVP-FAVAR and the FAVAR, the former surpasses the latter throughout the forecast horizon for both macroeconomic variables, except for the first three months where the latter scores lower RMSFEs. Moreover, the results of the TVP-FAVAR are not statistically different from the benchmark model, the VAR. In contrast, the FAVAR model statistically different from the VAR model in forecast horizons 5 to 12. It is worth mentioning that the two models of GDP growth for the 12-month horizon show comparable performance. These results point to the important contribution of financial variables in predicting macroeconomic variables.

As a robustness test we remove the two crisis periods, the 2002 exchange rate crisis and the 2008 GFC, from our models and re-estimate the forecasting ability of the TVP-FAVAR (or FAVAR) against the benchmark VAR model[5].

[4]See columns 4 and 5 of Table 1.

[5]The tabulated results are available upon request.

Table 1.1: RMSFE

	TVP-FAVAR		FAVAR	
	GDP	INFLATION	GDP	INFLATION
1	0.509*	0.411*	0.344*	0.382*
2	0.501*	0.444*	0.418*	0.448*
3	0.516*	0.449*	0.516*	0.515*
4	0.521*	0.453*	0.596	0.593*
5	0.543*	0.461*	0.654	0.682
6	0.569*	0.469*	0.705	0.791
7	0.598*	0.473*	0.734	0.882
8	0.635*	0.481*	0.753	0.966
9	0.673*	0.480*	0.771	1.048
10	0.716*	0.481*	0.782	1.101
11	0.743*	0.474*	0.785	1.165
12	0.780	0.479*	0.777	1.213

Significance test given as Diebold-Mariano test for predictive accuracy. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. RMSFE > 1 indicates better VAR forecasting performance relative to the TVP-FAVAR (or FAVAR) model. RMSFE < 1 indicates better TVP-FAVAR (or FAVAR) forecasting performance relative to the VAR model. RMSFE $= 1$ indicates equal forecasting performance.

The RMFSEs for these estimations are higher than those in Table 1.1 across all forecast horizons. In general, relative to the VAR model, both the TVP-FAVAR and the FAVAR models depict equal performance in tranquil periods. However, when estimating inflation, the FAVAR outperforms the VAR model at 10 percent for the first five forecast horizons. The VAR model performs better than both the TVP-FAVAR and the FAVAR model when estimating GDP growth; however, this performance (RMSFEs) is statistically insignificant. This suggests that factors are important for inflation but not growth during tranquil times. In particular, time variation in the FCI does not improve predictability during tranquil periods; however, in crisis periods, the VAR model fails to learn about the structural break in the data. In such cases the TVP-FAVAR is an appropriate model as it only adds additional dynamics to the model in terms of unobserved variables. Additionally, the time-varying dimension of the model facilitates learning about regime change.

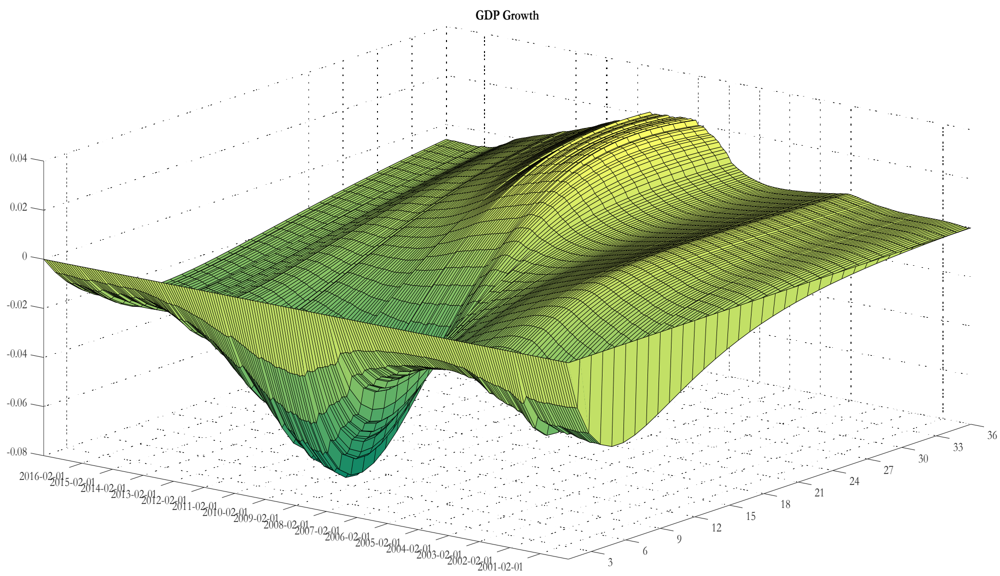
These results are consistent with the recent findings in the literature on the asymmetric relationship between financial conditions and GDP growth rate. Adrian et al. (2019) find a strong connection between extremely negative outcomes in GDP growth and extremely positive outcomes of the FCI, whereas there is a weak link between positive outcomes in GDP and negative outcomes in FCI.

1.5.4 Impulse Responses

Finally, we examine the response of both the GDP growth rate and inflation to a tightening of financial conditions. Figure 1.8 illustrates a three-dimension response of the GDP growth rate, which changes with time and over a forecast horizon of 36 months to a percentage tightening of financial conditions. The identification scheme of the tighter financial conditions is based on the Cholesky restriction, where the FCI is ordered last after GDP growth and the inflation rate. We use two lags in the FAVAR, based on the Bayesian information criteria, and the IRFs are calculated over 36 months. Figure 1.8 exhibits the expected sign: the real economy reacts negatively to financial conditions tightening.

It is clear from the picture painted in Figure 1.8 that the effects of the FCI on the real economy vary over time. We observe two episodes of contraction of the real economy caused by tight financial conditions, namely at the beginning of the sample and during the GFC. Recall that, during these two periods, the

Figure 1.8: Time-Varying IRFs of GDP growth



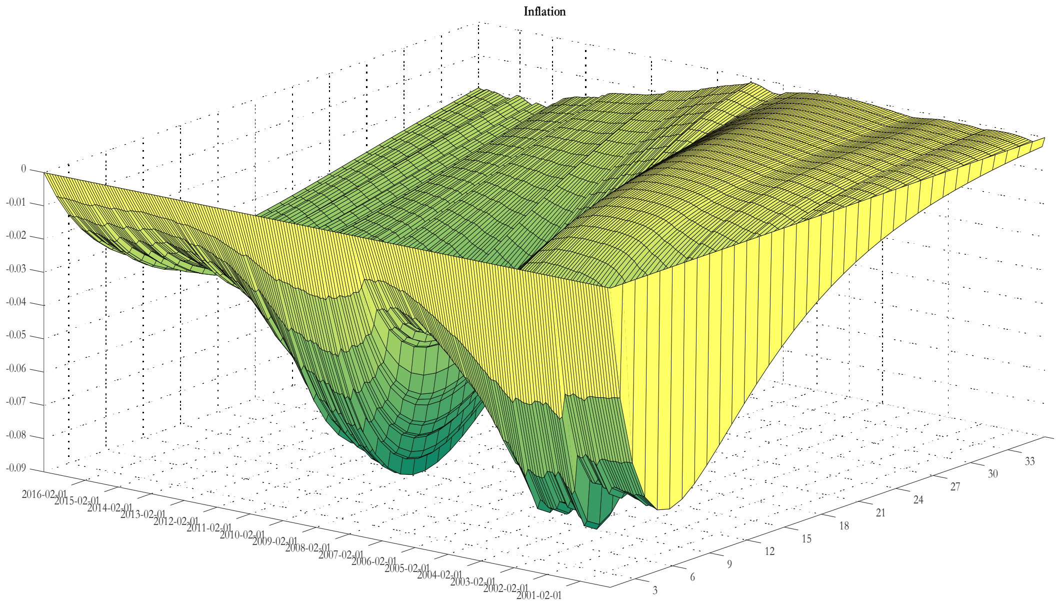
FCI is above 0. The monetary policy authority reacted to the depreciation of the currency in 2001 by raising its policy rate, which in turn put downward pressure on the real economy.

It is worth noting that a percentage rise in the FCI had negligible effects on the real economy during the tranquil period which preceded the GFC. Then came the strong reaction caused by the increase in risk originating from the GFC. In this case, a percentage increase in the FCI had considerable effects on the real economy. Unlike in the first episode, the effects of the GFC induced a recession. The IRF reached the maximum of about 0.08 and then reverted slowly in the following years. The effects of tight financial conditions on the real economy were extremely small from 2013 till the end of the sample. The results confirm the findings based on the forecasting exercise of asymmetry in the relationship between the two variables.

Note that Figure 1.9 is based on the same identification as Figure 1.8. The picture is somewhat similar to that of GDP growth.

Following a tightening of financial conditions, inflation decreased as a result of

Figure 1.9: Time-Varying IRFs of Inflation



a contraction in the real economy. This suggested that stress in the financial market was deflationary. In general, the effects reached the maximum after four months and then died out gradually. This implied that the shock to the FCI had temporary effects on both the real economy and inflation. Similarly to the effects on the real economy, the effects on inflation changed with time too. In addition, the inflation reaction followed the same pattern as the real economy, with two episodes of strong reaction: the massive depreciation at the beginning of the sample and the GFC effect around 2008 and 2009. Unlike the real economy, the effects on inflation were stronger between 2002 and 2003 than during the GFC. They reached a maximum of more than 0.08 in 2002 and remained high until 2003. Prior to the GFC, the FCI shock registered a weak effect on inflation. The effects reverted downward, attaining a maximum of about 0.08 during the GFC, and then died slowly to its pre-GFC level.

Like the real economy, the IRF has been stable, closer to 0 towards the end of the sample. Importantly, the maximum effects on both the real economy and inflation are comparable, even though the effects on the latter lag in the first period. Hence, it is crucial for policymakers to take the shock from the financial market into account since its effects are detrimental to the real economy, rather than attempting to clean up the mess after the burst of the bubble, as suggested by some economists prior to the GFC.

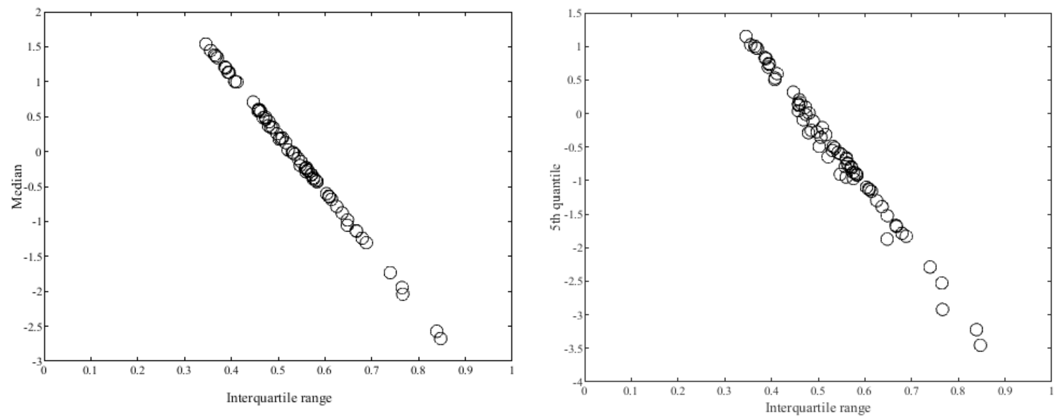
1.5.5 Quantile Regression

In this subsection, we run a quantile regression to assess the validity of the asymmetric relationship between financial conditions and GDP growth as the results obtained with the forecasting exercise and IRFs seem to suggest[6]. The quantile regression links current financial conditions with future GDP growth. Moreover, it highlights the asymmetric relationship between the two variables in that loose financial conditions seem to be a bad predictor of a future boom, whereas tight financial conditions predict with high accuracy future tail decline in GDP growth. It means instead of estimating the point forecasts of GDP growth as conducted here above with the TVP-FAVAR, the quantile regression uncovers the entire future distribution of GDP growth. We start with a simple scatter plot of, on the one hand, median and interquartile range, and on the other hand, the 5^{th} quantile and the interquartile range (Figure 1.10). The figure reveals a strong negative relationship in both cases which suggests that tight financial conditions decrease the median of the future GDP growth while, at the same time, they increase interquartile range and vice-versa. Similarly, tail negative risks are strongly associated with a rising interquartile range.

The asymmetric relationship between the two variables is more visible in Figure 1.11, which depicts the expected shortfall, which represents a measure of downside risk, and the expected longrise, which is a measure of upside risk. An increase in the FCI signals higher downside risks to the South African economy, while loose financial conditions predict the opposite. Interesting

[6]To avoid sidetracking readers with a separate section describing the implementation of quantile regression, we instead refer them to the recent work of Adrian et al. (2019), which we follow closely.

Figure 1.10: One Quarter Ahead Median, 5^{th} Quantile, and Interquartile Range of the Distribution of GDP Growth



(a) Median and Interquartile Range

(b) 5^{th} Quantile and Interqaurtile Range

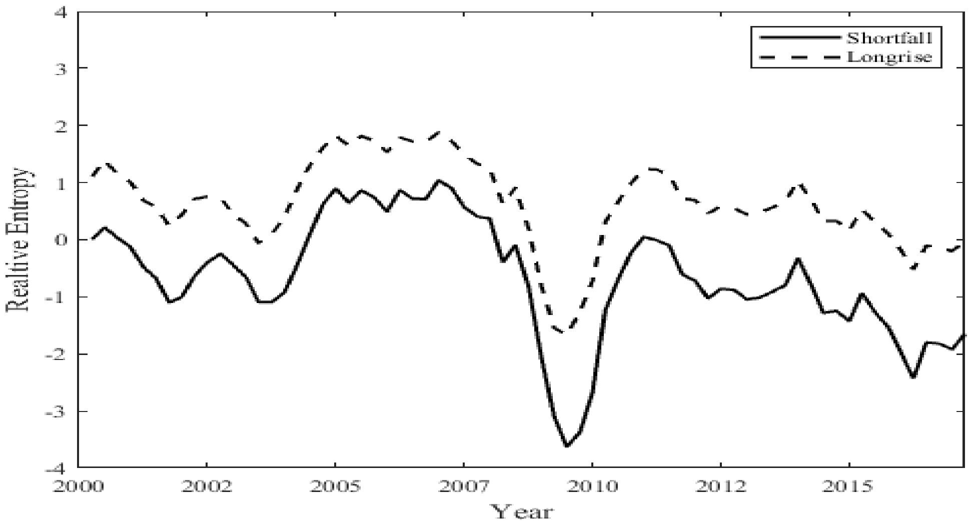
This figure shows the scatter plot of the median and interquartile range (left figure (a)) and the 5^{th} quantile and the interquartile range (right figure (b)) of the distribution of GDP growth.

observations emerge from these results. Consistent with Adrian et al. (2019), downside tail risks are more pronounced than upside risks to GDP growth. It is worthwhile noting that upside risks are muted for to US compared with South Africa. Unsurprisingly, IMF (2017b) obtain similar results for South Africa [7]. Specifically, periods of an unprecedented rise in GDP growth (from 2003 to 2006) which coincided with loose financial conditions, with the annual GDP growth reaching the maximum of 6 percent in 2006, were not accompanied by a substantial rise in upside risks. Surprisingly, negative FCI, which prevailed after the GFC until the end of the sample, did not trigger upside risk to the economy as expected. Contrarily, it was followed by rising downside risks to the economy. Kabundi and Rapapali (2019) provide an explanation for this conundrum. In contrast, the rise in FCI during the period leading to the GFC induced marked tail downside risks to GDP growth. Finally, the increase in FCI between 2001 and 2002 did not generate significant downside risks of the

[7]More precisely, see Figure 3.2 panel 3.

same magnitude as those registered during the GFC.

Figure 1.11: One Quarter Ahead GDP Growth Entropy and Expected Shortfall and Longrise



This figure depicts the expected shortfall, which represents a measure of downside risk, and the expected longrise, which is a measure of upside risk, over time.

1.6 Conclusions

This chapter estimates the financial conditions index (FCI) for South Africa using 39 monthly data series from the 6 main sectors of the financial market observed from January 2000 to April 2017. We use a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR), which includes, in addition to the FCI, two macroeconomic variables, namely the annual inflation rate and an estimated measure of real economic activity. The TVP-FAVAR model outperforms the vector autoregressive (VAR) model and the constant-loadings factor-augmented vector autoregressive (FAVAR) in forecasting inflation and the real gross domestic product (GDP) growth over all the forecast horizons for both variables. Moreover, the TVP-FAVAR beats the constant-loadings FAVAR throughout the forecast horizon for both macroeconomic variables, except in the first three months.

The results suggest that benefits can be gained from accounting for the change(s) in parameters. The changing nature of parameters becomes even clearer when we assess the response of GDP growth and inflation to tighter financial conditions. The two variables react differently at each point in time.

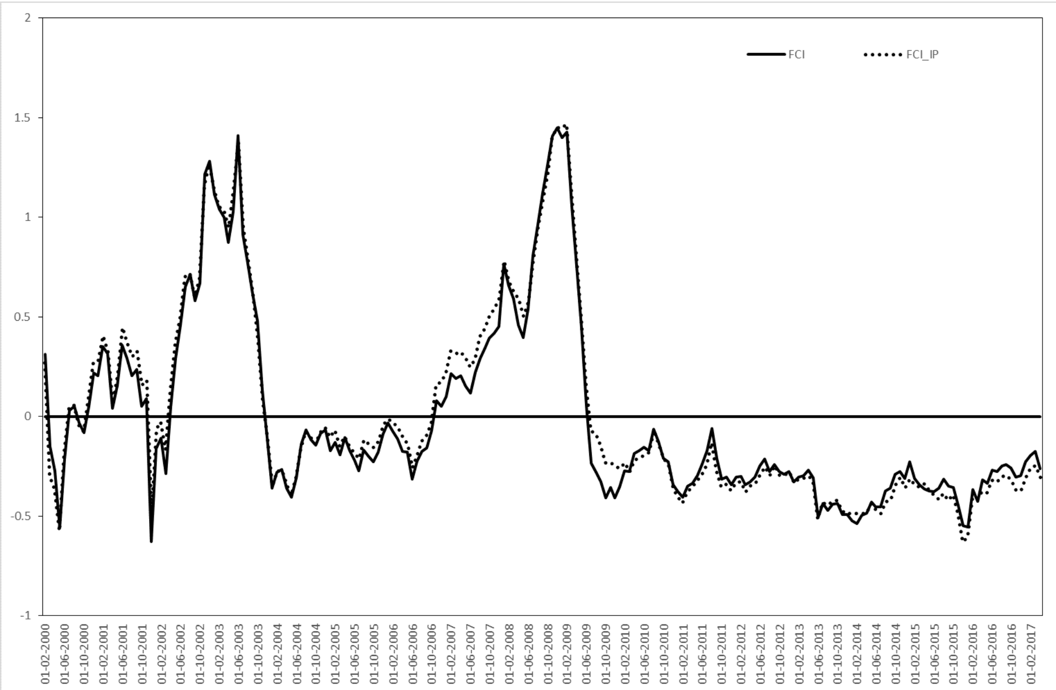
The results also display strong effects during the Global Financial Crisis (GFC) compared with the relatively tranquil episodes and therefore pointing to the asymmetric relationship between FCI and GDP growth. Policymakers could thus use the FCI as a warning signal for a possible crisis. Moreover, the FCI could also serve as an additional variable in models used for forecasting macroeconomic variables. Finally, it could help policymakers to understand the transmission mechanism of monetary policy and financial shocks to the real economy.

Appendices

A1.1 Summary Table

A1.2 Robustness Measure

Figure A1.1: Baseline FCI and FCI using Industrial Production Growth



The figure represents our baseline FCI constructed using our nowcast GDP (FCI) and the FCI constructed using industrial production growth (FCI_IP). Since the FCIs are standardized values above 0 indicate stress in the financial market while those below represent an ease of financial tensions. The FCIs have a high correlation coefficient of 99.22 percen

Table A1.1: List of variables

No.	Description	Definition	Frequency	Transformation	Source
		Credit Market			
1	All monetary institutions	Credit (Total loans and advances) extended to the domestic private sector	D	5	S
2	R186 10.5% (2026) - Government stock	Government stock	D	2	S
3	Yield Market: Eskom bonds & T-bill	Eskom bonds - 91 day Treasury Bill	D	1	S
4	Yield Market: 0-3 year government bond & T-bill	0-3 year government bond - 91 day Treasury Bill	D	1	S
5	Yield Market: 3-5 year government bond & T-bill	3-5 year government bond - 91 day Treasury Bill	D	1	S
6	Yield Market: 5-10 year government bond & T-bill	5-10 year government bond - 91 day Treasury Bill	D	1	S
7	Yield Market: Long-term government bond & T-bill	Long-term government bond - 91 day Treasury Bill	D	1	S
8	Secondary Market: JSE All Bond yield	JSE All Bond yield	D	2	S
9	Differential between repurchase rate & T-bill	Differential between repurchase rate - 91 day Treasury Bill	D	1	S
10	Margin between prime rate and 3-months Negotiable certificates of deposits (NCDs)	Prime rate - 3 month NCD's	D	1	S
11	Margin between 3-months NCD's and Reserve Bank debentures	3 month NCD - Reserve Bank debentures	D	1	S
		FX Market			
12	South African (SA) rand against US dollar (ZAR)	Exchange rate: SA rand against US dollar	D	5	S
13	Nominal effective exchange rate of the rand - 20 trading partners: Effective Jan. 2010 - Trade in manufactured goods	Nominal effective exchange rate of the rand	D	5	S
14	FX crash	$FXcrash_t = \frac{x_t}{\max[x_t \in (x_{t-i} \vert i=1,...,12)]}$	D	1	S
		Real Estate Market			
15	South Africa: ABSA House Price Index (SA, 2000=100)	House Price Index as calculated by commercial bank ABSA	M	5	S
16	FNB house prices	House prices as calculated by First National Bank	M	5	S
		Foreign Market			
17	U.S 3 month LIBOR	3 month Libor of the United States	D	2	B
18	U.S 90 day T-bill rate	90 day treasury bill rate of the Unite States	D	2	B
19	TED (US)	3 month LIBOR - U.S 90 day treasury bill rate	D	1	B
20	Vix	CBOE Volatility Index	D	1	B
21	S&P 500 stock in gold index	S&P 500 stock in gold index	D	5	B
22	Oil price in US dollars (Brent crude)	Price of Brent Crude oil in U.S dollars	D	5	B
23	Gold price - London (US dollar)	Gold price	D	5	B
24	Global Total Return index	Global Total Return index	D	5	B
		Funding Market			
25	Negotiable certificates of deposits (NCDs): 3 months	3 months NCDs	D	2	S
26	Negotiable certificates of deposits (NCDs): 6 months	6 months NCDs	D	2	S
27	Negotiable certificates of deposits (NCDs): 12 months	12 months NCDs	D	2	S
28	Prime overdraft rate & T-bill	Prime overdraft rate - 91 day Treasury Bill	D	1	S
29	Inter-bank funds & T-bill	Inter-bank funds - 91 day Treasury Bill	D	1	S
30	Bankrate and average & fixed repo rate	Bankrate / fixed repo rate	D	2	S
31	TED (SA)	3 month JIBOR - SA 91 day treasury bill rate	D	1	A
32	Financial beta	$\beta_{fin} = \frac{cov\left(r_{fin,t}\vert_{t-1}^{t}, r_{JSE,t}\vert_{t-1}^{t}\right)}{var\left(r_{JSE,t}\vert_{t-1}^{t}\right)}$	D	1	A
33	Bank beta	$\beta_{bank} = \frac{cov\left(r_{bank,t}\vert_{t-1}^{t}, r_{JSE,t}\vert_{t-1}^{t}\right)}{var\left(r_{JSE,t}\vert_{t-1}^{t}\right)}$	D	1	A
		Equity Market			
34	Stock crash	$Stockcrash_t = \frac{x_t}{\max[x_t \in (x_{t-i} \vert i=1,...,12)]}$	D	1	A
35	All share (J203) Price index	All share Price index	D	5	S
36	Financials (J580) Price index	Financials Price index	D	5	S
37	Banks (J835) Price index	Banks Price index	D	5	S
38	All share total return (J203T) Price index	All share total return Price index	D	5	S
39	General Mining (J154) Price index	General Mining Price index	D	5	S
		Macroeconomic Activity			
1	GDP	Nowcast of GDP growth	M	1	A
2	Inflation	Year -on-year change in consumer prices	M	1	S
3	Industrial Production Growth	Year -on-year change in industrial production	M	1	W
X	Prime Overdraft Rate	Benchmark rate at which private banks lend out to the public.	M	1	S

Frequency: D = Daily, M = Monthly. Note, variables with daily frequencies have been averaged to monthly frequencies

Transformation: 1 = Level, 2 = First difference, 5 = First log difference;

Source: A = Author's calculation, B = Bloomberg, S = South African Reserve Bank, W = World Bank Global Economic Monitor dataset;

2 The Impact of Bank Capital Changes on Lending Volumes: An Analysis of South African Banks

Abstract

This chapter estimates a non-linear fixed effects model that interacts banks' capital ratios with their liquidity levels to analyze the impact of bank capital changes on lending volumes, using monthly bank-level data from January 2008 to July 2020 on 25 South African banks. The analysis utilizes capital and liquidity measures presented by the Basel III regulatory framework. This chapter analyzes the marginal effects of bank capital on lending at the mean of liquidity to interpret the interaction between bank capital ratios and liquidity levels. The results indicate that, at average liquidity levels, banks with higher capital ratios increase the volume of commercial loans and decrease the amount of retail loans, implying that banks prefer to lend to firms than to households. As banks strengthen their solvency position, they are better situated to increase the capacity of their "risker" loan portfolio by raising their volume of enterprise loans. This then comes with the consequence of reducing household credit.

2.1 Introduction

The 2008 Global financial crisis (GFC) highlighted the need to maintain financial stability within the banking sector. The consequences of the GFC illustrated the need for regulators to strengthen the current capital requirements (thus ensuring the stability of capital buffers) and the importance of sustaining sound liquidity risk management. Bank capital requirements aim to improve bank solvency and provide a cushion during crisis periods. In particular, during the GFC, a shortage of bank capital was highlighted as a factor impacting banks' ability to issue loans. However, bank capital losses were insufficient to explain the sudden reduction in bank lending volumes. Liquidity also played a significant role in the GFC as numerous banks had not prudently managed their liquidity. An essential function of banks is performing liquidity transformation by funding long-term, illiquid assets with short-term liquid liabilities. Banks are thus at risk if short-term liabilities invested in illiquid assets are claimed at short notice, which happened during the GFC. In response, the Basel Committee on Banking Supervision (BCBS) released a capital and liquidity reform package in 2010, now known as Basel III (Basel Committee on Banking Spervision, 2010). The Basel III framework revised and strengthened the existing capital regulations and introduced a new set of liquidity indicators to ensure banks have sufficient stable funding and liquid assets to prevent banks from aggressively engaging in liquidity transformation.

Basel III included the implementation of a liquidity coverage ratio (LCR) that ensures banks have an adequate stock of unencumbered high-quality liquid assets (HQLA) which can easily be converted into cash, a net stable funding ratio (NSFR) that requires banks to hold enough stable funding to cover the duration of its long-term assets, and also tightened existing capital requirements[1] (Basel Committee on Banking Spervision, 2010). To comply

[1]The NSFR aims to address maturity mismatching between assets and liabilities, while the LCR requires banks to hold enough liquid assets for a 90-day liquidity stress scenario

with the new Basel regulations, banks had to build up their capital and improve the liquidity of their assets and the stability of their funding. In their efforts to comply, banks would have to modify their balance sheet structures. Doing so would possibly affect their core banking activity as providers of credit. Bank loans are subject to higher risk weights than trading securities. They qualify as semi-liquid or (in some cases) illiquid assets compared to short-term securities such as treasury bills which qualify as liquid assets (Berger and Bouwman, 2009).

The main objective of the Basel III reforms is to prevent spillovers from the financial sector into the real economy during periods of adverse economic shocks. In this context, an array of literature has examined the effects of financial shocks on bank capital and its impact on the supply of bank credit. For example, Melander and Bayoumi (2008) show that negative shocks to bank capital result in banks reducing their volume of credit, while Berrospide and Edge (2010) find modest effects of bank capital changes on lending. However, during the GFC, authors such as Gambacorta and Marques-Ibanez (2011) and Carlson et al. (2013) found that the relationship between capital ratios and loan growth was significant and stronger when credit declined. Additionally, these authors found that although most banks decreased their lending, those with weaker capital ratios had a greater reduction in credit supply.

The literature examining the impact of liquidity on bank lending finds that liquidity has both positive effects on commercial lending growth (particularly for large U.S. banks) and adverse effects on retail lending growth for European banks (Naceur et al., 2018; Roulet, 2018). Cornett et al. (2011) and Berrospide (2012) find that to manage (or hoard) liquidity, banks subsequently saw a decline in lending during the GFC. In contrast, Ivashina and Scharfstein (2010) find that decreased bank lending is associated with less access to deposit financing.

The relationship between bank capital and liquidity is complex. Bank capital is a crucial determinant for liquidity creation, while liquidity creation varies by bank size Berger and Bouwman (2009). While examining this relationship, Acosta Smith et al. (2019) find that the optimal liquidity holdings are different depending on the level of banks' capital ratios. They show that banks with higher capital ratios have a more stable liability structure and, therefore, require lower liquidity holdings because the probability of failure is minor. In this case, banks see less need to hold liquidity above regulatory requirements. On the other hand, when bank capital ratios are low, the likelihood of failure is high. Banks could face early liquidation if the liquidity holdings are low, which encourages banks to hold more liquidity. Additionally, Berrospide (2012) shows that capital played a significant role in the increased holdings of liquid assets during the GFC. The impact of this relationship on bank lending volumes differs on bank size. Kim and Sohn (2017) show that, for large banks, increases in capital ratios impact bank lending only when liquidity is rising, while it is negative for low liquidity ratios. Moreover, this result is more significant during crisis periods. The authors suggest that increases in capital ratios raise bank lending only after large banks have retained sufficient liquid assets. This relationship is statistically insignificant and negative for small and medium banks.

The literature on South Africa is in its infancy. Against this backdrop, this chapter seeks to contribute to the limited literature by examining how changes in capital ratios affect bank lending in South Africa, given their level of liquidity holdings. Banks in South Africa have high capital ratios. The Basel III Tier 1 capital adequacy ratio is six percent. Still, South Africans have held approximately twelve percent of Tier 1 capital over the last five years[2]. Following Acosta Smith et al. (2019), this chapter postulates that since South African banks have high capital ratios (defined as the ratio of Tier 1 capital to risk-weighted assets), they only need to hold liquidity (proxied by the net

[2]In November 2020, in response to the adverse effects of the Covid-19 pandemic on global markets, the BCBS increased the minimum Tier 1 capital adequacy requirement from 6 percent to 10.5 percent of risk-weighted assets.

stable funding ratio - NSFR) at least at the minimum requirement. Similar to Kim and Sohn (2017), this chapter investigates how changes in banks' capital impact their lending activities, given their level of liquidity holdings. Over the last five years, gross loan growth in South Africa has hovered around four percent, lower than in other emerging markets. The Basel III regulatory measures are designed to mitigate risk within the banking sector. This chapter seeks to determine if these capital and liquidity measures challenge banks' core business: lending.

To achieve this, the chapter estimates a non-linear fixed effects model for 25 South African commercial banks along the lines of Kim and Sohn (2017). The analysis studies the interaction of bank capital and liquidity and its effect on bank lending using monthly data from January 2008 to July 2020. By examining this non-linear relationship, the chapter determines how the bank capital and liquidity mix affect changes in lending. Additionally, because banks have high Tier 1 capital ratios, this chapter postulates that banks only need to hold liquidity (proxied as the NSFR ratio) that is just above the minimum requirement (the chapter defines this as average levels of liquidity). Therefore, in interpreting the results, the chapter analyzes the marginal effects of bank capital on bank lending at the mean of liquidity. By doing so, the analysis can deduce how bank capital affects bank lending at average liquidity levels. This focuses the results on the effect of capital on bank lending and further aids in simplifying the interpretation of the interaction term.

The main results indicate that increases in bank capital on commercial loan growth are positively related to average bank liquidity levels (above the regulatory minimum). Conversely, the chapter also finds that increases in bank capital ratios on retail loans are negatively related to average bank liquidity levels. The results suggest that when banks face fewer concerns over their solvency, they are willing to increase their portfolio of riskier loans by lending more to corporations and less to households. Indeed, Honohan and Beck (2007), Nana and Samson (2014), and Allen et al. (2011)

find that African banks prefer lending to the financial and non-financial sectors. Büyükkarabacak and Valev (2010) demonstrate that household credit growth increases banks; debt levels without much impact on their long-term income (possibly because household lending is generally through mortgages). Additionally, household credit growth increases bank vulnerabilities that can lead to a banking crisis. Conversely, loans to firms also increase banks' debt levels but are associated with increased income.

The remainder of this chapter is organized as follows; section 2 outlines the relevant literature, section 3 provides a brief background on Basel III and its implementation in South Africa, section 4 discusses the data and outlines the empirical approach, and section 5 presents the results. In contrast, the final section provides concluding remarks.

2.2 Selected Literature

The literature examining the impact of bank capital changes on bank lending has gained momentum following the 2008 Global financial crisis (GFC). For instance, Gambacorta and Marques-Ibanez (2011) and Carlson et al. (2013) find that banks with weaker capital ratios reduced credit supply more during the GFC than banks with higher capital ratios. In particular, these authors find a positive relationship between capital ratios and loan growth when credit is declining. Melander and Bayoumi (2008) find that adverse shocks to bank capital result in banks reducing their volume of credit. Increases in bank capital are positively associated with increases in credit growth, and this relationship holds during the GFC (Berrospide and Edge, 2010; Carlson et al., 2013). Researchers have found that this positive relationship was not observed before the GFC and suggest that capital became more important for credit growth following the crisis (Gambacorta and Marques-Ibanez, 2011; Cornett et al., 2011).

The literature examining the relationship between liquidity and credit growth has grown since the GFC and following the development of the Basel III measures aimed at strengthening banks' liquidity management and financial stability. Gambacorta and Mistrulli (2004) and Kishan and Opiela (2000) control for liquidity while looking at the bank-lending channel and find that the liquidity variables are positively related to bank-lending. DeYoung and Jang (2016) examines how U.S. banks manage their liquidity positions and find that banks of all sizes targeted the traditional loans-to-core deposits ratio. However, the evidence is more robust for smaller banks. The authors conclude that as banks increase in size, they set lower liquidity targets but manage them more efficiently. During the GFC, banks who hoarded liquidity saw a decline in bank lending (Berrospide, 2012; Cornett et al., 2011). Additionally, Ivashina and Scharfstein (2010) find that decreased bank lending is associated with less access to deposit financing. The positive relationship between liquidity requirements and lending may not hold following crisis periods. Following the consequences of the 2008 GFC, i.e., deteriorating economic conditions and tighter access to credit, more stringent liquidity requirements led to reduced bank lending activities (Berger and Bouwman, 2009). This happens as banks shrink their assets to meet liquidity regulations.

Roulet (2018) and Naceur et al. (2018) examine the effect of Basel III regulatory ratios on European and American banks' lending. Roulet (2018) uses a panel fixed model to find that liquidity requirements reduced lending of large European banks following the GFC period. Similarly, Naceur et al. (2018) find that Basel III-related liquidity variables have positive and perverse effects on gross lending growth. Increases in the ratio of non-required stable funding to total assets have a positive and significant impact on commercial lending growth for U.S. banks as these banks potentially hold more buffer stocks of liquid assets in anticipation of unexpected liquidity shocks. For European banks, an increase in the ratio of non-required stable funding to total assets has a positive impact on commercial lending growth but a negative effect on retail lending growth. These authors also find that the ratio of the available amount of stable funding to total assets has a significant and negative impact on retail lending growth for large U.S. banks and a substantial and positive impact on commercial lending growth for small U.S. banks. They suggest that large banks might benefit from more substantial access to external funding, which may underline the importance of funding structure as a driver of bank-lending behaviour.

Another strand of the literature that documents the relationship between capital and liquidity finds that solvency and liquidity measures are substitutable, suggesting that banks' capital levels may indicate their liquidity stock before a crisis hits. Higher levels of liquidity stock may be a buffer against unexpected liquidity disruptions that ultimately result in reduced bank lending. By examining the impact of a panel of UK banks' capital position on its choice of liquidity transformation, Acosta Smith et al. (2019) find that capital and liquidity requirements are substitutes. That is, banks with higher capital ratios tend to hold less liquidity as the probability of failure due to liquidity problems is low. As such, they imply that establishing new liquidity regulations is unnecessary. However, the related literature provides mixed results. Berger and Bouwman (2009) find that bank capital is a crucial determinant for liquidity creation while Berrospide (2012) finds that increased levels of capital increase holdings of liquid assets for banks.

Evidence for international and Euro area banks shows a negative relationship between capital and liquidity (Casu et al., 2019; Distinguin et al., 2013). Khan et al. (2017) finds a negative relationship between high capital buffers and funding liquidity. In contrast, during recessions Sorokina et al. (2017) find that the correlation between capital positions and liquidity of US banks changes sign. Closely related to Acosta Smith et al. (2019), Berger and Bouwman (2009) find that for US banks, higher capital is positively associated with more liquidity creation for larger banks, while they find the converse for smaller banks. Similarly, DeYoung et al. (2018) find that capital is positively associated with liquidity for small US banks.

This chapter closely follows the approach by Kim and Sohn (2017), who use a panel of US commercial banks to examine how bank capital and liquidity affect bank lending. They use quarterly data and run a fixed-effects regression in which they interact bank capital and liquidity to determine whether the level of liquidity affects how bank capital impacts lending. They find that increases in bank capital on credit growth are positively related to bank liquidity which indicates that increases in bank capital on credit growth are negative for low levels of bank liquidity but positive for high levels of liquidity. This relationship is stronger during crisis periods. These findings suggest that policy action that injects capital and supports liquidity should be used together.

2.3 Background

Under the Basel III regulation, two liquidity requirements were introduced: the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). The LCR intends to provide enough cash to cover funding needs over a 30-day period of stress and comprises two main elements; the value of the stock of unencumbered high-quality liquid assets (HQLA) in stressed conditions; and total net cash outflows. Under this liquidity standard, a bank must "hold a stock of unencumbered HQLA to cover the total net cash outflows over a 30-day period under the prescribed stress scenario" (Basel Committee on Banking Spervision, 2013, p.13). HQLA are assets that can be easily and immediately converted into cash without loss of value.

On the other hand, the NSFR intends to address contractual maturity mismatches over the entire balance sheet and requires banks to hold enough stable funding to cover the duration of their long-term assets and tighten capital requirements. The contractual maturity mismatch profile of a bank pinpoints the gap between contractual inflows and outflows of liquidity over specified time periods. That is, it is the "contractual cash and security inflows and outflows from all on- and off-balance sheet items, mapped to defined time bands based on their respective maturities" (Basel Committee on Banking

Spervision, 2013, p.46). The NSFR requires that the ratio of available stable funding relative to the amount of required stable funding should be at least equal to 100 percent (Basel Committee on Banking Spervision, 2014).

In January 2013, the South African Reserve Bank (SARB) began gradually implementing the Basel III framework to address bank-specific and broader systemic risks. Table 2.1 below presents the timeline of the implementation of both the capital and liquidity-related Basel III measures. The implementation of this new regulation focused on raising the quality of capital (by concentrating on common equity and the quantity of capital) to "ensure banks are better able to absorb losses" (SARB, 2015). The capital buffers were increased such that banks are able to build up enough buffers during credit expansions that would be drawn down during credit contractions (in line with the Basel III countercyclical measures). Additionally, the capital buffers are also there to address the issues of the largest banks being 'too big to fail'. The liquidity standards were introduced to improve banks' resilience to acute short-term stress as well as to improve longer-term funding. These Basel III measures were gradually phased until January 2019, as seen in Table 2.1, to give banks the time to meet the higher (or new liquidity) standards.

Table 2.1: Timeline of Basel III Implementation in South Africa

	Basel III	2013	2014	2015	2016	2017	2018	2019
Common Equity Tier 1 Capital Ratio	4.5%	3.5%	4.0%	4.5%	4.5%	4.5%	4.5%	4.5%
Liquidity Coverage Ratio	100%			60%	70%	80%	90%	100%
Net Stable Funding Ratio	100%						100%	100%

This table shows the timeline of the Basel III regulation implementation in South Africa.

Source: South African Reserve Bank.

2.4 Data and Empirical Approach

2.4.1 Data

This chapter uses monthly balance sheet data of 25 South African commercial banks from January 2008 to July 2020 collected from the South African Reserve Bank (SARB). Unlike studies such as Naceur et al. (2018) and Roulet (2018), this chapter uses monthly data that covers the GFC, the duration of the Basel III implementation, and part of the Covid-19 pandemic. Following Naceur et al. (2018), the dependent variables used in this chapter are the growth rates of gross, commercial, as well as retail and other loans. This chapter calculates gross loans as the sum of installment sales, leasing transactions, mortgages, credit card debt, overdrafts, and unsecured debt. The chapter makes this calculation as it is a common approach used by the SARB, given the available data. Additionally, the listed variables are all good indications of credit. Commercial loans are calculated as the subset of gross loans that capture all loans to the financial and non-financial sectors. In contrast, retail and other loans are the subset that captures all household-level and public-sector loans. The growth rate of gross, commercial, as well as retail and other loans is taken as its annual logarithmic variation.

The variables of interest are capital and liquidity. The capital measure used is the Tier 1 capital adequacy ratio, computed by taking the ratio of Tier 1 capital to risk-weighted assets. Tier 1 capital is a bank's core capital held in its reserves to fund business activities for its clients. It includes equity, capital, and disclosed reserves. The size of a bank's Tier 1 capital reserves is used to measure the institution's solvency. Basel III regulations mandate that banks' Tier 1 capital ratio must be at least six percent [3].

[3] Basel III regulations were effective from 2013. However, in November 2020, the BCBS increased the minimum Tier 1 capital adequacy ratio to 10.5 percent. Before 2013, Basel II required a four percent Tier 1 capital adequacy ratio. On average, South African banks have exceeded both ratios throughout the sample.

The liquidity variable is a proxy for the Basel III net stable funding ratio (NSFR) as defined by Vazquez and Federico (2015) as follows;

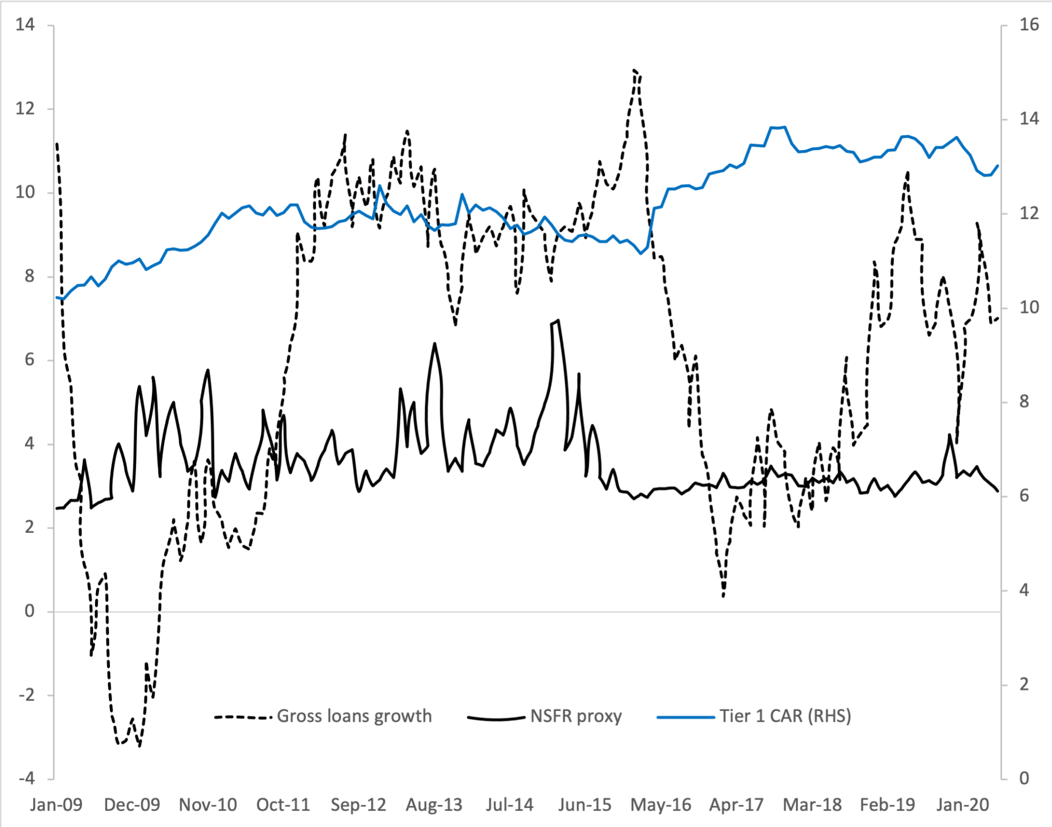
$$\text{NSFR Proxy}_{it} = \frac{\sum_{it} w_i L_{it}}{\sum_{it} w_j A_{jt}} \geq 1$$

and is computed as the ratio of a bank's weighted sum of liabilities (L_i) to its assets (A_i). Basel Committee on Banking Spervision (2013) define the NSFR as the ratio of stale funding to required stable funding. “Available stable funding" is the fraction of banks' capital and liabilities that should be reliable for at least over one year. “Required stable funding" is measured based on the profile of the banks' liquidity portfolio. Weights are assigned to assets based on their residual maturity (or liquidity value). The weights approximate “the amount of a particular asset that would have to be funded, either because it will be rolled over, or because it could not be monetized through sale or used as collateral in a secured borrowing transaction over the course of one year without significant expense" (Basel Committee on Banking Spervision, 2013, p.46). The ratio should be at least 100 percent. In other words, the NSFR indicates the degree of stability of a bank's liabilities relative to the liquidity of its assets. As such, it is a measure of liquidity risk. Vazquez and Federico (2015) covers all balance sheet liabilities and assets and assigns risk weights to each variable that indicate its level of liquidity (based on the criteria provided by (Basel Committee on Banking Spervision, 2013). Liabilities include customer deposits, long-term funding, and other reserves. Less liquid assets (such as fixed assets) and long-term liabilities (such as customer deposits) are assigned larger weights. Basel Committee on Banking Spervision (2013) requires banks' NSFR to be at least one. Table A2.1 in the Appendix describes the components used and associated weights.

Figure 2.1 below graphs the Tier 1 capital ratio, the NSFR proxy (to ensure stationarity), and the annual variation in gross loans for South African banks. The Basel III requirement for Tier 1 capital adequacy is six percent and was phased in 2013. Before that, the Basel II capital requirement was four percent. As seen in Figure 2.1 below, South African banks are well-capitalized and have exceeded the Basel II and III minimum requirements of four and six percent since 2008. Budnik et al. (2019) show that well-capitalized banks have a higher threshold to withstand unfavourable shocks and slow down the reduction of credit to the real economy during periods of economic downturn. Banks with high capital ratios have a loss-absorbing buffer that enhances bank solvency during adverse macroeconomic shocks. The NSFR proxy has been above one throughout the period indicating low liquidity risk for banks. Therefore, liquidity risk is not pertinent for banks. Looking at the figure, there is no clear relationship between the three variables prior to 2016. However, since 2016, increases in gross loan growth are met with increases in the Tier 1 capital ratio, while liquidity remains above minimum requirements. This chapter, therefore, expects to find a positive relationship between the Tier 1 capital ratio and gross loans, and average values of liquidity.

This chapter also uses a set of bank-level and macro-level control variables that are common in the literature on bank capital and credit. Bank-level variables include return on equity to control for profitability, the natural logarithm of total assets for bank size, net interest margin (the ratio of net interest income to gross loans), which gives an indication of banks' profitability and growth, non-performing loans as a ratio of gross loans to control for asset quality, the year-on-year logarithm change in consumer deposits as an indication of bank funding, and the z-score which is calculated as the sum of the return on equity and Tier 1 capital adequacy ratio over a four-year rolling average of the return on equity's standard deviation. The z-score is used as a proxy for bank risk. Macro-level variables include the year-on-year logarithm change in manufacturing production used to control for demand and the year-on-year growth rate of the 90-day JIBOR (an indicator of interest rates). Table A2.2 in the appendix presents all variable definitions and summary statistics.

Figure 2.1: Gross Loans, Capital, and Liquidity



This figure shows the average Tier 1 Capital Adequacy Ratio (CAR) for South African banks, the NSFR proxy (as defined by Vazquez and Federico (2015)), and the year-on-year change in gross loans of South African banks over the period January 2008 - July 2020.

2.4.2 Empirical Specification

Following Kim and Sohn (2017) the empirical specification considers how the relationship between bank capital and liquidity impacts bank-lending growth by running a fixed effects model that interacts with the liquidity and capital variables such that the capital ratio can change as the liquidity ratio varies. By doing so, the chapter is able to examine whether the relationship between capital and bank lending depends upon liquidity. Additionally, by employing a fixed effects model this chapter is able to account for unobserved individual heterogeneity. The chapter, therefore, includes bank-specific fixed effects and controls for bank and macro-specific determinants of lending The empirical specification is as follows:

$$\Delta \mathrm{Loans_{ir,t}} = \beta_0 + \beta_1(\mathrm{Capital}_{it-1}) + \beta_2(\mathrm{Liquidity}_{it-1}) + \beta_3(\mathrm{Liquidity}_{it-1} \text{ x } \mathrm{Capital}_{it-1}) + \sum_{\mathrm{j=1}}^{\mathrm{J}} \kappa_{\mathrm{j}} \mathrm{X_{ji,t-1}} + \sum_{\mathrm{k=1}}^{\mathrm{k}} \kappa_{\mathrm{k}} \mathrm{X_{ki,t-1}} + \varepsilon_{\mathrm{i,t}} \tag{2.1}$$

where i denotes the number of banks, r the type of loans, and t the monthly time dimension. The dependent variable $\Delta \mathrm{Loans_{ir,t}}$ measures the annual variation of either total, commercial, retail, or retail and other loans[4]. X_{ji} is the j^{th} bank-specific determinants of bank lending identified in existing literature. In particular, X_{ji} includes the natural logarithm of total assets to control for bank size; the NPL ratio for asset quality, the annual growth rate of customer term deposits for bank funding, the net interest margin for growth, and the z-score for bank risk. X_{ki} is the k^{th} macro-specific determinants of bank lending, specifically the chapter uses the annual variation in manufacturing production to control for demand and the year-on-year change in the 3-month JIBOR to control for rates.

The variables of interest are the Tier 1 capital adequacy ratio ($Capital_{it-1}$ calculated as the ratio of Tier 1 capital to risk-weighted assets) and the NSFR proxy ($Liquidity_{it-1}$) defined by Vazquez and Federico (2015). The chapter takes the natural logarithm of liquidity to maintain stationarity. As a reminder, the liquidity measure is calculated as follows:

$$\mathrm{NSFR\ proxy}_{it} = \mathrm{Liquidity}_{it} = \frac{\sum_{it} w_i L_{it}}{\sum_{it} w_j A_{jt}} \geq 1$$

The liquidity measure is computed as the ratio of a bank's weighted sum of liabilities (L_i) to its assets (A_i). The liquidity measure with a ratio greater than one (as regulated by the Basel Committee on Banking Spervision (2014)) indicates lower liquidity risk.

[4]Commercial loans are defined as loans from the financial and non-financial sector, retail loans are loans from the household, and retail and other loans include loans from the household sector with loans from the public sector.

The coefficient β_3 of equation 2.1 above is not straightforward to interpret as equation 2.1 is a non-linear model. The effect of capital on lending is dependent on the change in liquidity. Thus, interpreting the coefficient of the interaction term β_3 is tricky as this coefficient depends on both values of capital and liquidity. Unlike Kim and Sohn (2017), this chapter opts to ease the interpretation of the non-linear model above by examining the marginal effects of capital at the mean of liquidity. That is, the chapter investigates the relationship of bank capital and lending at an average level of bank liquidity. The chapter does this as follows:

$$\frac{\partial \text{Loans}_{it}}{\partial \text{Capital}_{it-1}} = \beta_1 + \beta_3 \text{Liquidity}_{it-1} \tag{2.2}$$

In this case, the marginal effects of capital given in equation 2.2 is taken at an average level of $Liquidity_{it-1}$. Additionally, β_1 is the coefficient of the capital ratio found in equation 2.1 above.

The standard errors of equation 2.2 (the marginal effects of capital at the mean of liquidity) is calculated as follows:

$$\hat{\sigma}_{\frac{\partial \text{Loans}_{it}}{\partial \text{Capital}_{it-1}}} = \sqrt{var(\hat{\beta}_1) + (\text{Liquidity}^2_{it-1})var(\hat{\beta}_3) + 2(\text{Liquidity}_{it-1})cov(\hat{\beta}_1\hat{\beta}_3)}$$

It is important to note that even if the covariance term is negative, it remains possible for $\beta_1 + \beta_3\text{Liquidity}_{it-1}$ (the marginal effects at the mean found in equation 2.2 above) to be significant at the mean of $Liquidity_{it-1}$ even if all of the model parameters are insignificant.

Numerous studies have found a positive relationship between bank capital and lending (Berrospide and Edge, 2010; Cornett et al., 2011; Gambacorta and Marques-Ibanez, 2011). Few studies have examined how changes in bank capital and liquidity affect bank lending. Kim and Sohn (2017) finds that an increase in bank capital ratio on credit growth is positively associated with the level of bank liquidity. This chapter closely follows Kim and Sohn (2017) and aims to build on it by analyzing the interaction of bank capital and liquidity and its impact on different types of credit growth for South African banks. This chapter will thus draw inference from Kim and Sohn (2017).

2.5 Empirical Results

2.5.1 Main determinants of bank-lending growth

The results pertaining to equation 2.1 and 2.2 are presented in Table 2.2 below. The chapter begins by examining the linear relationship between liquidity, capital, and bank lending. Column (1) presents results for dependent variable gross loan growth, (3) commercial loan growth, and (5) retail and other loan growth. The capital coefficient is positive for commercial loans growth in column (3) and negative for gross loans growth in column (1) and retail and other loans growth in column (5). These results suggest that capital requirements may set even higher incentives for South African banks to favour borrowers from the financial sector and expand lending there; as solvency increases, banks are willing to increase their "riskier" loan portfolio. Honohan and Beck (2007), Nana and Samson (2014), and Allen et al. (2011) find that African banks prefer lending to corporations. The results also suggest that higher capital regulatory pressures tend to weaken banks' willingness to expand their retail and other lending activities. Büyükkarabacak and Valev (2010) show that although raises in household credit growth increase banks' debt levels, they do so without much impact on banks' long-term income (as household lending is generally through mortgages). However, loans to firms are associated with increased income. Therefore, as banks' solvency increases, they are more willing to lend to increases these "riskier" loans given a long-term income return.

Focusing on the liquidity variable again of columns (1), (3), and (5) it is seen that the liquidity coefficient is also negative for retail and other loans (while statistically insignificant for the rest). This may be due to banks being better able to reduce their retail and other lending activities amid pressures to shrink their assets when holding buffer capital stocks. Naceur et al. (2018) argue that banks who strengthen their capitalization substitute retail and other loans assets into risk-free, more liquid government bond securities.

Once again, focusing on columns (1), (3), and (5) of Table 2.2, the control variables indicate that bank size (the logarithm of total assets) is significant and negative on all loan categories (except gross loans), suggesting that small banks tend to grant more loans. According to Stein (2002), small banks have comparative advantages in producing soft information, which helps them to expand their credit activities. Deposit growth is positive and significant for all loan categories. As the cost of funding increases, banks may increase lending rates and, as a by-product, deposit rates too. Higher deposit rates would increase deposit growth, and a more significant amount of deposits would enable banks to expand their portfolio of assets, namely lending volumes. The net interest margin is negative and significant for retail and other loans, also suggesting that smaller banks (or banks growing slowly) extend more loans. The z-score is positive and significant for retail and other loans while negative for all other loan categories, suggesting that banks with higher levels of risk-taking reduce commercial loans and increase retail and other loans. Finally, the macroeconomic variables are positively associated with all loan categories.

When focusing on columns (2), (4), and (6) of table 2.2, results indicate that the interaction of capital and liquidity is negative for all categories of loans. This suggests that more capitalized banks will increase their loans, at constant liquidity levels. However, this is done by less than weaker capitalized banks. Following Acosta Smith et al. (2019), this chapter postulates that banks with high capital ratios have a low need to hold liquidity and will maintain at least the minimum requirement. Therefore, and for ease of interpretation, this chapter examines the marginal effects of capital at the mean of liquidity ($\partial \text{Loans}_{it}/\partial \text{Capital}_{it-1}$). Results suggest that at the mean liquidity level, increases in bank capitalization allow banks to reduce both retail and gross

Table 2.2: Relationship between Capital, Liquidity and All Loans

	Δ Gross loans		Δ Commercial loans		Δ Retail & Other loans	
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity (t-1)	0.008	0.031***	0.012	0.106***	-0.220***	-0.041
	(0.009)	(0.012)	(0.018)	(0.024)	(0.045)	(0.061)
Capital (t-1)	-0.838***	-0.691***	0.430***	0.997***	-1.693***	-0.483
	(0.062)	(0.078)	(0.139)	(0.169)	(0.342)	(0.444)
Liquidity x Capital (t-1)		-0.127***		-0.547***		-0.942***
		(0.041)		(0.094)		(0.221)
Deposits Growth (t-1)	0.215***	0.213***	0.205***	0.191***	0.117***	0.104**
	(0.009)	(0.009)	(0.019)	(0.019)	(0.044)	(0.044)
Log Total Assets (t-1)	-0.008	-0.009	-0.123***	-0.127***	-0.375***	-0.377***
	(0.009)	(0.009)	(0.014)	(0.014)	(0.032)	(0.032)
NPL ratio (t-1)	-0.191*	-0.163*	0.514**	0.618***	0.439	0.636
	(0.099)	(0.099)	(0.222)	(0.222)	(0.473)	(0.473)
NIMs (t-1)	-1.916	-0.867	-6.158	-3.662	-33.809***	-28.918***
	(2.050)	(2.075)	(4.369)	(4.365)	(10.569)	(10.596)
Z-score (t-1)	-0.020***	-0.019***	-0.029**	-0.023**	0.049**	0.054**
	(0.005)	(0.005)	(0.011)	(0.011)	(0.025)	(0.025)
Manufacturing growth (t-1)	0.415***	0.392***	1.963***	1.911***	1.758***	1.696***
	(0.096)	(0.096)	(0.176)	(0.175)	(0.385)	(0.384)
Δ JIBOR (t-1)	0.131***	0.138***	0.641***	0.672***	0.904***	0.939***
	(0.030)	(0.030)	(0.055)	(0.055)	(0.120)	(0.120)
$\partial \text{Loans}_{it}/\partial \text{Capital}_{it-1}$		-0.796***		0.557***		-1.237***
		(0.063)		(0.139)		(0.357)
Observations	2456	2456	2813	2813	2593	2593
Number of Banks	25	25	25	25	25	25
R-Squared	0.275	0.278	0.158	0.169	0.097	0.103

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports fixed effects regression results examining both the linear and nonlinear relationship between bank lending and bank-specific characteristics. The sample period is from January 2008 to July 2020. For the dependent variables, yearly growth rates of gross, commercial, and retail and other loans are used in columns (1)-(6). Odd-numbered columns present linear regression results, while even-numbered columns present regression results, including the interaction between capital and liquidity.

loans but subsequently increase commercial loans. This result is consistent with the linear regression results in columns (1), (3), and (5). Banks with higher capital levels favour lending to the financial sector. Once again, even though corporations may present more risk, higher solvency allows banks to expand these loans in light of higher future income. In contrast, as most household credit is in mortgages, increases in household credit growth have minimal impact on banks' future income. This would surely discourage banks from increasing the amount of credit to households.

2.5.2 Do loan categories matter?

An interesting question is whether banks follow the same pattern of switching from household and public sector-level loans to firm-level loans when analysing different loan categories. In this regard, this chapter examines loans granted from all banks, firms, and households and the public sector in different loan categories; namely all loans, overdrafts, and instalment and credit card debt. The year-on-year log change of these loan categories is taken.

Results pertaining to all loans are presented in Table 2.3. Results for installment, credit card debt, and overdrafts can be found in Table A2.3 and A2.4 of the Appendix. The liquidity variable in columns (1) and (5) is positive meaning that the more liquidity banks have, the more credit they are willing to extend on aggregate (column (1)) and to households and the public sector (column (5)). However, as before, the capital variable is positive for loans to firms and negative for loans to aggregate banks and loans to households and the public sector. Once again, this further substantiates the findings above that banks favour borrowers from the corporate sectors, even though corporations present more "risk" to banks than households. Once again, this chapter analyzes the marginal effects of capital on loans at the mean of liquidity ($\partial \text{Loans}_{it}/\partial \text{Capital}_{it-1}$) are presented. Results suggest that as capital ratios change, banks increase their loans to firms (column (4)) and decrease loans to households and the public sector (column (6)), which supports the findings

Table 2.3: How capital and liquidity affect the annual variation in mortgages

	All Banks		Firms		HH & PS	
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity (t-1)	0.222***	0.107*	0.119	2.177***	0.191***	-0.116
	(0.037)	(0.060)	(0.143)	(0.357)	(0.058)	(0.093)
Capital (t-1)	-3.446***	-4.515***	4.177***	7.973***	-4.137***	-7.003***
	(0.263)	(0.515)	(0.905)	(1.074)	(0.408)	(0.794)
Liquidity x Capital (t-1)		0.722**		-13.812***		1.934***
		(0.300)		(2.206)		(0.461)
Deposits Growth (t-1)	0.124**	0.111**	-0.105	0.258*	0.235***	0.200**
	(0.054)	(0.054)	(0.144)	(0.152)	(0.084)	(0.084)
Log Total Assets (t-1)	-0.282***	-0.278***	-0.705***	-0.792***	-0.332***	-0.321***
	(0.026)	(0.026)	(0.073)	(0.073)	(0.041)	(0.041)
NPL ratio (t-1)	-0.367	-0.421	1.188**	1.335***	-0.615	-0.760*
	(0.276)	(0.276)	(0.491)	(0.481)	(0.427)	(0.426)
NIMs (t-1)	8.593	4.591	3.962	4.642	19.651	8.851
	(7.912)	(8.071)	(14.908)	(14.599)	(12.244)	(12.443)
Z-score (t-1)	-0.056***	-0.060***	0.266***	0.194***	-0.022	-0.033
	(0.014)	(0.015)	(0.036)	(0.037)	(0.023)	(0.023)
Manufacturing growth (t-1)	0.543**	0.519**	-0.547	-0.234	0.591	0.536
	(0.235)	(0.235)	(0.420)	(0.414)	(0.381)	(0.379)
Δ JIBOR (t-1)	0.352***	0.357***	1.079***	0.959***	0.363***	0.373***
	(0.072)	(0.072)	(0.144)	(0.143)	(0.114)	(0.113)
$\partial \text{Loans}_{it}/\partial \text{Capital}_{it-1}$		-4.100***		6.559***		-5.908***
		(0.378)		(0.965)		(0.585)
Observations	1490	1490	913	913	1458	1458
Number of Banks	14	14	11	11	14	14
R-Squared	0.292	0.295	0.216	0.249	0.196	0.206

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports fixed effects regression results examining the nonlinear relationship between mortgages and bank characteristics. The dependent variable is the yearly growth rate mortgages - from all banks in columns (1) and (2), from firms in columns (3) and (4), and from households and the public sector in columns (5) and (6). The sample period is from January 2008 to July 2020.

above.

2.5.3 Asymmetries in bank lending

Capital and liquidity changes may impact bank lending depending on whether it is in an upward, or downward phase of the economic cycle. A prime example of this is illustrated during the Covid-19 pandemic. As a direct consequence of the Covid-19 pandemic, GDP growth fell by just 7 percent in 2020. The pandemic also impacted the ability of borrowers to meet their obligations in accordance with contractual terms. In response, the South African Reserve Bank (SARB) released a set of relief initiatives to improve the flow of funds in the banking system. These included significantly reducing the repo rate from 6.5 percent in January 2020 to 3.75 percent in May 2020 to assist borrowers to meet their debt obligations. The SARB also made additional liquidity available by purchasing government bonds. Additionally, the prudential authority (PA) at the SARB also implemented relief measures by temporarily reducing the minimum capital requirements for banks relating to credit risk to enable banks to continue to extend credit to the real economy during this period of financial stress without the need for higher capital requirements. Finally, the PA lowered the Basel III liquidity coverage ratio (the ratio setting out the liquid assets a bank has to maintain in relation to its anticipated outflows) from 100 percent to 80 percent.

To account for the pass-through of asymmetric changes over the economic cycle, this chapter runs the following fixed effects regression:

$$
\begin{aligned}
\Delta \text{Loans}_{\text{i,t}} = {} & \beta_0 + \beta_1(\text{Capital}_{it-1}) + \beta_2(\text{Liquidity}_{it-1}) \\
& + \beta_3(\text{Dummy}_t) + \beta_4(\text{Liquidity}_{it-1} \text{ x Capital}_{it-1}) \\
& + \beta_5(\text{Liquidity}_{it-1} \text{ x Dummy}_t) \\
& + \beta_6(\text{Capital}_{it-1} \text{ x Dummy}_t) \\
& + \beta_7(\text{Liquidity}_{it-1} \text{ x Capital}_{it-1} \text{ x Dummy}_t) \\
& + \sum_{\text{j=1}}^{\text{J}} \kappa_{\text{j}} \text{X}_{\text{ji,t-1}}
\end{aligned}
\tag{2.3}
$$

where Dummy represents one of two dummy variables; a Low Growth Dummy that takes the value 1 in periods where the growth rate of manufacturing productivity is negative, and 0 in all other periods, and a Repo Ease Dummy that takes the value 1 in periods where the repo rate is decreasing and/or remains low after a reduction, and 0 in all other periods. All other variables are as previously described.

Results can be seen in Table 2.4. Columns (1) and (2) has dependent variable gross loans, (3) and (4) commercial loans, and (4) and (5) retail and other loans. During periods of low economic growth, increases in liquidity or capital have a negative and significant impact on commercial loans. During the same period of low growth, for constant levels of liquidity, banks with higher capital levels increase commercial loans more than weaker capitalized banks (column (3)). Conversely, during periods of repo easing banks increase commercial loans (but decrease gross loans) when liquidity or capital increases. However, the relationship between capital and liquidity, during periods of repo easing, causes a decrease in commercial loans but an increase in gross loans. Once again, this chapter looks at the marginal effects. At the mean of liquidity, changes in capital result in an increase in commercial loans and a decrease in both gross loans and retail and other loans for periods of both low growth and repo easing.

Table 2.4: Periods of Low Growth and Repo Easing on Loans

	Δ Gross loans		Δ Commercial loans		Δ Retail & Other loans	
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity (t-1)	0.044***	0.058***	0.177***	0.024	-0.167**	-0.139*
	(0.013)	(0.014)	(0.026)	(0.031)	(0.066)	(0.072)
Capital (t-1)	-0.658***	-0.451***	1.806***	0.315	-0.579	0.052
	(0.082)	(0.114)	(0.176)	(0.253)	(0.467)	(0.599)
Liquidity x Capital (t-1)	-0.183***	-0.250***	-1.085***	-0.194	-0.068	-0.292
	(0.048)	(0.061)	(0.107)	(0.141)	(0.257)	(0.309)
Low Growth Dummy	-0.032		0.288***		0.011	
	(0.021)		(0.045)		(0.104)	
Low Growth Dummy * Liquidity (t-1)	-0.014		-0.187***		0.067	
	(0.013)		(0.029)		(0.066)	
Low Growth Dummy * Capital (t-1)	0.011		-2.815***		-1.062*	
	(0.115)		(0.248)		(0.594)	
Low Growth Dummy * Liquidity * Capital (t-1)	0.064		1.730***		-0.335	
	(0.067)		(0.146)		(0.347)	
Repo Ease		0.039**		-0.140***		0.107
		(0.020)		(0.046)		(0.099)
Repo Ease Dummy * Liquidity (t-1)		-0.040***		0.058*		0.070
		(0.013)		(0.030)		(0.065)
Repo Ease Dummy * Capital (t-1)		-0.344***		0.476*		-1.236**
		(0.109)		(0.256)		(0.568)
Repo Ease Dummy * Liquidity * Capital (t-1)		0.203***		-0.382**		-0.733**
		(0.065)		(0.154)		(0.339)
$\partial \text{Loans}_{it}/\partial \text{Capital}_{it-1}$ for periods of Low Growth	-0.791***		0.468***		-1.071***	
	(0.064)		(0.138)		(0.351)	
$\partial \text{Loans}_{it}/\partial \text{Capital}_{it-1}$ for periods of Repo Easing		-0.762***		0.257*		-1.256***
		(0.065)		(0.145)		(0.353)
Observations	2435	2456	2792	2813	2573	2593
Number of Banks	25	25	25	25	25	25
R-Squared	0.280	0.279	0.205	0.134	0.127	0.152

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports fixed effects regression results examining both the linear and nonlinear relationship between bank lending and bank-specific characteristics, accounting for periods of low growth and repo easing. The sample period is from January 2008 to July 2020. For the dependent variables, yearly growth rates of gross, commercial, and retail and other loans are used in columns (1)-(6).

2.5.4 Robustness Tests

As robustness tests, this chapter runs equation 2.1 using various measures of liquidity. This is because the net stable funding ratio (NSFR) may not demonstrate liquidity risk as banks simply have to meet their minimum requirement. As a robustness check, the liquidity measure used draws from the theory of the liquidity coverage ratio and maturity mismatching. Maturity mismatches can shed light on a bank's liquidity, as it shows how banks organize the maturity of their assets and liabilities. For instance, if banks' liabilities outweigh their assets it signifies that banks are not using their assets efficiently. This could give rise to tighter liquidity. Similarly, if its assets outweigh its liabilities it signifies looser liquidity positions. This chapter makes this calculation by finding the ratio of asset-liability mismatch to total funding.

The asset-liability mismatch is calculated as the difference between the contractual maturity of assets (i.e. the sum of advances, trading, hedging, and other investment instruments, and other assets) and the contractual maturity of liabilities (i.e. the sum of stable deposits, volatile deposits, trading and hedging, instruments, and other liabilities). This chapter uses short-term ('next-day') assets and liabilities to determine whether the mismatch is excessive. The results are in the Appendix and can be seen in Table A2.5. These results confirm the key results; given average levels of liquidity stock, as capital positions widen, banks see an increase in commercial loan growth with a subsequent decrease in retail and other loan growth.

Another measure of liquidity calculated is a liquidity index based on Berger and Bouwman (2009) concept of liquidity creation. Berger and Bouwman (2009) categorize assets and liabilities into liquid, semi-liquid, and illiquid, where liquid assets and illiquid liabilities receive a weight of -0.5, illiquid assets and liquid liabilities 0.5, and semi-liquid assets and liabilities 0. The liquidity index is calculated by taking the ratio of the weighted sum of assets and liabilities to the weighted sum of liabilities. This chapter calculates liquid assets as the sum of debt securities, central bank money and gold, other public-sector interest-bearing securities, and ‘next-day" contractual maturity of assets. Illiquid assets as the sum of commercial and other loans and intangible assets. Semi-liquid assets as the sum of retail loans, public overdrafts, and loans granted to banks. Liquid liabilities as the sum of ‘next-day" contractual maturity of liabilities, overnight customer deposits, and short- and medium-term customer deposits. Illiquid liabilities and equity as the sum of total equity, other liabilities, and long-term customer deposits. Finally, semi-liquid liabilities as other borrowed funds.

Table A2.6 in the appendix provides the main results and the marginal effects of capital changes. Once again, banks prefer to reduce loans to the retail and public sector given increases to capital (at constant liquidity levels).

2.6 Conclusion

This chapter analyzes the impact of the Basel III capital and liquidity regulations on bank lending by assessing how capital and liquidity affect bank gross, commercial, and retail lending volumes. Using monthly data from January 2008 - July 2020 on a panel of 25 South African banks, it finds that given average liquidity levels, increases in bank capital are associated with increases in commercial loan growth and decreases in retail and other loan growth. One possible reason is that although commercial loans are easy to securitize as they come from large companies, corporations inherently represent more ‘risk". However, as banks increase their solvency, they are more willing to expand their risky loan portfolio. Büyükkarabacak and Valev (2010) explain that corporate loans provide banks with a greater future income projection than household loans as household credit is mainly in mortgages and increases generate minimal future income. Thus, given more solvency, banks are less willing to provide loans to households.

Additionally, this chapter examines how capital and liquidity affect different loan categories, in particular loans to firms and loans to households and the public sector. Once again, finds evidence that, for all types of loans and even overdrafts, banks prefer to increase the amount of loans granted to firms and reduce those to households (given capital increases at constant levels of liquidity). These results hold during periods of low growth or repo easing. This, yet again, substantiates the main findings that banks have a greater incentive to provide loans to firms (given higher expected earnings) than to households.

These results suggest that policy actions should be geared more toward capital changes (such as capital injections) and less toward liquidity support (as long as banks have met minimum liquidity requirements). Additionally, policy actions intended to encourage and sustain bank lending are effective. The results also suggest that policy action should safeguard banks against excessively increasing their risky loan portfolio. Finally, these results also support international regulations highlighting the importance of sufficient capital and liquidity management (such as the Basel III accord).

Appendices

A2.1 NSFR components

Table A2.1: NSFR Proxy Balance Sheet Components and Weights

Assets	weights	Liabilities	weights
1. Total Earning Assets	100	1 Deposits & Short term funding	
1.A Loans		1.A Customer Deposits	
1.A.1 Total Customer Loans		1.A.1 Customer Deposits-Current	85
Retail Loans		1.A.2 Customer Deposits-Savings	70
Commercial Loans		1.A.3 Customer Deposits-Term	70
Other loans		2 Long term funding	100
1.B Other Earning Assets	35	2.A Total Long Term Funding	100
1.B.1 Loans and Advances to Banks		Senior Debt	
1.B.2 Derivatives		Subordinated Borrowing	
1.B.3 Other Securities		Other Funding	
Trading securities		2.B Pref. Shares and Hybrid Capital	100
Investment securities		3 Other Reserves	100
1. C Remaining earning assets			
2 Fixed Assets	100		
3 Non Earning Assets	100		
3.A Other Intagibles			
3.B Other Assets			

This table presents the balance sheet components, together with assigned weights, to different assets and liabilities for the computation of the Net Stable Funding Ratio proxy.

A2.2 Summary Table

Table A2.2: Summary Statistics

		mean	sd	count
Dependent variables				
Gross loans growth	Yearly growth rate of gross loans	0.11	0.205	3207
Commercial loans growth	Yearly growth rate of commercial loans	0.13	0.38	3883
Retail and Other loans growth	Yearly growth rate of retail and other loans	0.08	0.89	3656
Mortgages growth	Yearly growth rate of mortgages	0.14	0.38	2289
Overdrafts growth	Yearly growth rate of overdrafts	0.11	0.39	3751
Instalment and Credit card debt growth	Yearly growth rate of instalment and credit card debt	0.14	0.94	1893
Bank specific variables				
Liquidity	NSFR proxy	3.5	6.43	3929
ln(Liquidity)	Natural logarithm of the NSFR proxy	0.71	0.94	3929
Tier 1 CAR	Tier 1 Capital Adequacy Ratio	0.24	0.32	4470
NII to Gross loans	Ratio of net interest income to gross loans	0.004	0.006	3780
ln(Total Assets)	Natural logarithm of Total Loans	16.57	2.23	3929
NPL to Gross loans	Ratio of non-performing loans to gross loans	0.04	0.07	3780
RWA density	Ratio of risk weighted assets to total assets	0.66	0.26	3778
Return on Equity	Ratio of net income to shareholders' equity	11.71	11.25	3780
z score	Proxy of bank risk	2.16	1.12	3022
Customer Deposits Growth	Yearly growth rate of customer term deposits	0.12	0.36	3872
Macroeconomic variables				
Manufacturing growth	Yearly growth rate of manufacturing production	-0.002	0.04	3700
Repo	Repurchase rate	6.62	1.80	3775
JIBOR	90 day JIBOR	6.83	1.79	3775
Liquidity robustness variables				
Contractual Maturity to Total Funding	Ratio of next day contractual maturity of assets to total funding	-0.57	2.96	3,618
Liquid Assets to Total Assets	Liquidity ratio	0.09	0.06	3929
Liquidity Index	Berger and Bouwman liquidity index	0.22	0.19	3628
Total liabilities to Total Assets	Longer term liquidity ratio	0.85	0.13	3929

A2.3 Additional Loan Categories

Table A2.3: Impact on Instalment and Credit Card Debt

	All Banks		Firms		HH & PS	
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity (t-1)	0.290**	-0.482***	0.036	-0.197	-0.140	-0.062
	(0.139)	(0.186)	(0.149)	(0.331)	(0.151)	(0.200)
Capital (t-1)	-1.312**	-7.206***	-3.593***	-4.291***	-0.861	-0.269
	(0.652)	(1.155)	(0.945)	(1.293)	(0.710)	(1.220)
Liquidity x Capital (t-1)		4.355***		1.564		-0.445
		(0.709)		(1.978)		(0.745)
Deposits Growth (t-1)	-0.026	-0.166	1.952***	1.944***	-0.327*	-0.314
	(0.185)	(0.184)	(0.243)	(0.244)	(0.194)	(0.195)
Log Total Assets (t-1)	-0.323***	-0.321***	-0.130*	-0.126*	-0.449***	-0.451***
	(0.061)	(0.061)	(0.069)	(0.070)	(0.073)	(0.073)
NPL ratio (t-1)	-3.249***	-3.849***	-0.337	-0.431	-2.888***	-2.831***
	(0.653)	(0.651)	(0.551)	(0.563)	(0.670)	(0.677)
NIMs (t-1)	192.140***	173.017***	49.321***	47.903***	85.014***	87.140***
	(18.332)	(18.339)	(16.478)	(16.578)	(19.409)	(19.738)
Z-score (t-1)	-0.027	-0.045	0.016	0.017	-0.040	-0.038
	(0.035)	(0.035)	(0.033)	(0.033)	(0.037)	(0.037)
Manufacturing growth (t-1)	3.228***	2.740***	3.398***	3.425***	0.810	0.857
	(0.572)	(0.569)	(0.583)	(0.584)	(0.592)	(0.598)
Δ JIBOR (t-1)	0.330*	0.283	0.332*	0.304	-0.077	-0.072
	(0.180)	(0.178)	(0.189)	(0.192)	(0.192)	(0.192)
$\partial \text{Loans}_{it} / \partial \text{Capital}_{it-1}$		-5.521***		-4.017***		-0.427
		(0.940)		(1.087)		(1.017)
Observations	1288	1288	915	915	1243	1243
Number of Banks	14	14	13	13	12	12
R-Squared	0.180	0.203	0.279	0.279	0.080	0.081

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports fixed effects regression results examining both the nonlinear relationship between instalment and credit card debt and bank characteristics. The dependant variable is the yearly growth rate instalment and credit card debt - from all banks in columns (1) and (2), from firms in columns (3) and (4), and from households and the public sector in columns (5) and (6). The sample period is from January 2008 to July 2020.

Table A2.4: Impact on Overdrafts

	All Banks		Firms		HH & PS	
	(1)	(2)	(3)	(4)	(5)	(6)
Liquidity (t-1)	0.016	0.131***	0.022	0.123***	-0.204***	-0.009
	(0.018)	(0.025)	(0.019)	(0.025)	(0.050)	(0.069)
Capital (t-1)	0.575***	1.268***	0.545***	1.150***	-1.420***	-0.096
	(0.140)	(0.171)	(0.142)	(0.173)	(0.384)	(0.500)
Liquidity x Capital (t-1)		-0.663***		-0.579***		-1.022***
		(0.095)		(0.096)		(0.248)
Deposits Growth (t-1)	0.193***	0.176***	0.199***	0.184***	0.126**	0.113**
	(0.020)	(0.019)	(0.020)	(0.020)	(0.050)	(0.049)
Log Total Assets (t-1)	-0.132***	-0.137***	-0.129***	-0.134***	-0.332***	-0.335***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.037)	(0.037)
NPL ratio (t-1)	0.443**	0.574**	0.460**	0.574**	0.596	0.818
	(0.225)	(0.223)	(0.227)	(0.226)	(0.530)	(0.531)
NIMs (t-1)	-14.358***	-11.328***	-8.900**	-6.253	-31.869***	-26.552**
	(4.403)	(4.386)	(4.444)	(4.436)	(11.825)	(11.858)
Z-score (t-1)	-0.018	-0.012	-0.020*	-0.014	0.102***	0.106***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.028)	(0.028)
Manufacturing growth (t-1)	1.697***	1.625***	2.020***	1.957***	1.256***	1.174***
	(0.182)	(0.181)	(0.184)	(0.183)	(0.444)	(0.443)
Δ JIBOR (t-1)	0.656***	0.699***	0.653***	0.690***	1.087***	1.135***
	(0.057)	(0.142)	(0.058)	(0.058)	(0.139)	(0.139)
$\partial \text{Loans}_{it}/\partial \text{Capital}_{it-1}$		0.720***		0.671***		-0.937**
		(0.141)		(0.142)		(0.401)
Observations	2738	2738	2738	2738	2518	2518
Number of Banks	25	25	25	25	25	25
R-Squared	0.147	0.162	0.158	0.169	0.079	0.085

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports fixed effects regression results examining both the nonlinear relationship between overdrafts and bank characteristics. The dependant variable is the yearly growth rate overdrafts - from all banks in columns (1) and (2), from firms in columns (3) and (4), and from households and the public sector in columns (5) and (6). The sample period is from January 2008 to July 2020.

A2.4 Robustness Checks

Table A2.5: Robustness Test: Contractual Maturity to Total Funding

	(1)	(2)	(3)
CM to Total Funding (t-1)	-0.008*	0.030***	-0.020
	(0.004)	(0.008)	(0.016)
Capital (t-1)	-1.036***	0.299*	-1.340***
	(0.069)	(0.154)	(0.356)
CM to Total Funding x Capital (t-1)	0.052***	-0.101***	0.010
	(0.014)	(0.030)	(0.056)
Deposits Growth (t-1)	0.212***	0.211***	0.013
	(0.009)	(0.020)	(0.041)
Log Total Assets (t-1)	-0.019**	-0.123***	-0.329***
	(0.009)	(0.014)	(0.029)
NPL ratio (t-1)	-0.159	0.484**	0.262
	(0.099)	(0.225)	(0.425)
NIMs (t-1)	-4.638**	-4.964	-23.505**
	(2.080)	(4.449)	(9.491)
Z-score (t-1)	-0.019***	-0.024**	0.036*
	(0.005)	(0.011)	(0.022)
Manufacturing growth (t-1)	0.444***	2.011***	1.486***
	(0.095)	(0.177)	(0.346)
$\triangle$ JIBOR (t-1)	0.137***	0.623***	0.819***
	(0.030)	(0.055)	(0.108)
$\partial \text{Loans}_{it}/\partial \text{Capital}_{it-1}$	-1.061***	0.352**	0.352**
	(0.068)	(0.154)	(0.358)
Observations	2391	2748	2528
Number of Banks	24	24	24
R-Squared	0.293	0.161	0.098

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports fixed effects regression results examining both the linear and nonlinear relationship between bank lending and bank-specific characteristics, where the liquidity is measured as the ratio of contractual maturity of assets to total funding (CM to Total Funding in table) This chapter uses next day contractual maturity of assets. The sample period is from January 2008 to July 2020. Column (1) has dependent variable gross loan growth, column (2) commercial loans growth, and column (3) and retail and other loans growth.

Table A2.6: Robustness Test: Berger and Bowman (2009) Liquidity Index

	(1)	(2)	(3)
Liquidity Index (t-1)	0.468***	1.010***	-0.219
	(0.067)	(0.140)	(0.335)
Capital (t-1)	-0.893***	0.512***	-1.772***
	(0.070)	(0.153)	(0.359)
Liquidity Index x Capital (t-1)	-1.896***	-2.372***	-1.374
	(0.283)	(0.605)	(1.437)
Deposits Growth (t-1)	0.205***	0.182***	0.011
	(0.009)	(0.020)	(0.041)
Log Total Assets (t-1)	-0.005	-0.089***	-0.366***
	(0.009)	(0.015)	(0.030)
NPL ratio (t-1)	-0.127	0.702***	0.300
	(0.100)	(0.224)	(0.432)
NIMs (t-1)	-0.362	-5.489	-26.686***
	(2.079)	(4.358)	(9.529)
Z-score (t-1)	-0.020***	-0.033***	0.039*
	(0.005)	(0.011)	(0.022)
Manufacturing growth (t-1)	0.385***	1.851***	1.609***
	(0.096)	(0.177)	(0.349)
Δ JIBOR (t-1)	0.135***	0.662***	0.828***
	(0.030)	(0.055)	(0.109)
$\partial\text{Loans}_{it}/\partial\text{Capital}_{it-1}$	-1.277***	0.027	-2.067***
	(0.087)	(0.192)	(0.425)
Observations	2379	2736	2516
Number of Banks	24	24	24
R-Squared	0.287	0.176	0.096

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports fixed effects regression results examining both the linear and nonlinear relationship between bank lending and bank-specific characteristics, where the liquidity is measured as the liquidity index by Berger and Bouwman (2009). The sample period is from January 2008 to July 2020. Column (1) has dependent variable gross loan growth, column (2) commercial loans growth, and column (3) and retail and other loans growth.

3 The Bank-Sovereign Nexus and its Relevance Tested in South Africa

Abstract

This chapter studies the bank-sovereign nexus in South Africa by examining the impact of the banking sector's exposure to sovereign debt on sovereign credit risk and the subsequent spillover into the bank-lending channel. By doing so, this chapter tests the relevance of the nexus in South Africa. The analysis investigates how changes in banks' exposure to sovereign debt impact the sovereign's risk position and how the financial institution's increased exposure to the sovereign affects bank lending rates and volumes. The chapter utilizes a Markov regime-switching dynamic regression model and finds that during periods of economic distress, as banks' exposure to sovereign debt increases, sovereign risk reduces. The domestic sovereign finds it too costly to default as a default heightens the chances of a banking sector crisis, specifically during periods of economic stress. The chapter also finds that during periods of economic distress, higher bank exposure to the sovereign is linked with higher bank lending rates and lower loan volumes. This most likely happens as banks become more exposed to the domestic sovereign, and weaker capacity for government support (specifically during times of stress) may make markets more reluctant to fund banks, raising funding costs. This, in turn, inhibits

banks from extending credit.

3.1 Introduction

In the aftermath of the Covid-19 pandemic, countries have increased the amount of sovereign debt, bringing renewed attention to the bank-sovereign nexus. The bank-sovereign nexus reflects the interconnectedness between the banking system and sovereign credit risk, in which stress in the sovereign may create and amplify stress in the banking sector and vice versa. The literature identifies two direct channels of the bank-sovereign nexus. The first channel studies the transmission of sovereign risk to banks through holdings of government debt. The deterioration of sovereign creditworthiness reduces the market value of banks' holdings of sovereign bonds. This reduces both the solvency of domestic banks and their lending activity. Another implication for banks under this channel is that sovereign bonds are generally used as collateral by banks in secured funding transactions. As the value of sovereign bonds diminishes, the value of the collateral erodes. Additionally, the credit rating of government bonds acts as a ceiling for the credit rating of private debt and the importance of government guarantees on bank debt and is adversely impacted by downgraded sovereign debt ratings (Acharya et al., 2014). The second channel highlights the contagion from the banking sector to the sovereign. Under this channel, bank bailouts and guarantees on bank liabilities through government support weaken sovereign creditworthiness (Alter and Schüler, 2012; Kallestrup et al., 2016). Additionally, deteriorating financial conditions of the banking sector could result in banks reducing their supply of credit to the real economy, which could dampen economic growth through an economic slowdown or recession and diminish the sovereign's tax base (Cooper and Nikolov, 2018).

This chapter studies the bidirectional effects of the bank-sovereign nexus in South Africa. As such, this chapter investigates the impact of the banking sector's sovereign exposure on sovereign credit risk and the spillover into bank-lending rates and volumes. Engler and Steffen (2016) argue that bank exposures can act as a “disciplinary device" (or influence) on the sovereign. These authors show that sovereigns with a high share of public debt held by domestic banks find it costly to default as it can trigger a credit crunch, reduce economic activity, and worsen the sovereign’s budget prospects. This is a clear possibility for South African banks as they hold a large share of government bonds (over 20 percent in 2021). In addition, the literature suggests that sovereign default risk affects the financial sector due to banks’ considerable exposure to government debt. As sovereign borrowing costs increase, the value of assets on banks’ balance sheets reduces, which may result in tightening funding constraints and making loans to households and firms more risky (Palmén, 2020). Empirical results in the literature suggest that banks increased interest on credit during the sovereign debt crisis (Bofondi et al., 2018). Additionally, Palmén (2020) shows that a contractionary sovereign risk shock reduces banks’ retail lending rate. Evidence of this is not clear in South Africa. Olds and Steenkamp (2021) show that banks’ funding costs have decreased in level since the onset of the Covid-19 pandemic, but funding spreads have increased as deposit rates have not matched the fall in money market rates. They also show that the Emerging Market Bond Index (EMBI +) can explain increases in funding costs. However, Mbelu (2022, forthcoming) shows that retail and public sector loan volumes have decreased on average since 2008, but commercial loan volumes have increased.

The chapter seeks to answer the following questions: Does the banking sector’s exposure to the sovereign lead to higher sovereign default risk in South Africa? Put differently, does increased banking sector exposure to the sovereign make it more or less likely for the sovereign to default? How do South African banks’ increased holding of sovereign debt affect their bank lending rates and loan volumes?

To the best of my knowledge, this chapter likely contributes to the literature as the first to empirically investigate both directions of the sovereign-bank nexus in a single chapter. Additionally, this chapter adds to a small strand of the literature that examines the impact of sovereign credit risk on bank lending rates and loan volumes. Moreover, in addition to bank lending rates, this chapter also assesses the transmission to bank loan volumes which allows the chapter to distinguish between the impact on banks' income and prices. Finally, this chapter is the first to provide results for South Africa, an important emerging market country and leading African economy.

In answering these research questions, this chapter employs a Markov regime-switching dynamic regression model (MSDR). This model describes the dynamic behaviour of a series in the presence of regime changes. The chapter runs the MSDR model in two steps; in the first step, it examines the impact of changes to the banking sector's exposure to the sovereign on sovereign credit risk[1] while in the second step the impact of banks' exposure to the sovereign on their lending rates and loan volumes is assessed.

The results indicate that during periods of stress, as banks' exposure to the sovereign increases, sovereign risk reduces. That is, it becomes more costly for the domestic sovereign to default, particularly during periods of economic distress, as a sovereign default may magnify the chances of a banking sector crisis. Additionally, as banks increase their sovereign debt holdings, they increase lending rates and reduce (gross, commercial, and retail) loan volumes. Higher banks' exposure to the sovereign reduces the sovereign's ability to support banks which makes depositors reluctant to fund banks, resulting in banks raising funding costs. Higher exposure to the sovereign increases the sovereign's borrowing costs which diminishes banks' balance sheets, resulting in higher funding costs. In both cases, higher funding costs discourage banks from extending credit.

The rest of the chapter is structured as follows; section 2 briefly describes the literature, section 3 outlines the data and empirical approach, section 4

[1]Sovereign credit default swaps (CDS spreads) is used as a proxy for sovereign credit risk.

provides results, and the final section concludes with final remarks.

3.2 Selected Literature

The 2009-2012 European sovereign debt crisis sparked a large literature strand investigating the sovereign-bank nexus. A key contribution to this literature is that of Brunnermeier et al. (2016), who established a “diabolic loop" or a “doom loop" of risk contagion. The first channel studies the transmission of risk from sovereigns to banks via holdings of government debt. The deterioration of sovereign creditworthiness reduces the market value of banks' holdings of sovereign bonds. This reduces both the solvency of domestic banks and their lending activity. Buch et al. (2016), Bolton and Jeanne (2011), De Bruyckere et al. (2013), and Gennaioli et al. (2014) provide evidence of this channel during the sovereign-debt crisis. Another implication for banks under this channel is that sovereign bonds are generally used as collateral by banks in secured funding transactions. As the value of sovereign bonds diminishes, the value of the collateral erodes. Additionally, the rating of government bonds acts as a ceiling for the rating of private debt and the value of government guarantees on bank debt and is adversely impacted by downgraded sovereign debt ratings (Acharya et al., 2014).

The second channel examines the contagion between the banking sector and the sovereign. First, bank bailouts and guarantees on bank liabilities weaken sovereign creditworthiness (Alter and Schüler, 2012; Kallestrup et al., 2016). Secondly, deteriorating financial conditions of the banking sector could result in banks reducing their supply of credit to the real economy, which could dampen economic growth through an economic slowdown or recession and diminish the sovereign's tax base (Cooper and Nikolov, 2018).

Another strand of the literature focuses on sovereign defaults. One theory behind this strand is that sovereign debt can only exist because government default is costly to the economy and erodes the tax base (Borensztein and

Panizza, 2009). However, how costly this depends on banks' exposure to the sovereign. Gennaioli et al. (2014) show that the probability of sovereign default decreases with banking exposure. Podstawski and Velinov (2018) hypothesizes that increasing banking exposure acts as a disciplinary device as it raises the cost of default for the sovereign, thus reducing default risk. However, these authors find evidence that increasing bank exposure increases default risk (of Euro area countries in the periphery) but, at the same time, decreases credit risk of core Euro area countries.

The last discussed strand of the literature looks at the impact of domestic sovereign bond purchases on the supply of credit to the private and non-financial sectors. It finds that banks with increased sovereign exposure tend to reduce their credit supply. For instance, Becker and Ivashina (2018) find a negative relationship between banks' sovereign exposure and bank credit. In particular, they find that bank credit reduces as domestic sovereign debt holdings by lenders increase. Balcilar et al. (2016) shows that purchases of sovereign bonds crowd out bank credit to the private sector as banks find it increasingly difficult to obtain credit from abroad at times of sovereign stress while also absorbing a growing share of sovereign issuances. Some studies document a positive relationship between banks' sovereign exposure and credit supply; however, this increase is higher for non-exposed impact (Popov and Van Horen, 2015). This, once again, suggests a negative impact on credit supply. Finally, focusing on sovereign credit risk, Altavilla et al. (2017) shows that increased sovereign risk negatively impacts lending to the private sector (specifically in stressed Euro area countries).

This chapter contributes to this discussion by studying the bidirectional impacts of the bank-sovereign nexus in South Africa. Hesse and Miyajima (2022) find the bank-sovereign nexus "relatively moderate" in South Africa after examining the size of sovereign debt in banks' balance sheets but warns that banks face high risks going forward as an increase in exposure could weaken banks' balance sheets and limit the role of fiscal consolidation. South

African banks' exposure to the sovereign has risen over the last ten years. In 2021, the IMF showed that banks in advanced economies hold about 7 percent of public debt (as a share of total banking assets), while banks in emerging markets hold about 17 percent. Although below the emerging market average, South African banks hold about 15 percent of public debt (as a share of total banking sector assets). This figure has risen and coincided with the adoption of new liquidity regulations that require banks to hold high-quality liquid assets. It continues to rise as public debt (as a share of GDP) grows (reaching 70 percent at the end of 2021). Additionally, as of June 2017, all three major rating agencies downgraded South Africa's sovereign credit to sub-investment standard, which has meant that banks have had to increase their exposure. Additionally, IMF (2022) shows that well-capitalized banks may act as shock absorbers in times of distress by becoming stable buyers of sovereign debt. This is the case in South Africa, whose banking system is well-capitalized.

This chapter explores the implication of banks' increased sovereign exposure by examining whether it results in a greater or lower chance of sovereign default. It also explores the spillover effect on the economy through bank lending. Bank lending growth has been muted at approximately 8 percent in South Africa over the last ten years (advanced economies' gross loans have grown on average at 12 percent while emerging markets have risen around 15 percent over the previous decade).

3.3 Data and Empirical Approach

3.3.1 Data

The analysis of this chapter covers the top five commercial banks in South Africa. The chapter focuses on these banks as they hold approximately 96 percent of the banking sector's assets. Additionally, specific vital variables (such as funding costs and the weighted lending rate) are only available for these five banks. The chapter uses monthly data spanning from January 2008 to November 2020. This period allows the chapter to cover the term before the South African sovereign credit was downgraded, the introduction of the regulated high-quality liquid assets (HQLA) in which banks have increased their holdings of government securities, and part of the Covid-19 pandemic period. The data contains the sovereign default swaps (CDS spreads) with a 5-year maturity and USD currency collected from Bloomberg. This is a standard proxy for sovereign credit risk in the literature. The banking sector's sovereign exposure is measured as the sum of loans and securities with the central government, municipalities, and public sector entities collected from the South African Reserve Bank (SARB). The chapter takes the year-on-year percentage change of the banking sector sovereign exposure and the CDS spread to ensure stationarity.

In addition to these variables, the chapter collects several exogenous control variables. These include the annual variation in total government loans (to control for sovereign debt), the year-on-year percentage change in manufacturing production volumes (to control for demand), the banking sector Tier 1 capital adequacy ratio (as a control for stability), a proxy for the net stable funding ratio to control for banks liquidity, and the FTSE/JSE All-Share Index (to control for asset price developments)[2], primarily collected from the SARB. The chapter also includes a credit ratings downgrade dummy variable (that takes the value of 1 from June 2017 until the end of the sample period), which accounts for the period in which all three major credit rating agencies reduced South Africa's sovereign credit rating to sub-investment standard. Sovereign ratings typically impose a ceiling on domestic credit ratings, including banks. Therefore, a sovereign rating downgrade may trigger downgrades of banks themselves, raising their funding costs, impairing market access, and creating profitability, funding, and liquidity challenges. These downgrades may also force banks to hold more high-quality liquid assets (HQLA) or to liquidate. The top five South African banks hold almost 90

[2]The FTSE/JSE All-Share Index (ALSI) is collected from Bloomberg.

percent of HQLA in Level 1 unencumbered assets, mainly in government securities and central bank reserves (SARB, 2021). The chapter interacts this credit ratings downgrade dummy variable with a measure of funding costs collected from Olds and Steenkamp (2021).

In examining the impact of sovereign credit risk and banking sector sovereign exposure on bank lending rates and loan volumes, the chapter uses weighted lending rates from Greenwood-Nimmo et al. (2021), bank loan volumes collected from the SARB, and funding costs from Olds and Steenkamp (2021). Net interest margins (to control for bank profitability and growth), non-performing loans (as a control for asset quality), and inflation (to control for price movements) are used as control variables and are all collected from the SARB.

Table A3.1 in the Appendix provides descriptive statistics for all variables used in our analysis. Olds and Steenkamp (2021) show that banks' funding costs have increased in levels since the start of the Covid-19 pandemic. The literature finds evidence that increasing sovereign borrowing costs reduces the value of banks' assets, which may induce banks to tighten their funding costs and thus reduce loans.

3.3.2 Stylized Facts

The bank-sovereign nexus in South Africa has increased the risk of financial instability. Linkages between the banking sector and the sovereign operate in both directions. The banking sector's exposure to sovereign debt has increased over the past decade. It accounts for more than 15 percent of total banking sector assets[3], which is slightly lower than the emerging markets 2021 average of 17 percent but much higher than the advanced economies average of approximately seven percent (see figure 3.1 for South African banks exposure). In particular, South African banks hold roughly 23 percent

[3]Banking sector sovereign exposure is calculated as the sum of loans and securities with the central government, municipalities, and public sector entities.

of government bonds while pension funds hold approximately 29 percent (Smith, 2020). Additionally, sovereign creditworthiness is deteriorating. The increase in the banking sector's sovereign exposure is also due to banks holding government bonds as high-quality liquid assets (HQLA) as part of their Basel III regulatory requirements. The top five banks have approximately 90 percent of HQLA, mainly in government securities and central bank reserves (SARB, 2021). However, the quality of these assets can be devalued by the sovereign's public finances such as when Moody's Investors Service downgraded South Africa's local and foreign currency-denominated debt rating to sub-investment grade in March 2020[4]. This means that South Africa's government bonds have been excluded from the FTSE World Government Bond Index, reducing the potential pool of investors, and has further adversely affected the credit ratings of the major South African banks[5]. Additionally, the downgrade of sovereign debt to sub-investment grade placed a greater burden on banks to become stable buyers of government debt. Well-capitalized banks act as shock absorbers when the government is distressed by working as a buyer of sovereign credit, which has been the case in South Africa (IMF, 2022).

Figure 3.1 shows a high correlation between banks' exposure to the sovereign and public debt to GDP ratio. The government's debt as a ratio to GDP has escalated since 2020 (the onset of the Covid-19 pandemic). At the same time, banks have steadily increased their holding of public debt since 2008, seeing a sharper rise in 2020. Banks have also increased their share of long-term government bonds they have held since 2016 and ownership of domestic government bonds. Without enough fiscal space to support the economy following the pandemic, rising sovereign debt has worsened indicators

[4]Moody's was the last major rating agency to reduce the sovereign's credit rating from 'Ba1' to 'Baa3' with a negative outlook. Both Fitch and S&P have rated the sovereign's credit 'BB-' with a negative and stable outlook, respectively.

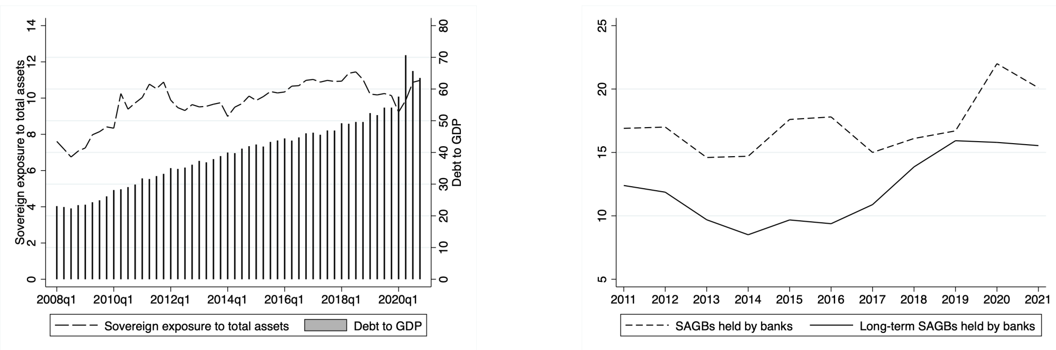
[5]For instance on November 27, 2020 Fitch ratings agency downgraded the Long-Term Issuer Default Ratings (IDRs) of the top 5 South African banks from 'BB' to 'BB-' just seven days after downgrading the sovereign's Long-Term IDRs from 'BB' to 'BB-'.

of sovereign risk (such as the CDS spread). This has tightened the relationship between banks and the sovereign, increasing financial institutions' exposure to the domestic economy. Additionally, in early 2022 foreign investors reduced their holdings of South African government bonds by eight percent since the onset of the pandemic. This meant that domestic banks increased their holdings (as seen in Figure 3.1). As significant holders of domestic government bonds, South African banks are vulnerable to price fluctuations or liquidity constraints during economic stress, such as rising global and domestic interest rates, increased geopolitical risks, and further increases in domestic government bond issuance. Additionally, SARB (2022) indicates that South African banks' capacity to absorb domestic government bonds may have become constrained.

Figure 3.1: South Africa's Banking Sector Exposure to the Sovereign

(a) Banks sovereign exposure and Public debt to GDP (%)

(b) Banks share of South African Government Bonds (SAGB) held by banks (%)

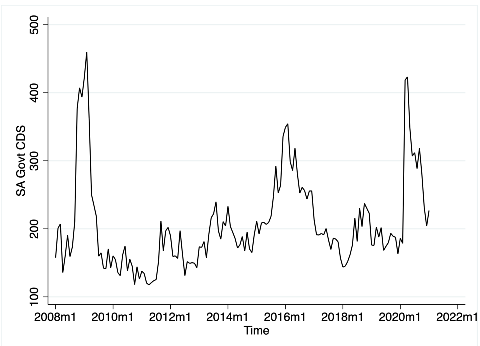


Source: Author's calculations, SARB (2020), National Tresuary (2022) and Haver Analytics. Note: This figure shows (a) South African banks' sovereign exposure as a share of their total assets and the ratio of public debt to GDP. (b) The share of domestic banks holding South African Government Bonds (SAGBs).

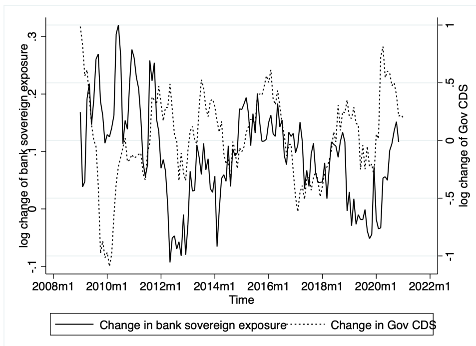
For over 10-year South African banks have exceeded their capital and liquidity buffers. This aided in withstanding the Covid-19 shock and provided support for the economy. Despite this, the consequences of the Covid-19 related lockdowns encouraged the South African Reserve Bank (SARB) to temporarily reduce regulatory requirements on commercial lenders to ensure a flow of credit to the economy. Even though this relief support has reached its maturity, South African banks are now facing the consequences of rising inflation as the war in Russia and Ukraine continues. The steady rise of risk weighs on sovereign exposure and threatens these strong capital buffers. Additionally, the extent to which the restructured loans are repaid remains unclear. Still, according to Moody's forecast, should non-performing loans increase and become high, they would reduce capital buffers[6]. Both factors could force banks to reduce the supply of credit to the economy, weighing on economic activity and government tax revenue. Dell'Ariccia et al. (2018) and Bellia et al. (2019) show that during periods of economic downturn, as sovereign debt increases, banking sector capital ratios may reduce through balance sheet valuations and loan losses. Finally, in March 2020, sovereign credit default swaps (CDS spreads) in South Africa gradually widened, signaling increased risk perception (refer to Figure 3.2).

Figure 3.2: Bank Sovereign Exposure and Government CDS

(a) South African Government Credit Default Swaps



(b) Bank Sovereign Exposure and SA Government CDS



Note: This figure shows (a) South African Government Credit Default Swaps (CDS) with a five-year maturity and USD currency and (b) the year-on-year log change of banks; exposure to the sovereign as well as the year-on-year log change of the SA government CDS.

Figures 3.2 show periods in which the CDS spread gradually widens (signaling

[6]In 2021 bad loans stood at around 5 percent of total loans and approximated 4.5 percent during the first quarter of 2022.

periods of increased distress) and periods in which it loosens (signaling periods of tranquillity). During the years 2008, 2016, and 2020 the CDS spread widen to over 300 basis points before loosening back to below 200 basis points. These periods of signaling distress are linked to the Global Financial Crisis (2008), ”Nene-gate" when then (and internationally trusted) finance mister Nhlanhla Nene was abruptly removed from his position by former president Jacob Zuma (2016) and the Covid-19 shock (2020). Given the structural break observed in this series, this chapter estimates a two period model dependent on regime changes. It estimates an MSDR model as it allows for quick adjustments after a change of state and as we have monthly data, this again seems reasonable. This type of model is particularly useful as it may allow the chapter to take into account the periods of high and low loan growth or periods of rising and falling sovereign credit risk.

Figure 3.3: Bank Sovereign Exposure and Government CDS

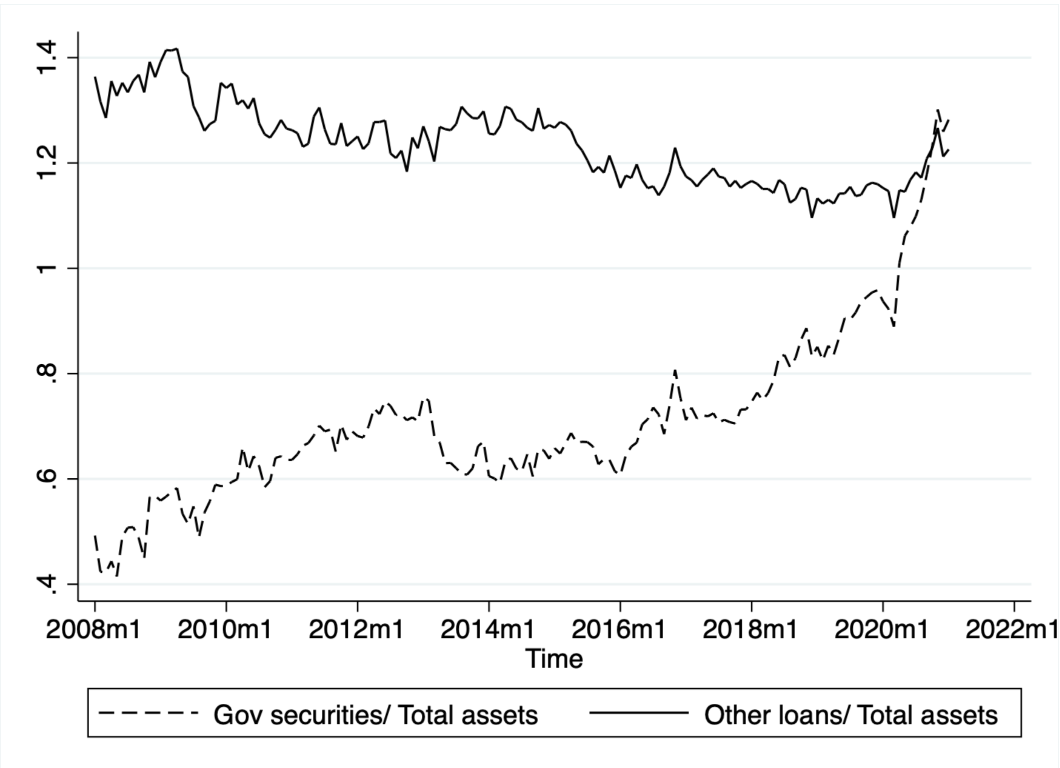


Figure 3.3 shows various types of sovereign credit the top five banks hold as a ratio of banks' total assets, namely government securities and other loans.

Government securities are debt instruments of the state such as treasury bills, treasury notes, and treasury bonds while other loans are loans (of various maturities) issued by the banks to the sovereign. The largest five banks hold approximately 90 percent of HQLA which are mainly in domestic government securities. These banks are primary dealers in the sovereign debt market, absorbing and transferring the debt to secondary markets. Although banks' holdings of government securities are rising, on average, banks continue to hold more loans to the public sector. Additionally, banks have ramped up their holdings of both government securities and loans to the sovereign since 2020 (when the government largely increased its share of debt to GDP, also seen as a period of distress in the economy).

3.3.3 Empirical Approach

This chapter runs a Markov regime-switching dynamic regression (MSDR) model following Kim (1994). The benefit of running such a model is that it allows for a regime-dependent impact, i.e., it allows for the effects to be affected by regime changes, such as if the economy were to enter a state of financial distress. By doing so, the MSDR model allows space to identify regime-dependant impacts of increases in exposure to the risk positions of the sovereign sector. Few papers have used this method in examining the bank-sovereign nexus. One such piece is Podstawski and Velinov (2018), which deploys a Markov Switching Structural Vector Autogressive in heteroscedasticity (MSH-SVAR) model to investigate what effect changes in bank exposure have towards the sovereign risk position and find a destabilizing effect running from bank exposure to sovereign risk.

The chapter runs the MSDR in two steps; in the first step, it will examine the impact of changes to the banking sector's exposure to the sovereign on sovereign credit risk (CD)[7] while in the second step, it will assess the impact of changes in sovereign credit risk on bank lending rates or volumes.

[7]Sovereign credit default swaps (CDS) is used as a proxy for sovereign credit risk.

The reduced form version of the MSDR model is given as:

$$\begin{aligned} y_t = v\left(S_t\right) + B_1\left(S_t\right) y_{t-1} + B_2\left(S_t\right) y_{t-2} + \cdots + A_p\left(S_t\right) y_{t-p} \\ + \alpha_0\left(S_t\right) x_t + \alpha_1\left(S_t\right) x_{t-1} + \cdots + \alpha_n\left(S_t\right) x_{t-n} + \mu_t \end{aligned} \tag{3.1}$$

where y_t is a vector of endogenous variables. In the first step of the analysis, it is the sovereign credit default swap (CDS_t) and banks' sovereign exposure (Exp_t), while in the second step, it is banks' lending rates or volumes (LR_t). Thus, $y_t = [CDS_t, EXP_t]'$ in the first step of our analysis, while $y_t = [LR_t, CDS_t]'$ in the second step of the analysis. x_t is a vector of N exogenous variables (listed in the data section) with state-invariant coefficients, B_i and α_j are parameter matrices, v is a vector of state-dependent constant terms, and μ_t is a vector of error terms that are normally and independently distributed conditional on a given state S_t (all coefficients are governed by a Markov process that can take on different states).

The chapter also notes issues of reverse causality that are inherently within the bank-sovereign nexus. Potential contagion is present from the banking sector to the sovereign, and reverse. In one direction, banks generally hold non-negligible amounts of sovereign debt. An increase in the likelihood of sovereign default would weaken banks' balance sheet positions. Additionally, the reduction in the value of domestic sovereign bonds harms banks' funding conditions, which they use as collateral for refinancing operations. In the opposite direction, deteriorating financial conditions may result in banks reducing credit supply to the economy, potentially leading to an economic slowdown and impairing the sovereign's tax base. A worsening fiscal position would reduce the sovereign's creditworthiness and increase its default risk. Moreover, banks' decision to invest in sovereign credit relies on their lending opportunities. To mitigate endogeneity concerns, the chapter uses one-year lags of the exogenous variables,x_t. The idea is that while the error term μ_t is correlated with the exogenous variables x_{t+1}, the lagged error term μ_{t-1} may not be. Numerous authors, such as Deghi et al. (2022), follow this approach in this field.

The evolution of y_t depends on the switching intercept at time t. The latent state S_t that governs the intercept at time t has a transition matrix, which allows for two possible intercepts at time t;

$$P = \begin{pmatrix} \rho_{11} & \rho_{21} \\ \rho_{21} & \rho_{22} \end{pmatrix} \tag{3.2}$$

The MSDR model can be better represented as;

$$y_t = \sum_{i=0}^{\infty} B_i(S_{t-i}) + \sum_{i=0}^{\infty} \alpha_i(x_t) + \sum_{i=0}^{\infty} \gamma^i \mu_t \tag{3.3}$$

which describes how a one-time change in a state accumulates over time.

Running an MSDR model is fundamentally helpful because, as seen in Figure 3.2 above, the data presents some structural breaks around periods of economic distress. These periods can be thought of as being different states of nature. An MSDR is suited for this exact reason as it can endogenously determine different volatility states and help this chapter decipher tranquil (normal) periods as states with low volatility from periods of distress (turmoil) as high volatility states.

3.4 Results

3.4.1 Impact of bank sovereign exposure on sovereign credit risk

The main results are in column (1) of Table 3.1 below. The dependent variable is the year-on-year percentage change of government CDS. It is illustrated that changes in bank sovereign exposure increase changes in sovereign credit risk during normal (tranquil) times but reduce changes in sovereign credit risk during periods of distress[8]. This is similar to the results obtained by Podstawski and Velinov (2018) after generating the MSH-VAR model with a state invariant shock transmission, which indicates that after accounting for changing states (regimes), rising bank exposure stabilizes sovereign risk in the cluster of core European countries but destabilizes sovereign risk for the cluster of periphery European countries. Podstawski and Velinov (2018) suggest that the regime dependency reflects the tightening of the sovereign-banking nexus through increased Eurozone financial distress. Indeed, regime dependency appears to be a key characteristic in disentangling this nexus. In the South African results context, increased bank exposure acts as a "disciplinary device" on the sovereign (Engler and Steffen, 2016). As the government has a high share of public debt held by domestic banks, defaulting is costly, as defaulting can trigger a credit crunch, reduce economic activity, and worsen the sovereign's budget prospects. This helps explain the reduction in the sovereign credit risk during periods of distress.

Figure 3.4 shows the smoothed probability of being in the distress period over our sample period. These periods of distress coincide with the global financial crisis (2008), the sovereign debt crisis (2010), Nene-gate (when the former finance minister was abruptly terminated) in 2016, and part of the Covid-19 pandemic period (2020 & 2021).

Returning focus to column (1) of Table 3.1 and looking at the set of control variables, the change in banks' holdings of long-term bonds is also negatively correlated with sovereign credit risk, again emphasizing our results that higher exposure reduces the likelihood of sovereign default risk. In addition, the change in the all-share price index (ALSI) and the Tier 1 capital adequacy ratio (capital) are also negatively associated with sovereign credit risk. These imply that more robust financial markets (given by the ALSI) and higher bank solvency reduce the chances of the domestic sovereign defaulting on its credit

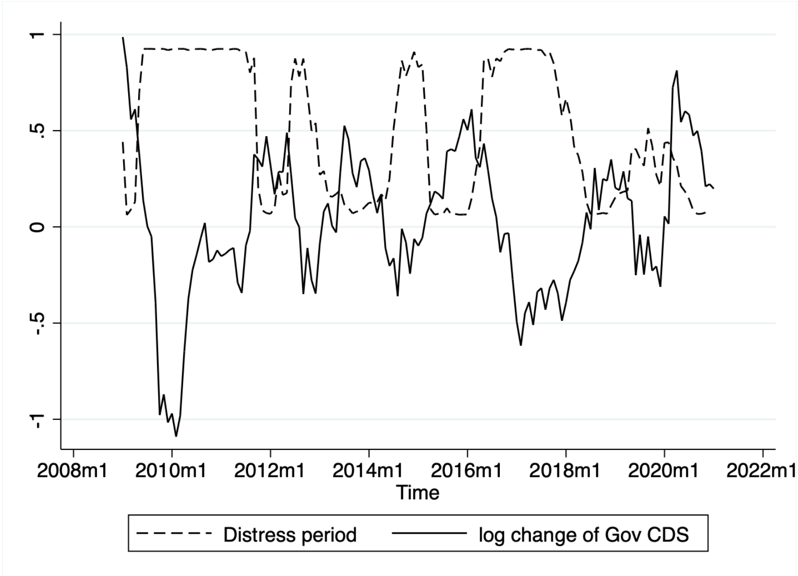
[8]Distress times are measured as periods of high volatility in the bank-sovereign exposure variable while tranquil times are the converse.

Table 3.1: Relationship between Bank Sovereign Exposure and Sovereign Credit Risk

	Top 5	African base	Global banks	SA only
	(1)	(2)	(3)	(4)
Δ Gov loan debt (t-1)	1.419**	1.357***	0.994*	-0.599
	(0.692)	(0.444)	(0.601)	(0.642)
Δ Banks LT bond holdings (t-1)	-0.873***	-0.903***	-0.922***	0.014
	(0.117)	(0.106)	(0.129)	(0.150)
Manufacturing growth (t-1)	0.279	0.621**	0.281	0.847***
	(0.265)	(0.281)	(0.253)	(0.293)
Δ ALSI (t-1)	-2.228***	-2.596***	-2.472***	-1.469***
	(0.222)	(0.172)	(0.207)	(0.242)
Capital (t-1)	-0.152***	-0.060***	-0.110***	-0.078***
	(0.034)	(0.017)	(0.036)	(0.024)
Liquidity (t-1)	0.218	-0.039	-0.533	-1.286***
	(0.314)	(0.128)	(0.341)	(0.205)
Distress period				
Δ Bank-Sovereign Exposure (t-1)	-1.813***	0.601***	-1.494***	-0.395**
	(0.304)	(0.166)	(0.205)	(0.178)
Tranquil period				
Δ Bank-Sovereign Exposure (t-1)	1.368***	-0.537***	0.881***	-0.141
	(0.245)	(0.126)	(0.185)	(0.185)
Observations	143	143	143	143

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table provides the results of bank sovereign changes on sovereign credit risk for the aggregate of the top five banks as well as for three bank categories. Column (1) focuses on the results pertaining to the aggregate of the five banks, (2) the top 5 banks with branches in Africa, (3) the top 5 banks with branches across the globe, and (4) the top 5 banks operating only in South Africa. The dependent variable is the year-on-year log change of government CDS across all columns.

Figure 3.4: Period of distress and change in SA Government CDS for the aggregate banks



This figure shows the smooth probability of the period of distress and the year-on-year log change in SA CDS for the aggregate of the top 5 banks.

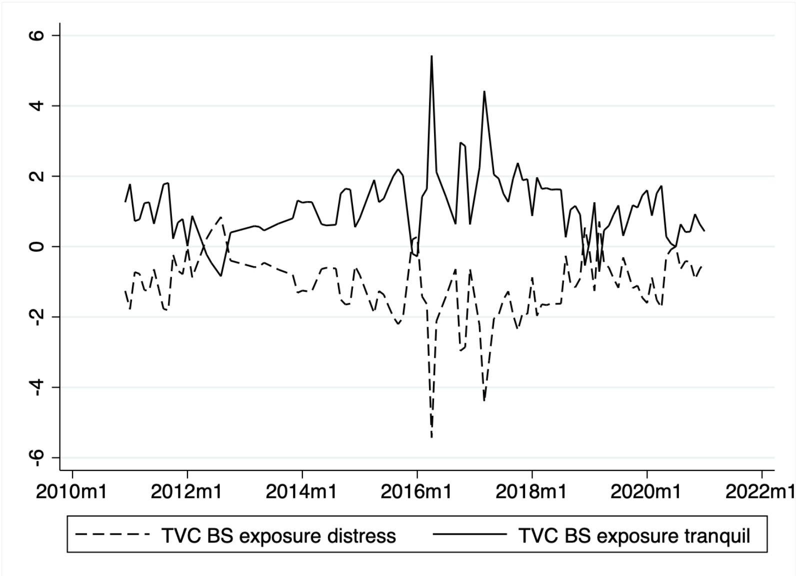
obligations.

The chapter considers that the top 5 banks may have heterogeneous characteristics and therefore group them into three categories, namely; banks only operating in South Africa (SA only), banks with branches across Africa (Africa base), and banks with branches across the globe (Global banks). Results are seen again in Table 3.1 where column (2) the African banks (3) Global banks, and (4) SA only. The dependent variable remains the year-on-year percentage change of government CDS across all columns. Once again, the main results hold, particularly for global (column 3) and SA-only banks (column 4).

In contrast, column (2) results, focusing on the top 5 banks operating in Africa, display the converse, in which a higher exposure to the sovereign worsens sovereign default risk during turbulent times. This result is closer to the literature on the sovereign-bank nexus that points toward a destabilizing effect from bank exposure to sovereign default risk as experienced during the

European debt crisis.

Figure 3.5: Rolling Window MSDR on Sovereign Risk with Aggregate Top 5 Banks: Time-varying Betas - Bank Exposure



This figure shows the time-varying coefficients (TVC) of the bank-sovereign (BS) exposure betas from the Markov switching regression presented above using a 36-month rolling window.

Finally, to get a better sense of how changes in the bank exposure affect sovereign risk during both the distress) and tranquil periods for the aggregate top 5 banks, this chapter runs a rolling window regression on equation 3.3 where the coefficients are allowed to change with time. A 36-month window is used to focus on the time-varying coefficients (TVC) of bank-sovereign (BS) exposure. Figure 3.5 shows this movement. The impact during distress periods is broad and negative, while the result is large and positive during the tranquillity period. This effect was magnified around 2016 during the “Nene-gate" and rose again in 2020 during the start of the Covid-19 pandemic suggesting policymakers should take action during such periods.

3.4.2 Impact of sovereign credit risk on bank lending

The literature describing the effect of sovereign risk shocks on bank lending has grown since the sovereign debt crisis. Most of this literature examines how sovereign risk influences loan supply and particularly focuses on loan volumes. For instance, Cantero-Saiz et al. (2014) quantifies the effect that sovereign risk has on the loan supply reaction of banks in the eurozone to monetary policy changes, Acharya and Steffen (2015) identifies bank's risks during the sovereign debt crisis as a carry trade, Bahaj (2020) investigates the financial and macroeconomic implications of changes in sovereign spreads, and Popov and Van Horen (2015) examines bank lending of European banks during the sovereign debt crisis. The literature finds that sovereign risk transmits to the real economy by tightening banks' funding costs conditions, which reduces bank lending.

A smaller part of the literature examines the effect of sovereign risk on banks' lending rates or volumes; Bofondi et al. (2018) defines sovereign risk as the change in the spread with the German Bund on the ten-year sovereign securities and shows that banks increased interest on credit during the sovereign debt crisis while Palmén (2020) shows that a contractionary sovereign risk shock reduces banks retail lending rate. This chapter adds to this smaller stand of the literature by examining the impact of a sovereign credit risk shock on bank lending rates and volumes.

Table 3.2 provides the results of bank exposure changes on the year-on-year change in bank lending rates for the aggregate of the top 5 banks and the 3 groups of banks. Column (1) focuses on the results of the aggregate of the 5 banks (2) African banks, (3) Global banks, and (4) SA-only banks. During distress periods, African banks increase bank lending rates following an increase in sovereign bank exposure, while global banks decrease them. However, the top 5, African banks, and global banks, reduce rates during tranquil times. While it appears global banks reduce rates regardless of the period type, the magnitude to which they reduce rates during tranquil periods is more significant than during distress periods. These results can be explained through funding costs. When banks hold more sovereign debt, the domestic sovereign's ability to support banks reduces. This may induce depositors to

Table 3.2: Relationship between Sovereign Credit Risk and Bank Lending Rates

	Top 5	African base	Global banks	SA only
	(1)	(2)	(3)	(4)
Manufacturing growth (t-1)	1.170***	1.322***	1.682***	1.555***
	(0.213)	(0.256)	(0.245)	(0.484)
Capital (t-1)	3.935	-1.057	-24.357***	4.185
	(4.370)	(2.681)	(6.106)	(6.793)
Liquidity (t-1)	-0.136	0.545***	0.323	-0.798
	(0.207)	(0.202)	(0.325)	(0.523)
NPL ratio (t-1)	3.241	-39.907***	-51.755***	-74.191***
	(3.717)	(2.250)	(4.925)	(9.630)
NIMs (t-1)	0.669	0.949	3.413***	-1.118
	(0.934)	(1.005)	(0.865)	(1.678)
Inflation (t-1)	-2.842	-0.374	-1.266	35.452***
	(2.431)	(2.068)	(3.186)	(5.664)
Δ Banks LT bond holdings (t-1)	-0.221***	0.048	-0.694***	0.455**
	(0.084)	(0.097)	(0.144)	(0.232)
credit downgrade x funding costs (t-1)	-0.379***	-0.768***	-0.492***	-0.170*
	(0.034)	(0.080)	(0.079)	(0.101)
Δ Funding Costs (t-1)	-0.629***	-0.272***	-0.431***	-0.598***
	(0.043)	(0.033)	(0.070)	(0.066)
Credit Downgrade	-0.067	-0.028	-0.078	-0.510***
	(0.078)	(0.072)	(0.074)	(0.142)
Δ SA Gov CDS (t-1)	-0.010	0.326***	0.393***	0.361***
	(0.037)	(0.055)	(0.060)	(0.135)
Distress period				
Δ Bank-Sovereign Exposure (t-1)	0.203	1.300***	-0.436*	-0.405
	(0.246)	(0.148)	(0.248)	(1.154)
Tranquil period				
Δ Bank-Sovereign Exposure (t-1)	-1.224***	-1.006***	-1.773***	0.005
Observations	143	143	143	143

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table provides the results of bank sovereign changes on banks' weighted lending rates for the aggregate of the top 5 banks and the three bank categories. Column (1) focuses on the results pertaining to the aggregate of the five banks, (2) the top 5 banks with branches in Africa, (3) the top 5 banks with branches across the globe, and (4) the top 5 banks operating only in South Africa. The dependent variable is the year-on-year log change of weighted bank lending rates across all columns.

lower their funding, thus tightening funding costs. This, in turn, makes banks less willing to extend credit and also more likely to increase bank lending rates. Indeed, the (IMF, 2022) show that banks with high exposure to sovereign credit cut back on lending during crisis times. The results obtained also aligned with Popov and Van Horen (2015), and Bofondi et al. (2018).

Tables 3.3, 3.4, and 3.5 provide the results of sovereign credit risk changes on banks' gross, commercial, and retail loans (respectively) for the aggregate of the top 5 banks as well the group of banks. For all three tables, column (1) is the top 5 banks, (2) African banks, (3) global banks, and (4) SA only. Focusing on Table 3.3, this time the results are mainly consistent across banks; during periods of distress, as banks exposure to the sovereign increases, banks tend to lower total loan volumes. Conversely, during normal times as banks' exposure to the sovereign increases, banks increase the volume of loans.

In Table 3.4, the results are similar. Banks reduce commercial lending volumes during turbulent periods as banks' exposure increases. The results differ for the aggregate top 5 banks, which always reduce commercial lending volumes regardless of the state of volatility (but reduce rates by a greater magnitude during distress periods). Finally, Table 3.5 enforces these results showing that banks reduce retail loans during turbulent periods and increase retail lending volumes during tranquil times. The exception to this is banks only operating in South Africa who always choose to increase retail lending volumes regardless of the state of volatility (but increase retail loans with a larger magnitude during tranquil times).

3.4.3 Robustness Tests

The literature typically uses the sovereign credit default swap (CDS) to measure the sovereign's external credit risk. The South African CDS spread rose to about 430 basis points in 2016 during the “Nene-gate" political turmoil (in which the then finance minister was abruptly dismissed) and to about 530 basis points in 2020 during the Covid-19-related global market turmoil.

Table 3.3: Relationship between Sovereign Credit Risk and Gross Bank Lending volumes

	Top 5	African base	Global banks	SA only
	(1)	(2)	(3)	(4)
Δ Cust deposits (t-1)	0.462***	0.409***	0.239***	-0.307***
	(0.128)	(0.089)	(0.061)	(0.095)
Manufacturing growth (t-1)	0.014	0.107**	-0.024	0.005
	(0.029)	(0.043)	(0.023)	(0.078)
Capital (t-1)	0.415	0.009	0.589	-2.111*
	(0.846)	(0.455)	(0.524)	(1.216)
Liquidity (t-1)	0.021	-0.015	0.031	-0.024
	(0.047)	(0.032)	(0.034)	(0.080)
NPL ratio (t-1)	0.040	-0.284	-1.200***	-0.859
	(0.788)	(0.410)	(0.323)	(1.307)
NIMs (t-1)	-0.155	-0.013	-0.289***	-0.038
	(0.156)	(0.150)	(0.072)	(0.214)
Inflation (t-1)	0.652**	0.994***	0.670***	1.642**
	(0.279)	(0.359)	(0.216)	(0.760)
Δ Banks LT bond holdings (t-1)	-0.048***	-0.050***	-0.054***	0.034
	(0.014)	(0.015)	(0.012)	(0.036)
credit downgrade x funding costs (t-1)	-0.017**	0.012	-0.020***	-0.009
	(0.008)	(0.015)	(0.006)	(0.015)
Δ Funding Costs (t-1)	0.006	0.003	0.001	-0.022**
	(0.005)	(0.005)	(0.004)	(0.009)
Credit Downgrade	-0.004	-0.022*	-0.012*	0.036
	(0.012)	(0.012)	(0.006)	(0.023)
Δ SA Gov CDS (t-1)	0.014	0.035***	0.012**	-0.036
	(0.009)	(0.010)	(0.005)	(0.022)
Distress period				
Δ Bank-Sovereign Exposure (t-1)	-0.142***	-0.064***	-0.098***	-0.030
	(0.040)	(0.021)	(0.015)	(0.042)
Tranquil period				
Δ Bank-Sovereign Exposure (t-1)	0.030	0.197***	0.052*	0.957***
Observations	143	143	143	143

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table provides the results of bank sovereign changes on gross loans for the aggregate of the top 5 banks as well as for three bank categories. Column (1) focuses on the results pertaining to the aggregate of the five banks, (2) the top five banks with branches in Africa, (3) the top 5 banks with branches across the globe, and (4) the top 5 banks operating only in South Africa. The dependent variable is the year-on-year log change of gross loans across all columns.

Table 3.4: Relationship between Sovereign Credit Risk and Commercial Bank Lending Volumes

	Top 5 (1)	African base (2)	Global banks (3)	SA only (4)
Δ Cust deposits (t-1)	0.159	0.290**	0.450***	-0.466***
	(0.130)	(0.127)	(0.102)	(0.088)
Manufacturing growth (t-1)	0.120***	0.148***	0.055	0.116
	(0.033)	(0.046)	(0.039)	(0.074)
Capital (t-1)	0.600	0.989	1.344	-4.769***
	(0.840)	(0.608)	(0.844)	(1.293)
Liquidity (t-1)	0.096**	-0.017	0.067	-0.201***
	(0.041)	(0.040)	(0.058)	(0.073)
NPL ratio (t-1)	-1.841***	-2.066***	-3.224***	-5.871***
	(0.561)	(0.501)	(0.527)	(1.314)
NIMs (t-1)	-0.267*	0.212	-0.414***	-0.342*
	(0.161)	(0.201)	(0.119)	(0.199)
Inflation (t-1)	-0.250	-1.189***	-0.081	-1.779**
	(0.299)	(0.436)	(0.364)	(0.721)
Δ Banks LT bond holdings (t-1)	-0.041***	-0.048**	-0.067***	0.181***
	(0.015)	(0.019)	(0.018)	(0.033)
credit downgrade x funding costs (t-1)	0.003	-0.009	-0.027***	-0.031**
	(0.008)	(0.019)	(0.010)	(0.014)
Δ Funding Costs (t-1)	-0.014***	-0.016**	0.001	-0.028***
	(0.005)	(0.007)	(0.006)	(0.008)
Credit Downgrade	-0.026**	-0.056***	-0.004	0.013
	(0.011)	(0.015)	(0.010)	(0.022)
Δ SA Gov CDS (t-1)	0.029***	0.065***	0.006	0.001
	(0.010)	(0.013)	(0.008)	(0.021)
Distress period				
Δ Bank-Sovereign Exposure (t-1)	-0.430***	-0.280***	-0.091***	-0.312***
	(0.040)	(0.052)	(0.026)	(0.044)
Tranquil period				
Δ Bank-Sovereign Exposure (t-1)	-0.102***	-0.027	-0.090	0.057
	(0.033)	(0.030)	(0.099)	(0.046)
Observations	143	143	143	143

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table provides the results of bank sovereign changes on bank commercial loans for the aggregate of the top 5 banks as well as for three bank categories. Column (1) focuses on the results pertaining to the aggregate of the five columns (2) the top 5 banks with branches in Africa, (3) the top 5 banks with branches across the globe, and (4) the top 5 banks operating only in South Africa. The dependent variable is the year-on-year log change of commercial loans across all columns.

Table 3.5: Relationship between Sovereign Credit Risk and Retail Bank Lending Volumes

	Top 5	African base	Global banks	SA only
	(1)	(2)	(3)	(4)
Δ Cust deposits (t-1)	0.836***	0.526***	0.194***	-0.633***
	(0.162)	(0.139)	(0.068)	(0.137)
Manufacturing growth (t-1)	-0.029	0.022	-0.060**	0.055
	(0.042)	(0.057)	(0.026)	(0.112)
Capital (t-1)	0.224	-0.037	-0.991*	-4.016**
	(1.115)	(0.672)	(0.581)	(1.734)
Liquidity (t-1)	-0.072	-0.028	0.028	-0.124
	(0.051)	(0.057)	(0.038)	(0.113)
NPL ratio (t-1)	0.401	0.655	-0.459	-0.025
	(0.778)	(0.634)	(0.387)	(1.889)
NIMs (t-1)	-0.154	0.007	-0.079	-0.042
	(0.201)	(0.217)	(0.082)	(0.312)
Infaltion (t-1)	1.090***	2.734***	0.874***	1.806
	(0.422)	(0.528)	(0.277)	(1.148)
Δ Banks LT bond holdings (t-1)	-0.058***	-0.053**	-0.078***	0.017
	(0.020)	(0.022)	(0.012)	(0.050)
credit downgrade x funding costs (t-1)	-0.034***	0.029	-0.012*	-0.032
	(0.010)	(0.024)	(0.007)	(0.022)
Δ Funding Costs (t-1)	-0.007	-0.011	-0.002	-0.027**
	(0.007)	(0.008)	(0.005)	(0.012)
Credit Downgrade	0.002	-0.064***	-0.008	0.031
	(0.016)	(0.017)	(0.007)	(0.033)
Δ SA Gov CDS (t-1)	0.002	0.019	0.016***	-0.040
	(0.013)	(0.015)	(0.006)	(0.032)
Distress period				
Δ Bank-Sovereign Exposure (t-1)	-0.265***	-0.018	-0.129***	0.120**
	(0.068)	(0.029)	(0.028)	(0.060)
Tranquil period				
Δ Bank-Sovereign Exposure (t-1)	0.091**	0.417***	-0.020	2.085***
	(0.040)	(0.056)	(0.020)	(0.154)
Observations	143	143	143	143

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table provides the results of bank sovereign changes on bank retail loans for the aggregate of the top five banks as well as for three bank categories. Column (1) focuses on the results pertaining to the aggregate of the five banks, (2) the top 5 banks with branches in Africa, (3) the top 5 banks with branches across the globe, and (4) the top 5 banks operating only in South Africa. The dependent variable is the year-on-year log change of retail loans across all columns.

Outside of these periods, the South African CDS spread trades around 200-300 basis points, considered the upper end of the “normal" range compared to other emerging market countries. Hesse and Miyajima (2022) argue that the CDS spread is not a good measure of sovereign credit risk for South Africa as it does not adequately capture sovereign risk seen in the high government debt-to-GDP ratio and the local currency sovereign term premia. They suggest other indicators of local currency risk demonstrating high risk in South Africa. One such measure is the swap spread, which is the difference between the fixed rate leg of interest swap contracts and the maturity mismatching sovereign yield. This spread is usually positive and widens as bank credit risk worsens relative to sovereign credit risk. Figure A3.1 in the appendix shows that these periods occurred during 2014-2016 (during former President Jacob Zuma's reign) and in 2020 at the onset of the Covid-19 pandemic.

This chapter uses the swap spread as a measure of credit risk as a robustness test presented in Table A3.2 in the appendix and finds that the results are robust to the use of this alternative measure. For all banks, increased bank exposures during periods of market stress act as an influence on the sovereign (Engler and Steffen, 2016). As the government has a high share of public debt held by domestic banks, it is costly to default as defaulting may cause a credit crunch, reducing economic activity and worsening the sovereign's budget prospects. In contrast, during normal times (except SA-only banks), increased bank exposure heightens sovereign credit risk.

The next robustness test is driven by the trends seen in Figure 3.3 in the stylized facts. Most banks are increasing the number of government securities. Government securities are a form of “high-quality liquid assets," and banks have begun holding more to comply with the Basel III requirements. As a robustness test, this chapter uses the ratio of government securities to total assets as a measure of banks' exposure to the sovereign. The results are seen in Table A3.3 in the appendix and align with the primary set of results. Once again, during times of distress, increased bank exposure results in a reduction in sovereign risk (except for SA-only banks), but during normal times, it results in higher sovereign credit risk.

3.5 Conclusion

During the Covid-19 pandemic, the South African banking sector-sovereign nexus has become a topic of concern as fears of its threat to financial stability have increased. SARB (2020) have discussed growing concerns about rising fiscal risks and the upward pressure the nexus causes on borrowing costs and the most significant fiscal deficit the country has seen in a century. This chapter quantifies the impact of the bank-sovereign nexus and its implications for bank lending rates and volumes. The main results indicate that during periods of economic distress, increases in banks' exposure to the sovereign result in lower sovereign credit risk. It becomes too costly for the domestic sovereign to default, as a default could cause a credit crunch and further impair the economy. Additionally, during periods of economic distress, increases in sovereign exposure are associated with higher bank lending rates and lower bank loan volumes. A possible explanation is that as banks become more exposed to the domestic sovereign, particularly during times of distress, markets may become more reluctant to fund banks, which raises funding costs. Higher funding costs encourage banks to increase bank lending rates and discourage banks from extending credit.

The IMF (2022) shows that spillovers from sovereign default risk and bank default risk to firms are large in magnitude. Future research could economically quantify the spillover effects into the firm-level channel and explore the mechanisms through which this happens. Additionally, future research can dive into the economic and institutional determinants that occur when sovereign default risk falls and who takes the burden of such an adjustment.

These results can guide financial stability. Using regulatory methods could aid in mitigating the risks associated with the bank-sovereign nexus. Regulatory measures, improving macro and micro-prudential frameworks, should be created to address the implications of bank-sovereign interconnectedness. It is also essential to introduce regulatory measures that support fiscal consolidation efforts and reduce the supply of government debt. Regulatory actions should also support structural reforms encouraging economic growth to help contain risks emanating from the nexus.

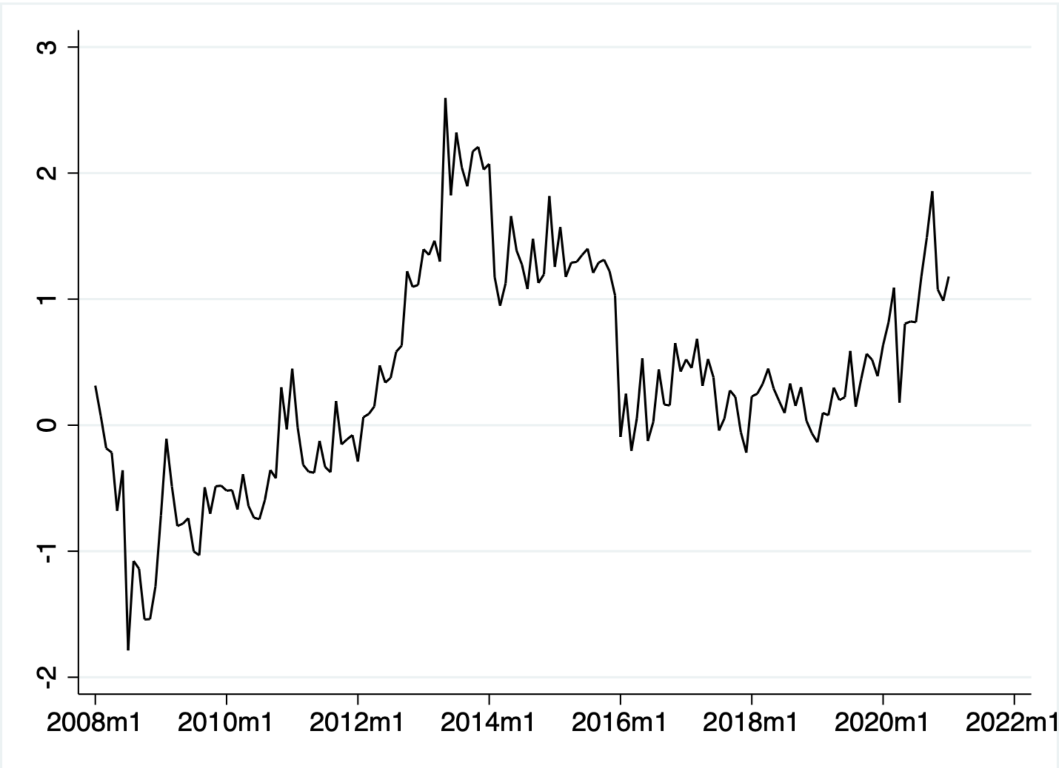
Appendices

Table A3.1: Descriptive Statistics, Variable Definitions, and Data Sources

	Description	Source	N	Mean	SD	Min	Max
CDS growth	The year-on-year log change of South African Sovereign Default Swap	Bloomberg	145	0.024	0.382	'-1.09	0.987
BS exposure growth	The year-on-year log change of Bank Sovereign Exposure	South African Reserve Bank	143	0.096	0.087	-0.093	0.32
Weighted lending rate	The year-on-year log change of banks weighted lending rate	South African Reserve Bank	144	-0.375	0.955	-3.041	1.003
Total Loans growth	The year-on-year log change of total loans	South African Reserve Bank and author's calculation	145	0.063	0.039	-0.072	0.174
Commercial Loans growth	The year-on-year log change of commercial loans	South African Reserve Bank and author's calculation	145	0.073	0.062	-0.088	0.179
Retail Loans growth	The year-on-year log change of retail loans	South African Reserve Bank and author's calculation	145	0.057	0.044	-0.135	0.22
Gov loan debt growth	The year-on-year log change of government loan debt	South African Reserve Bank	145	0.149	0.043	0.08	0.259
Banks ltbonds growth	The year-on-year log change of long-term bonds government bonds held by banks	Bloomberg	145	0.217	0.215	-0.19	1.096
Manufacturing growth	The year-on-year log change of manufacturing volumes	South African Reserve Bank	145	-0.014	0.084	-.0645	0.086
ALSI growth	The year-on-year change of the all share index	Bloomberg	145	0.059	0.135	-0.427	0.361
Capital	The ratio of tier 1 capital to risk-weighted assets	South African Reserve Bank	155	11.194	0.886	8.554	12.896
Liquidity	The natural logarithm of the net stable funding ratio	South African Reserve Bank and author's calculation	157	1.587	0.114	1.261	1.808
NPL ratio	The ratio of non-performing loans to gross loans	South African Reserve Bank	156	0.04	0.010	0.021	0.06
NIMs	Net interest margin	South African Reserve Bank and author's calculation	156	0.317	0.030	0.247	0.369
Inflation	The year-on-year change in the consumer price index	South African Reserve Bank	145	0.05	0.012	0.02	0.082
WACF growth	The year-on-year change of banks weighted funding costs	South African Reserve Bank	144	-0.456	1.195	-4.138	1.003
Cust Term Deposit growth	The year-on-year log change of banks customer term deposits	South African Reserve Bank and author's calculation	145	0.065	0.031	-0.096	0.159
Credit downgrade	Dummy variable equal to 1 in June 2017 to the end of the sample when all three major rating agencies downgraded sovereign credit to sub-investment status	Author's calculation	157	0.28	0.451	0	1

A3.2 Robustness Tests

Figure A3.1: The South Africa Swap Spread



This figure shows the swap spread in South Africa, which is calculated as the difference between the fixed rate leg of interest swap contracts and the maturity mismatching sovereign yield. The spread is usually positive (swap>sovereign yield).

Table A3.2: Robustness Test: Relationship between Sovereign Credit Risk and Bank Exposure

	Top 5	African base	Global banks	SA only
	(1)	(2)	(3)	(4)
Δ Gov loan debt (t-1)	-4.265***	-4.985***	-7.112***	-9.819***
	(1.234)	(1.073)	(1.413)	(1.356)
Δ Banks LT bond holdings (t-1)	-1.377***	-1.227***	-1.673***	-0.714***
	(0.194)	(0.194)	(0.188)	(0.222)
Manufacturing growth (t-1)	-1.028**	0.356	-2.301***	-1.464***
	(0.515)	(0.672)	(0.703)	(0.353)
Δ ALSI (t-1)	0.968**	0.697*	0.958***	3.381***
	(0.378)	(0.361)	(0.246)	(0.321)
Capital (t-1)	-0.015	0.003	0.054	-0.067*
	(0.062)	(0.050)	(0.080)	(0.039)
Liquidity (t-1)	-0.154	-0.437	0.625	-2.209***
	(0.519)	(0.384)	(0.903)	(0.419)
Distress period				
Δ Bank-Sovereign Exposure (t-1)	-2.246***	-0.385*	-1.484***	-0.797**
	(0.439)	(0.203)	(0.261)	(0.346)
Tranquil period				
Δ Bank-Sovereign Exposure (t-1)	6.777***	7.741***	2.228***	-2.742***
	(0.898)	(0.885)	(0.701)	(0.437)
Observations	143	143	143	143

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table provides the results of bank sovereign changes on sovereign credit risk where the swap spread is used to measure sovereign credit risk. Column (1) focuses on the results pertaining to the aggregate of the five banks, (2) the top five banks with branches in Africa, (3) the top five banks with branches across the globe, and (4) the top five banks operating only in South Africa. The dependent variable is the swap spread loans across all columns

Table A3.3: Robustness Test: Relationship between Sovereign Credit Risk and Government Securities

	Top 5	African base	Global banks	SA only
	(1)	(2)	(3)	(4)
Δ Gov loan debt (t-1)	-2.766***	0.167	0.334	1.398**
	(0.722)	(0.611)	(0.652)	(0.635)
Δ Banks LT bond holdings (t-1)	-1.131***	-0.829***	-0.943***	-0.211
	(0.093)	(0.099)	(0.111)	(0.148)
Manufacturing growth (t-1)	0.585***	0.925***	0.472**	0.691***
	(0.226)	(0.244)	(0.231)	(0.226)
Δ ALSI (t-1)	-1.707***	-1.950***	-2.193***	-1.741***
	(0.206)	(0.175)	(0.163)	(0.192)
Capital (t-1)	-0.127**	-0.153***	0.002	-0.235***
	(0.057)	(0.027)	(0.037)	(0.034)
Liquidity (t-1)	-0.483	0.304	-0.427	-0.992***
	(0.359)	(0.201)	(0.309)	(0.143)
Distress period				
Government securities to total loans (t-1)	-4.082*	0.822	-8.098***	2.076**
	(2.176)	(1.517)	(1.221)	(0.950)
Tranquil period				
Government securities to total loans (t-1)	2.380	6.457***	-1.354	6.385***
	(2.044)	(1.486)	(1.093)	(0.907)
Observations	143	143	143	143

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table provides the results of bank sovereign changes on sovereign credit risk where banks' holding of government securities is used to measure bank-sovereign exposure. Column (1) focuses on the results pertaining to the aggregate of the five banks, (2) the top five banks with branches in Africa, (3) the top five banks with branches across the globe, and (4) the top 5 banks operating only in South Africa. The dependent variable is the year-on-year log change of the CDS spread across all columns

Concluding Remarks

This thesis consists of 3 essays in the field of macroeconomics that analyze the financial system in South Africa. The backdrop to each chapter focuses on how financial systems respond during crisis periods such as the global financial crisis and the Covid-19 pandemic. The first chapter estimated a financial conditions index (FCI) for South Africa using a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) as proposed by Koop and Korobilis (2014). The method included the FCI and 2 macroeconomic variables (the annual inflation rate and an estimated measure of GDP). Results showed that the FCI is an indicator of growth as it leads the measure of GDP. Moreover, the TVP-FAVAR outperformed the FAVAR throughout the forecast horizon. The FCI can be used as an early warning signal of a possible financial crisis.

The second chapter analyzed the impact of Basel III capital and liquidity regulations on bank lending. It utilized a non-linear fixed affected model proposed by Kim and Sohn (2017) that interacts bank capital ratios with bank liquidity levels. Results showed that given average liquidity levels, higher bank capital ratios lead to higher commercial loans and lower retail loans. This suggests that banks have a preference for lending to firms over households. As banks' solvency increases, they may be willing to increase their portfolio of “risky" loans by extending more credit to corporations. Household credit is primarily extended in mortgage loans, which offer little future income for banks. In contrast, corporate loans offer higher future income.

The last chapter examined the bank-sovereign nexus in South Africa. It looked at how higher exposure to sovereign debt impacts sovereign credit, bank lending rates, and bank loans. The main results indicate that during periods of distress, increases in banks' exposure to the sovereign lead to lower sovereign credit risk. The cost of default is too high for the government as a default could lead to a banking crisis. Additionally, during periods of distress, higher banks' exposure to sovereign debt leads to higher bank lending rates and lower bank loan volumes. Banks may reduce lending as their capital constraints tighten which impairs their lending posture.

Future research could aim at constructing FCIs for other emerging market countries and also estimating FCIs that are forward-looking. Another area of future research could focus on the bank-sovereign nexus. The IMF (2022) shows that spillovers from sovereign default and bank default risk to firms are large in magnitude. Future research could economically quantify the spillover effects into the firm-level channel and explore the mechanisms through which this happens.

Bibliography

Acharya, V., I. Drechsler, and P. Schnabl (2014). A pyrrhic victory? bank bailouts and sovereign credit risk. *The Journal of Finance 69*(6), 2689–2739.

Acharya, V. V. and S. Steffen (2015). The "greatest" carry trade ever? understanding eurozone bank risks. *Journal of Financial Economics 115*(2), 215–236.

Acosta Smith, J., G. Arnould, K. Milonas, and Q.-A. Vo (2019). Capital and liquidity interaction in banking. *Bank of England Working Papers* (840).

Adrian, T., N. Boyarchenko, and D. Giannone (2019). Vulnerable growth. *American Economic Review 109*(4), 1263–89.

Allen, F., I. Otchere, and L. W. Senbet (2011). African financial systems: A review. *Review of Development Finance 1*(2), 79–113.

Allen, L., T. G. Bali, and Y. Tang (2012). Does systemic risk in the financial sector predict future economic downturns? *The Review of Financial Studies 25*(10), 3000–3036.

Altavilla, C., M. Pagano, and S. Simonelli (2017). Bank exposures and sovereign stress transmission. *Review of Finance 21*(6), 2103–2139.

Alter, A. and Y. S. Schüler (2012). Credit spread interdependencies of european states and banks during the financial crisis. *Journal of Banking & Finance 36*(12), 3444–3468.

Arregui, N., S. Elekdag, R. Gelos, R. Lafarguette, and D. Seneviratne (2018). Can countries manage their financial conditions amid globalization? *IMF Working Paper WP/18/15*.

Bahaj, S. (2020). Sovereign spreads in the euro area: Cross border transmission and macroeconomic implications. *Journal of Monetary Economics 110*, 116–135.

Bai, J. and S. Ng (2002, January). Determining the Number of Factors in Approximate Factor Models. *Econometrica 70*(1), 191–221.

Balcilar, M., K. Thompson, R. Gupta, and R. Van Eyden (2016). Testing the asymmetric effects of financial conditions in south africa: A nonlinear vector autoregression approach. *Journal of International Financial Markets, Institutions and Money 43*, 30–43.

Bańbura, M., D. Giannone, and L. Reichlin (2011). Nowcasting, in: Clements, m. p. and d. f. hendry. In *The Oxford Handbook on Economic Forecasting (Eds.)*, Volume 2, pp. 193–224. Oxford University Press.

Bańbura, M. and M. Modugno (2014). Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data. *Journal of Applied Econometrics 29*(1), 133–160.

Banerjee, A., M. Marcellino, and I. Masten (2008). Forecasting Macroeconomic Variables Using Diffusion Indexes in Short Samples with Structural Change. Economics Working Papers ECO2008/17, European University Institute.

Barkbu, B., B. Eichengreen, and A. Mody (2012). Financial crises and the multilateral response: What the historical record shows. *Journal of International Economics 88*(2), 422–435.

Basel Committee on Banking Spervision (2010). Basel iii: A global regulatory framework for more resilient banks and banking systems. *Bank for International Settlements*.

Basel Committee on Banking Spervision (2013). Basel iii: The liquidity coverage ratio and liquidity risk monitoring tools. *Bank for International Settlements*.

Basel Committee on Banking Spervision (2014). Basel iii: The net stable funding ratio. *Bank for International Settlements*.

Bates, B. J., M. Plagborg-Møller, J. H. Stock, and M. W. Watson (2013). Consistent factor estimation in dynamic factor models with structural instability. *Journal of Econometrics 177*(2), 289–304.

Becker, B. and V. Ivashina (2018). Financial repression in the european sovereign debt crisis. *Review of Finance 22*(1), 83–115.

Bellia, M., L. Calès, L. Frattarolo, A. Maerean, D. P. Monteiro, M. P. Guidici, L. Vogel, et al. (2019). The sovereign-bank nexus in the euro area: Financial & real channels. Technical report, Directorate General Economic and Financial Affairs (DG ECFIN), European ....

Berger, A. N. and C. H. Bouwman (2009). Bank liquidity creation. *The review of financial studies 22*(9), 3779–3837.

Bernanke, B. S. (1983). Non-monetary effects of the financial crisis in the propagation of the great depression.

Bernanke, B. S., C. S. Lown, and B. M. Friedman (1991). The credit crunch. *Brookings papers on economic activity 1991*(2), 205–247.

Berrospide, J. M. (2012). Bank liquidity hoarding and the financial crisis: An empirical evaluation.

Berrospide, J. M. and R. M. Edge (2010). The effects of bank capital on lending: What do we know, and what does it mean? *6*, 5–54.

Bicchetti, D. and D. Neto (2017). Monitoring financil stability in emerging and frontier markets. *UNCTAD Discussion Papers*.

Bofondi, M., L. Carpinelli, and E. Sette (2018). Credit supply during a sovereign debt crisis. *Journal of the European Economic Association 16*(3), 696–729.

Bolton, P. and O. Jeanne (2011). Sovereign default risk and bank fragility in financially integrated economies. *IMF Economic Review 59*(2), 162–194.

Borensztein, E. and U. Panizza (2009). The costs of sovereign default. *IMF Staff Papers 56*(4), 683–741.

Brave, S. and R. Butters (2011). Monitoring financial stability: A financial conditions index approach. *Economic Perspectives 35*(1), 22.

Brunnermeier, M. K., L. Garicano, P. R. Lane, M. Pagano, R. Reis, T. Santos, D. Thesmar, S. Van Nieuwerburgh, and D. Vayanos (2016). The sovereign-bank diabolic loop and esbies. *American Economic Review 106*(5), 508–12.

Brunnermeier, M. K. and Y. Sannikov (2014). A macroeconomic model with a financial sector. *American Economic Review 104*(2), 379–421.

Buch, C. M., M. Koetter, and J. Ohls (2016). Banks and sovereign risk: A granular view. *Journal of Financial Stability 25*, 1–15.

Budnik, K. B., M. Affinito, G. Barbic, S. Ben Hadj, E. Chretien, H. Dewachter, C. I. Gonzalez, J. Hu, L. Jantunen, R. Jimborean, et al. (2019). The benefits and costs of adjusting bank capitalisation: evidence from euro area countries. *European Central Bank Working Paper Series*.

Büyükkarabacak, B. and N. T. Valev (2010). The role of household and business credit in banking crises. *Journal of Banking & Finance 34*(6), 1247–1256.

Cantero-Saiz, M., S. Sanfilippo-Azofra, B. Torre-Olmo, and C. López-Gutiérrez

(2014). Sovereign risk and the bank lending channel in europe. *Journal of International Money and Finance 47*, 1–20.

Carlson, M., H. Shan, and M. Warusawitharana (2013). Capital ratios and bank lending: A matched bank approach. *Journal of Financial Intermediation 22*(4), 663–687.

Casu, B., F. di Pietro, and A. Trujillo-Ponce (2019). Liquidity creation and bank capital. *Journal of Financial Services Research 56*(3), 307–340.

Chavleishvili, S. and S. Manganelli (2019). Forecasting and stress testing with quantile vector autoregression. *ECB Working Paper*.

Claessens, S. and A. Kose (2017). Macroeconomic implications of financial imperfections: a survey. *BIS Working Papers* (677).

Cogley, T. and T. J. Sargent (2005). Drifts and volatilities: monetary policies and outcomes in the post wwii us. *Review of Economic dynamics 8*(2), 262–302.

Cooper, R. and K. Nikolov (2018). Government debt and banking fragility: The spreading of strategic uncertainty. *International Economic Review 59*(4), 1905–1925.

Cornett, M. M., J. J. McNutt, P. E. Strahan, and H. Tehranian (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of financial economics 101*(2), 297–312.

De Bruyckere, V., M. Gerhardt, G. Schepens, and R. Vander Vennet (2013). Bank/sovereign risk spillovers in the european debt crisis. *Journal of Banking & Finance 37*(12), 4793–4809.

Deghi, A., S. Fendoglu, H. Tabarraei, T. Iyer, Y. Xu, and M. Yenice (2022). The sovereign-bank nexus in emerging markets in the wake of the covid-19 pandemic.

Del Negro, M. and C. Otrok (2008). Dynamic factor models with time-varying parameters: measuring changes in international business cycles. *FRB of New York Staff Report* (326).

Dell'Ariccia, M. G., C. Ferreira, N. Jenkinson, M. L. Laeven, A. Martin, M. C. Minoiu, and A. Popov (2018). Managing the sovereign-bank nexus. *ECB Working Paper* (No. 2177).

DeYoung, R., I. Distinguin, and A. Tarazi (2018). The joint regulation of bank liquidity and bank capital. *Journal of Financial Intermediation 34*, 32–46.

DeYoung, R. and K. Y. Jang (2016). Do banks actively manage their liquidity? *Journal of Banking & Finance 66*, 143–161.

Diamond, D. W. and P. H. Dybvig (1983). Bank runs, deposit insurance, and liquidity. *Journal of political economy 91*(3), 401–419.

Distinguin, I., C. Roulet, and A. Tarazi (2013). Bank regulatory capital and liquidity: Evidence from us and european publicly traded banks. *Journal of Banking & Finance 37*(9), 3295–3317.

Doz, C., D. Giannone, and L. Reichlin (2011). A two-step estimator for large approximate dynamic factor models based on kalman filtering. *Journal of Econometrics 164*(1), 188–205.

Doz, C., D. Giannone, and L. Reichlin (2012). A quasi–maximum likelihood approach for large, approximate dynamic factor models. *Review of economics and statistics 94*(4), 1014–1024.

Dubey, P., J. Geanakoplos, and M. Shubik (2005). Default and punishment in general equilibrium 1. *econometrica 73*(1), 1–37.

Engler, P. and C. G. Steffen (2016). Sovereign risk, interbank freezes, and aggregate fluctuations. *European Economic Review 87*, 34–61.

Evans, M. (2005). Where are we now? real-time estimates of the macroeconomy. *International Journal of Central Banking 1*(2).

Gambacorta, L. and D. Marques-Ibanez (2011). The bank lending channel: lessons from the crisis. *Economic Policy 26*(66), 135–182.

Gambacorta, L. and P. E. Mistrulli (2004). Does bank capital affect lending behavior? *Journal of Financial intermediation 13*(4), 436–457.

Gauthier, C., C. Graham, and Y. Liu (2004). Financial conditions indices for canada. Technical report, Bank of Canada Working paper.

Gennaioli, N., A. Martin, and S. Rossi (2014). Sovereign default, domestic banks, and financial institutions. *The Journal of Finance 69*(2), 819–866.

Giannone, D., L. Reichlin, and D. Small (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics 55*(4), 665–676.

Giglio, S., B. Kelly, and S. Pruitt (2016). Systemic risk and the macroeconomy: An empirical evaluation. *Journal of Financial Economics 119*(3), 457–471.

Goodhart, C. A. E. and B. Hofmann (2001). Asset prices, financial conditions and the transmission of monetary policy. *Proceedings* (Mar).

Greenwood-Nimmo, M., D., Steenkamp, and R. van Jaarsveld (2021). Risk and return spillovers in a global model of the foreign exchange network. *Working Papers, South African Reserve Bank*.

Gumata, N., N. Klein, and E. Ndou (2012). A financial conditions index for south africa. *IMF Working Paper WP/12/196.*

Hakkio, C. S. and W. R. Keeton (2009). Financial stress: what is it, how can it be measured, and why does it matter? *Economic Review-Federal Reserve Bank of Kansas City 94*(2), 5.

Hatzius, J., P. Hooper, F. S. Mishkin, K. L. Schoenholtz, and M. W. Watson (2010, July). Financial Conditions Indexes: A Fresh Look after the Financial Crisis. NBER Working Papers 16150, National Bureau of Economic Research, Inc.

He, Z. and A. Krishnamurthy (2019). A macroeconomic framework for quantifying systemic risk. *American Economic Journal: Macroeconomics 11*(4), 1–37.

Hesse, H. and K. Miyajima (2022). South africa: The financial sector-sovereign nexus.

Honohan, P. and T. Beck (2007). *Making finance work for Africa.* The World Bank.

IMF (2017a, April). *IMF Global Financial Stability Report: Getting the Policy Mix Right*, Chapter 3, pp. 83–108. Technical report, International Monetary Fund.

IMF (2017b, October). *IMF Global Financial Stability Report October 2017: Is Growth at Risk?*, Chapter 3, pp. 91–118. Technical report, International Monetary Fund.

IMF (2022, October). *IMF Global Financial Stability Report April 2022*, Chapter 2. The Sovereign-Bank Nexus in Emerging Markets: A Risky Embrace, pp. 41–64. Technical report, International Monetary Fund.

Ivashina, V. and D. Scharfstein (2010). Bank lending during the financial crisis of 2008. *Journal of Financial economics 97*(3), 319–338.

Kabundi, A., E. Nel, and F. Ruch (2016). Nowcasting real gdp growth in south africa. *SARB Working Paper* (16/01).

Kabundi, A. and M. Rapapali (2019). The transmission of monetary policy in south africa before and after the global financial crisis. *South African Journal of Economics 87*(4), 464–489.

Kallestrup, R., D. Lando, and A. Murgoci (2016). Financial sector linkages and the dynamics of bank and sovereign credit spreads. *Journal of Empirical Finance 38*, 374–393.

Khan, M. S., H. Scheule, and E. Wu (2017). Funding liquidity and bank risk taking. *Journal of Banking & Finance 82*, 203–216.

Kim, C.-J. (1994). Dynamic linear models with markov-switching. *Journal of Econometrics 60*(1-2), 1–22.

Kim, D. and W. Sohn (2017). The effect of bank capital on lending: Does liquidity matter? *Journal of Banking & Finance 77*, 95–107.

Kindleberger, C. P. and R. Z. Aliber (2000). *Manias, panics and crashes: a history of financial crises*. Wiley.

Kishan, R. P. and T. P. Opiela (2000). Bank size, bank capital, and the bank lending channel. *Journal of Money, credit and banking*, 121–141.

Koop, G. and D. Korobilis (2012). Forecasting inflation using dynamic model averaging. *International Economic Review 53*(3), 867–886.

Koop, G. and D. Korobilis (2013). Large time-varying parameter vars. *Journal of Econometrics 177*(2), 185–198.

Koop, G. and D. Korobilis (2014). A new index of financial conditions. *European Economic Review 71*(C), 101–116.

Lorenzoni, G. (2008). Inefficient credit booms. *The Review of Economic Studies 75*(3), 809–833.

Loria, F., C. Matthes, and D. Zhang (2019). Assessing macroeconomic tail risk.

Mariano, R. S. and Y. Murasawa (2003). A new coincident index of business cycles based on monthly and quarterly series. *Journal of applied Econometrics 18*(4), 427–443.

Matheson, T. D. (2012). Financial conditions indexes for the united states and euro area. *Economics Letters 115*(3), 441–446.

Mbelu, A. (2022 forthcming). Is the capital and liquidity mix importnat for bank lending? an analysis of aouth african banks. *Working Papers, South African Reserve Bank*.

Melander, O. and T. Bayoumi (2008). *Credit matters: empirical evidence on US macro-financial linkages.* Number 8-169. International Monetary Fund.

Mendoza, E. G. (2002). Credit, prices, and crashes: Business cycles with a sudden stop. In *Preventing currency crises in Emerging markets*, pp. 335–392. University of Chicago Press.

Miglietta, A. and F. Venditti (2019). An indicator of macro-financial stress for italy. *Bank of Italy Occasional Paper* (497).

Naceur, S. B., K. Marton, and C. Roulet (2018). Basel iii and bank-lending: Evidence from the united states and europe. *Journal of Financial Stability 39*, 1–27.

Nana, P. N. and L. Samson (2014). Why are banks in africa hoarding reserves? an empirical investigation of the precautionary motive. *Review of Development Finance 4*(1), 29–37.

National Tresuary (2022). *Budget Review 2022*, Chapter 7: Government debt and contingent liabilities, pp. 79 –90. National Tresuary Republic of South Africa.

Oet, M. V., T. Bianco, D. Gramlich, and S. J. Ong (2012). Financial stress index: A lens for supervising the financial system. *Federal Reserve Bank of Cleveland Policy Discussion Paper* (12/37).

Olds, T. and D. Steenkamp (2021). Estimates of bank level funding costs in south africa. *Working Papers, South African Reserve Bank*.

Palmén, O. (2020). Sovereign default risk and credit supply: Evidence from the euro area. *Journal of International Money and Finance 109*, 102257.

Podstawski, M. and A. Velinov (2018). The state dependent impact of bank exposure on sovereign risk. *Journal of Banking & Finance 88*, 63–75.

Popov, A. and N. Van Horen (2015). Exporting sovereign stress: Evidence from syndicated bank lending during the euro area sovereign debt crisis. *Review of Finance 19*(5), 1825–1866.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies 72*(3), 821–852.

Purcell, T. (2022). Financial conditions index vs. inflation are conditions tight enough to slow inflation? *Lykeion, July*.

Quintana, J. M. and M. West (1988). Time series analysis of compositional data. *Bayesian Statistics 3*, 747–756.

Reinhart, C. M. and K. S. Rogoff (2009). *This time is different: Eight centuries of financial folly.* princeton university press.

Roulet, C. (2018). Basel iii: Effects of capital and liquidity regulations on european bank lending. *Journal of Economics and Business 95*, 26–46.

Samuelson, P. (1966). Science and stocks. *Newsweek, September 19*, 92.

SARB (2015). South africas implementation of basel ii and basel iii.

SARB (2020). *Financial Stability Review: First Edition 2020*, Chapter

Banking sector-sovereign nexus in South Africa, pp. 11–14. South African Reserve Bank.

SARB (2021). Financial stability review: Second edition. techreport, South African Reserve Bank.

SARB (2022). Financial stability review: First edition. Technical report, South African Reserve Bank.

Schularick, M. and A. M. Taylor (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review 102*(2), 1029–61.

Smith, M. (2020, June). Qe or not, south africa's bond buying is risky to fiscal stability. Technical report, S&P Global Market Intelligence.

Sorokina, N. Y., J. H. Thornton Jr, and A. Patel (2017). Why do banks choose to finance with equity? *Journal of Financial Stability 30*, 36–52.

Stein, J. C. (2002). Information production and capital allocation: Decentralized versus hierarchical firms. *The journal of finance 57*(5), 1891–1921.

Swiston, A. J. (2008, June). A U.S. Financial Conditions Index; Putting Credit Where Credit is Due. IMF Working Papers 08/161, International Monetary Fund.

Thompson, K., R. Van Eyden, and R. Gupta (2015). Identifying an index of financial conditions for south africa. *Studies in Economics and Finance 32*(2), 256–274.

Vazquez, F. and P. Federico (2015). Bank funding structures and risk: Evidence from the global financial crisis. *Journal of banking & finance 61*, 1–14.