Uncertainty, Financial Stress and Monetary Policy in South Africa

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Declaration

I, Theshne Kisten, declare that this thesis titled, "Uncertainty, Financial Stress and Monetary Policy in South Africa" represents my own work and has not been submitted to any other university or institution for any degree or examination purposes. Furthermore, I declare that all sources of information have been acknowledged and referenced accordingly.

Signed:

Date:

Abstract

In this thesis, we examine the role of economic uncertainty and financial market stress in the South African economy and its implications for monetary policy. Financial market disruptions and economic uncertainty are commonly listed as the main sources of economic turmoil and slow recovery experienced by many economies globally following the 2007-08 global financial crisis. Understanding how financial and uncertainty shocks impact the real economy and the ability of financial market information to predict economic conditions is imperative from a policy perspective, potentially informing prudent macroprudential and monetary policy. Against this backdrop, this thesis is organised into three main chapters.

In Chapter 2, we develop an index to monitor the intensity of stress in the South African financial sector, and examine the potential non-linearity in the transmission of financial shocks to the real economy. The index (called SAFSI) is constructed using a novel approach that selects and aggregates financial indicators based on their information content i.e. their ability to capture key periods of financial stress in the economy, thereby striking a balance between parsimony and efficacy. Furthermore, the use of time-varying correlations in the aggregation allows the index to capture the interconnectedness of financial markets as well as enabling each indicator to be assessed in terms of its systemic importance. In addition to capturing the benchmark episodes of financial stress in South Africa, the SAFSI successfully captures other global and idiosyncratic risks that affect the financial markets in the country. A regime-switching model reveals non-linearity in the transmission of financial shocks to the real economy. Specifically, financial shocks are more detrimental to the real economy during stressful periods than normal times. An unexpected shock

to financial stress conditions during financially vulnerable times is associated with a more prominent contraction in output and higher inflation. However, during normal times, the financial shock has a negligible impact on prices and interest rates, with a small output impact.

Chapter 3 examines the predictive ability of financial market information, captured by the SAFSI, by evaluating economic forecasts from three vector autoregression specifications: a mixed-frequency specification which includes quarterly and monthly time series data, a standard linear quarterly frequency model, and a threshold (non-linear) quarterly frequency specification. Out-of-sample forecasts reveal that accounting for intra-quarterly information improves the forecasting performance of financial information in terms of output growth and inflation, which are considered key economic indicators in formulating monetary policy decisions.

Finally, in Chapter 4 we examine the connection between economic uncertainty and financial market conditions in South Africa, documenting that the macroeconomic implications of an uncertainty shock differs across financial regimes. A non-linear VAR is estimated where uncertainty is captured by the average volatility of structural shocks in the economy, and the transmission mechanism is characterised by two distinct financial regimes (i.e. financially stressful versus normal periods). We find that while the deterioration of output following an uncertainty shock is much more prominent during normal periods than during stressful periods, it is much more persistent during stressful financial times. The share of output variance explained by the volatility shocks in good financial times is more than double the share in bad times. Uncertainty shocks are found to be inflationary in both regimes, with the impact being larger in the stress regime. While our estimates reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices.

Dedication

To the Supreme God and my truly amazing late grandfather, Thimmai Kisten, who has played an instrumental role in my life and was a strong proponent of academic enrichment and independence.

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I would like to express my warm and sincere gratitude to my family and friends that have supported and encouraged me throughout this tough journey. To my mum and dad, thank you for always ensuring that I never lacked anything in my upbringing and for providing me with a solid foundation. I will always be grateful for everything that you have done for me. Also a great thank you to my wonderful and loving husband that has been my strength and a constant source of motivation during this bumpy journey, ensuring my sanity. Lastly and most importantly, I would like to thank my supervisor Prof. Nicola Viegi and co-supervisor Prof. Rangan Gupta for providing their expert advise and guidance. This has been quite a stimulating learning experience and I am truly grateful for the knowledge that both of you have imparted on me.

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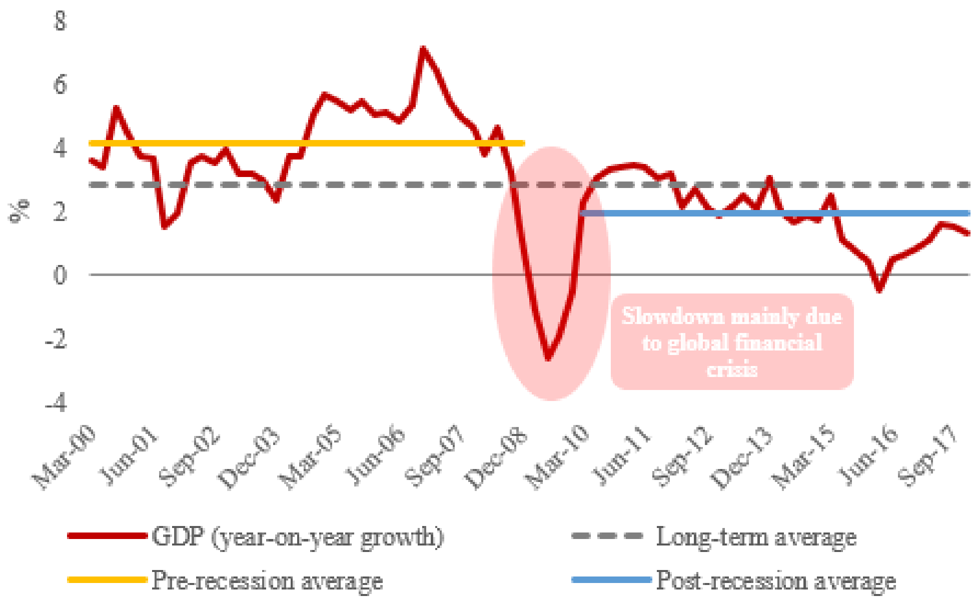
Chapter 1

General Introduction

"Financial markets essentially involve the allocation of resources. They can be thought of as the "brain" of the entire economic system, the central locus of decision making: if they fail, not only will the sector's profits be lower than they would otherwise have been, but the performance of the entire economic system may be impaired." - Joseph E. Stiglitz (Stiglitz (1993))

This thesis constructs a new index to monitor stress in the South African financial system by using a novel approach that selects and aggregates financial indicators based on their information content i.e. their ability to capture key periods of financial stress in the economy, thereby striking a balance between parsimony and efficacy. While we are aware that the literature on the construction of financial stress indexes is quite extensive for South Africa (see Gumata et al. (2012), Thompson et al. (2015), Kasaï & Naraidoo (2013), and Kabundi & Mbelu (2017), the approach we use serves as a technical improvement over these past measures and avoids the risk of combining informationally redundant data that would over-emphasize a given market segment, avoiding a high rate of false alarms. Following the construction of a financial stress index, we aim to shed light on the following issues. Does the state of financial market conditions influence the transmission of financial shocks to the real economy? Can financial market information accurately predict economic conditions, specifically within a mixed-frequency framework? What is the connection between economic uncertainty and financial market conditions i.e. does the macroeconomic implications of an uncertainty shock differ across financial regimes? Answers to these questions have important monetary policy implications, especially since macroeconomic volatility and financial market conditions are important determinants of growth performance and as such have the potential to weaken or distort monetary policy transmission.[1]

Figure 1.1: Real Gross Domestic Product (GDP) growth



Notes: The figure shows the growth of the South African economy pre- and post the global crisis, together with the long-term average growth over the period as well as the average growth before and after the economic downturn of 2009. *Source*: Statistics South Africa and Authors calculation

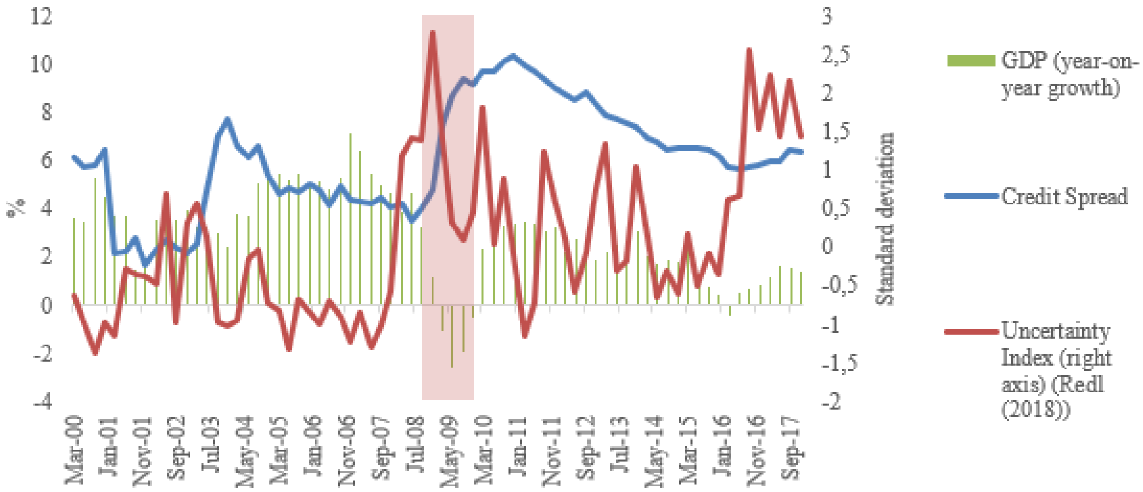
The financial system of an economy plays a fundamental role, enabling the flow of capital among economic agents and thereby facilitates economic activity. According to the International Monetary Fund (IMF) Financial System Stability Assessment for South Africa, the financial sector in the country amounts to almost three times the size of the economy (IMF (2014)). Being a major contributor to economic growth, it is without doubt that disruptions in these markets disrupt capital

[1]The financial stress index constructed in this thesis could serve as the basis for a number of interesting future studies. For example, the index could be updated and used to examine the macro-financial implications of the recent and ongoing Covid-19 pandemic (similar to recent studies including, for example, Zhang et al. (2020) and Albulescu (2020)), and to study the dynamics of GDP growth vulnerability within the Growth-at-Risk (GaR) framework (proposed by Adrian et al. (2019)) for South Africa.

flows and have significant implications for development and growth of an economy. Furthermore, shocks generated by financial markets are known to be powerful as those analysed by traditional real business cycle theory (Gilchrist & Zakrajšek (2012)). The 2007-2009 global financial crisis is evidential that turmoil in these markets may have severe macroeconomic consequences. Despite having a relatively rigid regulatory environment, the South African economy faced the pressure of the crisis in 2008 when a sudden stop in international capital flows eroded share prices and the exchange rate of the rand (Viegi (2008)). Deteriorating investor sentiment and international commodity prices resulted in the JSE All Share Index losing more than 20 per cent of its value and rand devaluation of more than 40 per cent against the US dollar in 2008. The effects of the crisis rapidly spread to the real economy plunging the South African economy into a recession in 2009 (Saayman (2010)). This has put forth increased focus on the development of improved measures to monitor instability in financial markets for the purpose of forecasting recessionary activity in the real economy and quantifying the extent to which financial market stress impacts the real economy. In particular, in this thesis we argue that there is a need for improved parsimony-promoting tools to measure financial stress in the context of growing complexities and instabilities in international and domestic financial markets.

Contrary to the late Milton Friedman's proposition of rapid recoveries following deep recessions (Friedman (1964), Friedman (1993)), many economies globally experienced slow economic recovery since the Great Recession of 2008-09. Figure 1.1 shows that economic growth in South Africa recovered post recession, albeit at a reduced rate. Average growth of the economy post-recession is about 50% lower than it was before the recession in 2009. In addition to financial market disruptions, many policy makers and economists following the seminal work of Bloom (2009) have attributed this anaemic recovery to heightened economic uncertainty. In particular, since higher levels of realised volatility and higher vulnerability to external shocks are more common in developing countries than in developed economies (Fernández-Villaverde et al. (2011), Bloom (2014)), fluctuations in uncertainty would reasonably be an important driver of business cycles in these developing regions. A simple plot of economic uncertainty, financial stress, and

Figure 1.2: Uncertainty, credit spreads, and economic activity



Notes: The figure shows the relationship between uncertainty, financial stress proxied by credit spreads, and economic activity captured by real GDP growth. Credit spread is calculated as the difference between the bank lending average rates on new fixed rate instalment sale agreements and negotiable certificates of deposit (NCDs) rate. The economic uncertainty measure in the figure was sourced from Redl (2018). The shaded region shows the economic downturn following the global financial crisis. *Source*: Authors calculations, South African Reserve Bank, Statistics South Africa, Redl (2018).

economic activity in South Africa depicted in Figure 1.2 shows that economic activity has not returned to pre-recession levels and this can be attributed to elevated levels of financial stress and uncertainty post-recession. Interestingly, as the global financial crisis hits South Africa we note that credit spreads spike after the spike in uncertainty, with a lag of about one year. It took about a year for the effects of the crisis that dislocated credit markets in the United States and Europe to spillover into South African credit markets, reflected in lending condition. This lagged effect helps to distinguish the role of financial stress from uncertainty as these two measures were not as highly correlated as in countries where the global financial crisis originated. Popescu & Rafael Smets (2010) argue that the impact of higher economic uncertainty is driven by its ability to increase financial uncertainty. While traditionally, the transmission of uncertainty shocks have been linked to real frictions (Bernanke (1983); Bloom (2009)), recent studies have documented the crucial role of financial frictions in the transmission mechanism (Arellano et al. (2010); Gilchrist et al. (2014); Christiano et al. (2014); Caldara et al. (2016)). However, most of the studies examining the link between financial conditions and country-specific uncertainty have focused on advanced economies only.

Our research unfolds against the backdrop provided above and as such the remainder of the thesis is organised as followed. Chapter 2 starts by constructing a new financial stress index for South Africa and then examines whether the index captures non-linearities in the transmission of financial shocks to the real economy. Chapter 3 we assess whether and the extent to which financial market information help in predicting economic condition in the country. In particular we evaluate whether a mixed-frequency specification enhances the predictive performance of financial information compared to traditional common-frequency specifications. In Chapter 4 we quantify the extent to which aggregate financial conditions influence the response of the South African economy to uncertainty shocks, specifically whether the macro-financial implications of an uncertainty shock differ across regimes.

Chapter 2

Monitoring financial stress

2.1 Introduction

The measurement of financial market stress and its implications for the real economy has gained increasing popularity, especially in the aftermath of the 2007-09 global financial crisis. Broadly defined, financial stress is associated with an interruption to the normal functioning of financial markets (Hakkio & Keeton (2009)). Recent empirical research have emphasised that financial market stress tends to be characterised by considerable co-movement of financial sector variables (see for example Hollo et al. (2012), Louzis & Vouldis (2012), Vermeulen et al. (2015), and Chatterjee et al. (2017)). It is against this backdrop that we construct a new comprehensive index of financial stress for the South African economy (SAFSI), that captures the interconnectedness of financial markets (assessing the systemic importance of indicators) and exploits the information content inherent in market-based indicators. As such, this chapter argues that there is a need for improved parsimony-promoting tools to measure financial stress in the context of growing complexities and instabilities in international and domestic financial markets. While the main focus of this chapter is on the construction of the financial stress index, we touch on the real implications of financial stress by using the SAFSI to examine the changing economic dynamics during financially stressful periods and normal periods, within a regime-switching framework.

We follow closely the methodology of Chatterjee et al. (2017) and as such offer two main contributions to the South African literature and emerging market literature in general.[1] Firstly, we identify key periods of financial stress in South African history, such as the 2008-2009 global financial crisis, and then use the partial 'Area Under the Receiver Operating Characteristic Curve' (pAUROC) metric, which is based on signalling theory, to filter the candidate raw market-based indicators on the basis of their ability to signal the contemporaneous materialisation of the identified stressful periods. In the case of the South African economy that has not experienced any significant crisis of a local nature, the key episodes identified are mainly instabilities and imbalances in the international financial realm that have been particularly problematic for the local economy in terms of sparking episodes of drastic capital outflows alongside severe currency depreciations. The pAUROC allows for the usefulness of each candidate indicator to be ranked according to its information content, accounting for the assumed balanced preferences of policymakers between missing financially stressful/ crisis events and receiving false alarms. Secondly, we employ the portfolio theory-based aggregation scheme following Hollo et al. (2012), Louzis & Vouldis (2012), Vermeulen et al. (2015), and Chatterjee et al. (2017) to consider the interconnectedness of financial markets by means of time-varying cross correlations (estimated by means of a multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model) to quantify the level of systemic stress. Such aggregation methods for constructing financial stress indexes (FSIs) have not previously been applied within the South African context. The literature on the construction of FSIs for South Africa is quite limited (see Gumata et al. (2012), Thompson et al. (2015), Kasaï & Naraidoo (2013), and Kabundi & Mbelu (2017)) with aggregation methods including mainly principle component analysis (PCA), Kalman filtering, and equal weights.

To account for the different aspects of financial stress, the SAFSI comprises 17 financial indicators that stem from six major markets including the equity, credit, foreign exchange, housing, commodity, and money market. Our monthly index covers the post-apartheid period of 1995 to 2017, due to data availability. The six market sub-indices are computed by taking the average of the

[1] Chatterjee et al. (2017) construct a financial stress index for the United Kingdom by building on some of the propositions of Duprey et al. (2017)

standardised individual stress indicators weighed by their information content which is captured by the pAUROC. Thus, in a particular market sub-index, more weight is given to those financial indicators that possess better information content. The six market sub-indices are aggregated over time by means of information weights and cross-correlations among them. We evaluate the performance of the constructed SAFSI in terms of its ability to capture the benchmark periods of financial stress as well as other periods of stress impacting the South African financial system. In this regard, the SAFSI is also compared to alternative measures of financial stress constructed using different aggregation techniques. The SAFSI spikes sharply during the benchmark periods of financial stress, and also reassuringly picks up instances of global and idiosyncratic risks that affect financial markets in South Africa. Compared to financial stress measures computed with either PCA or equal weights, the SAFSI does better in capturing most of the episodes of financial stress compared to the other stress measures. Furthermore, the financial stress measures computed with PCA and equal weights seem to overstate the intensity of financial stress, particularly during normal times.

There has been widespread discussion especially following the 2007-2009 financial crisis which have documented differing economic dynamics during stressful and normal time in the financial system (see for example van Roye (2014), Aboura & van Roye (2017), Hubrich & Tetlow (2015), Hollo et al. (2012), Chatterjee et al. (2017), van Roye (2014), Aboura & van Roye (2017), and Balcilar et al. (2016)). In light of this, we estimate a regime-switching model, specifically a threshold vector autoregressive model as specified in Alessandri & Mumtaz (2017) in order to examine economic dynamics. We examine whether our constructed index SAFSI captures non-linearities in the transmission of financial shocks by means of generalised impulse response functions. We find evidence that financial shocks have a larger impact on the real economy during financially stressful periods compared to normal periods. In particular, output declines by twice as much and prices increase significantly following an unanticipated negative financial shock during stressful times. However, during normal times, the impact of a financial shock on inflation and interest rates is negligible, while output contracts by a lesser extent. Given these findings, policymakers should acknowledge non-linearities in the financial sector-real economy nexus and distinguish between the two states of the world.

The remainder of the chapter is organised as follows. Section 2.2 reviews the literature on the construction of financial stress indexes (FSIs) and the assessment of its impact on economic activity. Section 2.3 covers the construction of the SAFSI, which includes the selection of market-based indicators, and the weights used to aggregate these indicators into a comprehensive FSI. Section 2.4 evaluates the performance of the SAFSI against alternative indicators. Section 2.5 studies the economic dynamics following a financial shock and Section 2.6 concludes.

2.2 Literature

The construction of financial stress indexes (FSIs) and the assessment of its impact on the real economy has attracted widespread interest, especially in the aftermath of the 2007-09 global financial crisis.[2] While the literature is quite extensive for advanced economies, it is quite limited for emerging economies mainly due to data constraints. The literature covers the various methods employed in empirical studies to construct FSIs, as well as briefly covering the economic dynamics. In general, the most common aggregation methods employed include principle components analysis (PCA), equal weights, variance-equal weights, dynamic factor modelling, and more recently portfolio theory and information weights. Common individual indicators used in past studies cover financial stress in the equity, credit, foreign exchange, and money markets, with few studies incorporating stress prevailing in the housing and commodities market.

During the pre-global financial crisis period, Illing & Liu (2006) employed various construction methods to construct an FSI for Canada, including PCA, equal weights, credit weights, transformations using sample cumulative distribution functions (CDFs), and variance-equal weights. Their index included daily data from the equity and debt markets, banking sector and foreign exchange

[2]No distinction between financial stress indexes (FSIs) and financial conditions indexes (FCIs) are made in this thesis, since the difference between them are relatively small. FCIs are aggregates of a variety of financial variables that aid in characterising the state of the financial markets. Similarly, FSIs monitor financial instability by looking at financial variables that indicate increased likelihood of a crisis.

market. In addition, the various indicators were compared in terms of their ability to signal a crisis. Similarly, Oet et al. (2015) use the various methods adopted by Illing & Liu (2006) but applied to the United States, and find that their constructed index is useful in decomposing stress, monitoring development and historical analysis. While Duca & Peltonen (2013) use the simplest technique of equally weighting financial indicators to constructs FSIs, Cardarelli et al. (2011), Balakrishnan et al. (2011), Park & Mercado Jr (2014) and Hubrich & Tetlow (2015) construct FSIs via variance-equal weighted averaging of financial variables. The disadvantage of the equal weights is that it does not account for different variances and correlations among variables, and hence the weights do not correspond to the variables' importance. While the variance-equal weighted averaging method accounts for different variances among financial variables, a drawback of this approach is that it assumes all variables are normally distributed, which is not always the case.

The Kansas City FSI introduced by Hakkio & Keeton (2009), is constructed via a PCA of 11 standardised financial indicators over the period February 1990 to March 2009. Their FSI includes seven spreads between different bond classes, expected stock price volatility, bank stock price volatility, cross-section dispersion of bank stock returns, and correlations between returns on stocks and treasury bonds. They find that the index captures known periods of financial stress, leads changes in credit standards, and that an increase in financial stress leads to persistent business cycle downturns. Hatzius et al. (2010) uses PCA to construct a FCI for the United States, but allow for unbalanced panels, and incorporates observed macroeconomic variables so as to purge the FCI of macro influences. The authors find that the constructed FCI can help predict economic activity. Other international studies that have adopted the PCA approach include, for example, Cevik, Dibooglu & Kutan (2013), Cevik, Dibooglu & Kenc (2013), and Stolbov & Shchepeleva (2016). These studies reveal that financial stress has important and significant implications on the real sector. The PCA approach constructs the FSI as a common factor from a group of several financial variables, resulting in an index that is stationary with zero mean, essentially lacking a dynamic pattern that is important to predict turning points in the business cycle. Allowing for time-variation in the parameters, Koop & Korobilis (2014) employ a dynamic factor model (based on PCA and Kalman filtering) to construct a FCI for the United States and find that index has predictive power for macroeconomic variables, in particular, output growth, inflation and unemployment. They postulate that accounting for time-variation in the parameters is important for accurate short-term forecasts. Other notable international studies in the literature that make use of this approach include Cevik et al. (2016), van Roye (2014), and Aboura & van Roye (2017).

Hollo et al. (2012) were the first to employ the principles of portfolio theory to construct a FSI for the euro area. Particularly, the authors aggregate five financial market segments by considering the time-varying cross correlation (estimated using exponentially weighted moving average (EWMA) method) between them, assigning more weight to situations in which several financial market segments experience high stress at the same time. Threshold VAR analysis reveals that shocks to the FSI are more detrimental to real economic activity during high-stress regimes than during low-stress regimes. Vermeulen et al. (2015), Louzis & Vouldis (2012), and Chatterjee et al. (2017) follow the methodology of Hollo et al. (2012), with the latter two studies extending the portfolio-theoretic approach by using instead a multivariate GARCH model to estimate time-varying cross-correlations between market segments. In particular, Chatterjee et al. (2017) extend on this method by constructing a comprehensive FSI for the United Kingdom (UK) over 45 years, using portfolio theory in conjunction with information weights to aggregate 6 market segments. They use past episodes of financial stress in the country to determine potential future financially stressful conditions. The authors use the partial AUROC (Area under the Receiver Operating Characteristic Curve) metric to rank the individual stress indicators in terms of their usefulness in signalling a binary crisis event. They find that the use of information and correlation weights to aggregate financial indicators reduces the risk of over-emphasising a given market segment, that could potentially result in a high percentage of false alarms i.e. incorrectly signalling a crisis. This represents a significant advantage over the construction methods discussed above. Employing threshold VAR analysis, the authors find that the transmission of shocks to the real sector in financially stressful periods significantly differs from tranquil periods. Other notable studies that take into account the underlying state of the economy when analysing the impact of financial shocks on the real economy include, but is not limited to, Hubrich & Tetlow (2015), van Roye (2014), Aboura & van Roye (2017), and Balcilar et al. (2016). Although examining different economies, these studies find similar evidence that economic activity reacts differently to financial shocks in stressful versus tranquil periods, with stressful periods being highly detrimental for the economy and conventional monetary policy is inadequate during such periods.

Focusing more on the South African economy, the literature on FSIs is quite extensive but there is room for technical improvement. While Gumata et al. (2012) construct a quarterly FCI over the period 1999 to 2011, from 11 nominal indicators, employing the alternative approaches of principle component analysis (PCA) and Kalman filtering with constant loadings, Thompson et al. (2015) improve on this method by aggregating 16 monthly financial variables (incorporating domestic and global measures) via recursive PCA. Thompson et al. (2015) also purge their FCI from endogeneity by regressing it on 3 macroeconomic variables, including output, inflation, and interest rates. Employing the FCI constructed by Thompson et al. (2015), Balcilar et al. (2016) were the first to explore whether non-linearities exist in the transmission of financial condition shocks in the South African economy. They make use of a non-linear logistic smooth transition vector autoregressive model (LSTVAR) and finds that inflation in the South African economy responds more to financial shocks during recessions, while output growth and interest rates responds more significantly during expansions. In this framework, however, the lower and upper regimes are determined by the asymmetric and dynamic interactions of all the variables in the system, and not necessarily by the nature of the switching variable itself (Evgenidis & Tsagkanos (2017)). Using a simpler method of equal weighted averaging of 5 variables, Kasaï & Naraidoo (2013) estimate a monthly FCI for the period 2000 to 2008. Their FCI is constructed for inclusion in the monetary policy reaction function of the South African central bank, reflecting the central bank's concern to maintain financial stability. In a recent study, Kabundi & Mbelu (2017) follow very closely the technique of Koop & Korobilis (2014) to construct an FCI for South Africa from 39 monthly financial market variables spanning the period January 2000 - April 2017. The constructed index captures financial conditions in the markets for credit, equity, funding, real estate, and foreign exchange, as well as foreign data. They then include 2 macroeconomic variables with the FCI to estimate a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model, finding that the responses of the macroeconomic variables change over time following a shock to financial conditions. These authors do not consider the potential interconnectedness of financial markets. We attempt to close this gap in the South African literature by employing correlation weights and information weights to aggregate financial market indicators, thereby considering the interconnectedness of financial markets and assessing the systemic dimension of financial stress.

2.3 Construction of the SAFSI

The literature has highlighted two main issues involved in the construction of a FSI. These include the selection of market-based indicators, and the weights used to aggregate these indicators into a comprehensive FSI. Firstly, all the raw candidate indicators are filtered based on their ability to signal the contemporaneous materialisation of the identified benchmark episodes of financial stress in South Africa. In this case, the 'partial AUROC' (pAUROC) metric is used to order indicators based on the information they convey. Secondly, the narrowed list of indicators are then standardised and aggregated into their respective market sub-indices using information weights as captured by the pAUROC metric. Finally, the market sub-indices are aggregated into a composite financial stress index (SAFSI) by means of information weights and time-varying cross-correlations of the market sub-indices. This section will elaborate on these three steps.

2.3.1 Selection of stress indicators

2.3.1.1 Candidate indicators of financial stress

Hakkio & Keeton (2009) postulate that financial stress is normally characterised by growing uncertainty about the fundamental value of assets and investor behaviour; increased asymmetry of information; and flights to quality and liquidity. In addition to these factors, Balakrishnan et al. (2011) also mention that financial stress is associated with concerns about the health of the banking system. To account for these different aspects of financial stress in an emerging economy, in this case South Africa, the SAFSI will cover indicators from 6 market segments (see Table A.1 in Appendix A) that are thought to be most significant for the SA economy. The SAFSI also captures vulnerabilities in the commodity market, given that SA is a resource-based and open economy that depends on developments in international markets, in contrast to Chatterjee et al. (2017).

The stress indicators in each market segment are measured in terms of volatilities, valuation losses, and risk spreads. The full list of raw candidate indicators considered are summarised in Appendix A, according to the corresponding market segments.[3] The indicators are all on a monthly basis, and cover the post-apartheid period of 1995 to 2017. The sample was chosen so to have the largest possible dataset for calibration and satisfy the objective of this chapter which focuses on the backward performance of the index rather than capturing the latest observations. Furthermore, changing the sample will not change the calibration and the results. The monthly SAFSI includes 17 financial indicators spanning six market segments including the equity (EM), credit (CM), foreign exchange (FX), money (MM), housing (HM), and commodities market (ComM). The inputs to the SAFSI are identified following the approach of Chatterjee et al. (2017), whereby indicators are selected based on their ability to identify financial stress conditions in SA.

2.3.1.2 Benchmark episodes of financial stress in South Africa

As in Chatterjee et al. (2017), the stress indicators are ranked and selected based on their ability to match benchmark episodes of financial stress in SA. Note, however, that most of the financial stress episodes in SA emanated from global risks. As such, the benchmark episodes mainly reflect the years in which the South African economy experienced severe financial stress due to adverse global developments. We evaluate the ability of the SAFSI to capture the identified episodes as well as other financially stressful periods. The periods below have been have been selected based on academic literature and published reports and have been widely accepted as episodes characterised

[3] See Appendix A for the formulae used to define all indicators. The variables used to calculate each stress indicator were obtained from three sources: South African Reserve Bank, Quantec, and Johannesburg Stock Exchange (JSE). The indicators highlighted in bold are the selected indicators based on their ability to identify the main financial stress episodes in the South African financial history.

by financial stress in SA.

- 1998-1999: The South African economy experienced a currency crisis in 1998, which originated from nominal shocks induced by a combination of relaxed monetary policy stance and shifts in financial market expectations following the East Asian financial crisis of 1997 and the Russian financial crisis of 1998 (Nowak & Ricci (2006)). The rand depreciated by 28 per cent in nominal terms against the U.S. dollar over the period April-August 1998. This was accompanied by interventionist policy responses by the central bank of SA, increasing the short-term interest rates and long-term bond yields by about 700 basis points (to 21.86 per cent). This exacerbated the crisis and deepened its macroeconomic impact, as output contracted during the third quarter of 1998 and the stock market declined heavily and remained below initial level for more than one year (Nowak & Ricci (2006)). Furthermore, total loans and advances of South African banks experienced a continuous decline in growth since August 1998 (following the rapid increase in the cost of borrowing), impacting negatively on the interest income of banks and the efficiency of the sector. Small banks in SA experienced liquidity pressures in 1999, which gradually eroded depositor confidence in some smaller to mid-sized banks (South African Reserve Bank (2002)).

- 2001-2002: The economy experienced a currency crisis in 2001 as the rand depreciated by 28 per cent, due mainly to the slowdown in global economic activity that began in 2000 (particularly due to the stock market crash/ internet bubble bursting) and that reduced world demand for South African goods and services (Nowak & Ricci (2006)). As a result, net capital outflows and a decline in the country's net international reserves were recorded during the last quarter of 2001. In addition to this, the efficiency of the SA banking sector deteriorated (return on assets and return on equity deteriorated) over the period 2001-2002 and participation of foreign banks in the local banking industry declined for the first time in 6 years (South African Reserve Bank (2002)). Over the period 2002 up to the first few months of 2003, the South African banking system was confronted with the exit of 22 banks. This was due to the contagion that set in following the imposition of curatorship over Saambou

Bank Limited (7th largest bank in SA) in February 2002 and the subsequent takeover of BOE Bank Limited (6th largest bank in SA) by Nedbank Limited which arose from the bank's liquidity strain (Havemann (2018),Schoombee (2004)). Saambou Bank Limited was seen by regulators as being systemically significant (as was BOE Bank Limted), given that the bank had both a large retail deposit base and a well-established branch network. These banks as well as smaller banks experienced large withdrawals of deposits as confidence in banking system dampened and consequently share prices of these banks deteriorated.

- 2008-2009: The global financial crisis of 2007-2009 dampened confidence among participants in financial markets. Despite a relatively rigid regulatory environment, the South African economy faced the pressure of the crisis in 2008 when a sudden stop in international capital flows eroded share prices and the exchange rate of the rand (Viegi (2008)). Deteriorating investor sentiment and international commodity prices resulted in the JSE All Share Index losing more than 20 per cent of its value and rand devaluation of more than 40 per cent against the US dollar in 2008. The effects of the crisis rapidly spread to the real economy plunging the South African economy into a recession in 2009 (Saayman (2010)). The mining and manufacturing sector were the main contributors to the contraction in economic growth amid subdued global and domestic demand conditions and electricity supply constraints. Share prices gained momentum towards the latter part of 2009, supported by an improvement in international equity markets and good performance in the local resources sector as commodity prices increased significantly and there were signs of recovery in the global economy. Similarly, the exchange value of the rand improved significantly towards the second half of 2009, while still maintaining its volatility. The South African banking system remained relatively stable during the financial crisis, however commercial banks' profitability suffered somewhat in 2009 amid rising bad debts, curtailment of credit extension and progressive decline in domestic demand (South African Reserve Bank (2009)).

2.3.1.3 Methodology used to capture benchmark episodes of financial stress

Given the episodes of financial stress identified above, this section will outline the technique employed to signal the materialisation of these stressful/crisis periods. The 'partial AUROC' metric will be used to rank the market-based indicators in terms of their information content. We start off this section by first briefly outlining the signalling approach before introducing the concepts of AUROC and partial AUROC.

2.3.1.3.1 Signalling approach

This approach is a type of early warning system that identifies indicators based on their ability to signal economic vulnerabilities early enough to enable policy makers to implement mitigative action.[4] Based on a predetermined threshold, an indicator issues a signal if it breaches this threshold, or else no signal is issued. As a result, four possible outcomes are possible.When a signal is issued and a crisis occurs, this is a good signal as the crisis is well predicted, but when no crisis occurs this is a false alarm or Type II error. On the contrary, when no signal is emitted and a crisis occurs, the observation is characterised as a missed signal or Type I error, but when no crisis occurs this is a good silence as a tranquil period is well predicted. However, in the South African context 'crisis' versus 'no crisis' would amount to ' stressful period' versus 'tranquil period', as the economy did not experience actual crisis but were confronted with significant financial stress over certain periods of the sample. From the four possible outcomes, the true positive rate (TPR) or signal ratio is the fraction of correctly predicted crisis, from which the fraction of missed crisis (Type I error rate) is 1-TPR. The false positive rate (FPR) or noise ratio, which is also referred to as the Type II error rate, represents the fraction of false alarms. The optimal threshold is identified by assessing the trade-off between Type I errors and Type II errors. A higher (lower) threshold increases (decreases) the probability of missing a crisis but at the same time decreases (increases) the probability of issuing a false alarm.

[4] For applications of this approach, see for example Kaminsky et al. (1998), Demirgüç-Kunt & Detragiache (1998), Kaminsky & Reinhart (1999), Lowe et al. (2002), Borio & Drehmann (2009), Drehmann et al. (2010), Drehmann et al. (2011), Alessi & Detken (2011), and Detken et al. (2014).

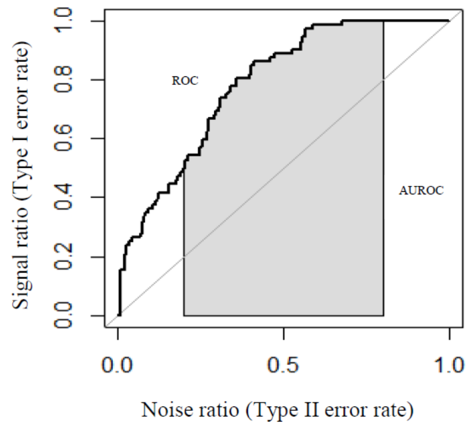
The predictive performance of indicators can be assessed through the noise-to-signal ratio (which is the ratio of falsely signalled crisis to correctly signalled crisis) since the number of observations (i.e. crisis and non-crisis) are fixed. A ratio of less than 1 implies that the indicator is useful or relevant, while a value of 1 results when purely random signals are issued by the indicator. However, the noise-to-signal ratio is not without a disadvantage due to its reliance on a specific threshold to minimise this ratio (while failing to consider the preferences of the policy maker), which is often reached at very low noise and signal ratios (Chatterjee et al. (2017)). However, this configuration is achieved at unjustifiably high threshold values. This high threshold implies that policymakers disregard Type I errors (missing a crisis), while being extremely averse to Type II errors (receiving false alarms). In practice, this is not reflective of the true preferences of policymakers, especially if the cost of macroprudential interventions are low and benefits high. For example, in the case of the recent global financial crisis, policymakers would have preferred a low threshold to avoid Type I errors rather than Type II errors (Chatterjee et al. (2017)).

2.3.1.3.2 Area under the receiver operating characteristic curve (AUROC)

The ROC or receiver operating characteristic curve plots the indicator's signal ratio against the noise ratio for every possible value of the threshold above which a signal is defined. The AUROC test has recently been introduced in economic studies to evaluate the predictive performance of an indicator irrespective of policy-maker preferences (See for example, Schularick & Taylor (2012) and Drehmann & Juselius (2014)).

Figure 2.1 displays the ROC and associated AUROC for a financial indicator in the money market, the interbank spread, which is the spread between the 3-month interbank rate and the 3-month treasury bill rate. Since it is a fraction of the area of a unit square, the AUROC metric ranges from 0 to 1, while the diagonal line has an area of 0.5, implying that random signals are emitted by the indicator. Therefore, an indicator is considered uninformative if its has an AUROC value of 0.5 or less, while a value larger than 0.5 means that the indicator is relevant and informative. Furthermore, an AUROC value of 1 implies that the indicator is fully informative. The AUROC

Figure 2.1: AUROC for the interbank spread



Notes: The solid line represents the ROC curve. The diagonal line corresponds to an uninformative indicator. The AUROC evaluates the performance of the financial indicator on the basis of its ability to capture the identified periods of financial stress in SA outlined in Section 2.3.1.2. The partial AUROC (pAUROC) is shown as the shaded region incorporating policy-maker preferences.

value for the interbank spread in Figure 2.1 is 0.78, which suggests that this indicator is relevant (the ROC is well above the diagonal line) as it detects a high percentage of crisis/ stressful episodes with few false alarms. The ROC curve slopes upwards since as the threshold value falls (i.e. moves away from the origin towards the opposite end of the chart), both the noise and signal ratio rise. This means that progressive lowering of the threshold, results in a continuous increase in the number of emitted signals - The percentage of well predicted crisis and false alarms goes from 0 to 100 per cent.

The evaluation criterion provided by the AUROC metric is robust, as it considers the indicator's accuracy for each possible threshold value. Therefore, it does not rely on the identification of a specific threshold and basically summarises the balance between Type I errors (missed crises) and Type II errors (false alarms). This is one of the advantages of the AUROC measure over the signalling approach discussed above. As such, the AUROC does not account for policy maker preferences over Type I and Type II errors. One way of accounting for policy making preferences, would be to define a loss function to rank indicators and analyse their usefulness.

2.3.1.3.3 Partial AUROC

The partial AUROC (pAUROC) metric is a modification of the AUROC measure where some conservative assumptions about policy maker preferences are made to enhance the performance of the measure. Alessi & Detken (2014) define the loss function of a policy maker as follows:

$$L(\theta) = \theta T_1 + (1 - \theta)T_2 \tag{2.1}$$

where T_1 depicts the Type I error rate corresponding to the fraction of missed crisis, and T_2 reflects the Type II error rate which represents the percentage of false alarms. The policy maker's relative risk aversion between the two types of errors is captured by the parameter θ, which ranges between 0 and 1. A value of $\theta > 0.5$, implies that the policy maker is more averse towards missing a crisis as opposed to receiving a false alarm. The loss function L is simply a weighted average of the two errors generated by the indicator breaching a given threshold. According to Alessi & Detken (2014), policymakers responsible for financial stability were more averse towards receiving a false alarm than missing a crisis, in the period preceding the global financial crisis. However, after the experience of the global financial crisis, the preferences of policymakers' have become more balanced. This balanced perspective of policymakers' preferences has highlighted the need to focus on the pAUROC rather than the full AUROC metric. In this case, the pAUROC cuts off areas associated with implausibly low and high values of a policy maker's aversion between the two types of errors discussed above. The pAUROC is estimated by specifying the restricted range of false positives and the computation of the partial area under the ROC curve.

In this chapter, we follow Chatterjee et al. (2017) by estimating the pAUROC of indicators where the parameter θ ranges from 0.2 to 0.8, hence assuming that policymakers in South Africa have balanced preferences. The pAUROC for the interbank spread is depicted by the shaded area in Figure 2.1, which restricts combinations of noise and signal ratios that are outside of the range $0.2 - 0.8$. This measure will be used to rank indicators in terms of their ability to identify episodes of financial stress in SA. The use of this measure (i.e. pAUROC metric) as information weights to aggregate the indicators across the different market segments into a comprehensive index is one of the main methodological contributions of the SAFSI compared to other FSIs that have been constructed for SA. Only stress indicators that have a pAUROC above 0.5 are considered for the construction of the SAFSI, as such indicators meaningfully coincide with the episodes of financial stress outlined in Section 2.3.1.2.

2.3.1.4 Selection procedure of indicators and standardisation

The full list of candidate financial indicators are narrowed down by selecting only those indicators which keep adding more information to the overall ability of the market segment to match the episodes of financial stress in SA. In this way, parsimony is preserved in the construction of the SAFSI. The indicators are first ranked according to their pAUROC, within each market segment (Table A.2 in Appendix A). Following this, we first disregard those indicators that have a pAUROC that is less than 0.5, as these indicators are regarded as uninformative. Secondly, the indicator with the largest pAUROC is always selected for a given market segment i.e. CMax_rBPI for the equity market. Thirdly, we consider the inclusion of the indicator that has the next largest pAUROC, for a given market segment i.e. CMax_rALSI for the equity market. The weighted average of this indicator with the previously selected indicator is then computed, which in this case is the temporary equity market segment S'_{EM}:

$$
\begin{aligned}
S'_{EM} \quad = \quad & \frac{CMax\_rBPI \times (pAUROC_{CMax\_rBPI} - 0.5)}{(pAUROC_{CMax\_rALSI} - 0.5) + (pAUROC_{CMax\_rBPI} - 0.5)} \\
& + \frac{CMax\_rALSI \times (pAUROC_{CMax\_rALSI} - 0.5)}{(pAUROC_{CMax\_rALSI} - 0.5) + (pAUROC_{CMax\_rBPI} - 0.5)}
\end{aligned}
\tag{2.2}
$$

The partial AUROC of the temporary market segment (i.e. $pAUROC_{S'_{EM}}$ for the above example) is then calculated. The incremental partial AUROC which can be positive or negative is calculated as $pAUROC_{S'_{EM}} - pAUROC_{CMax\_rBPI}$ for the example above. The indicator will be selected only if the incremental pAUROC is positive i.e. $pAUROC_{S'_{EM}} > pAUROC_{CMax\_rBPI}$, otherwise it will not be selected. This is because a positive incremental partial AUROC implies that adding the additional candidate stress indicator improves the informational content of the overall market segment.

This last step is repeated with the candidate stress indicator with the next largest partial AUROC, and so on, until all candidate indicators in the market segment are considered. According to Chatterjee et al. (2017), “the idea is that an individual stress indicator with lower informational content (i.e. lower pAUROC values) can nevertheless add relevant information to the overall market stress measure when considered jointly, if it captures a different aspect of financial stress, hence resulting in a higher pAUROC”. Table A.2 in Appendix A displays the AUROC and pAUROC values for the full list of the raw candidate stress indicators, however the 17 indicators highlighted in bold are those that were finally selected based on their information content as outlined in the steps above.

Since the selected raw stress indicators do not have the same unit, they are transformed based on their empirical cumulative distribution function (ECDF) before they are aggregated into the six market segments. The ECDF method for standardisation is chosen over the common method of standardisation (whereby one subtracts the sample mean from the observation and divide this by the sample standard deviation), as this method of standardisation assumes that variables are normally distributed. Since not all standard stress indicators are normally distributed (for example, in the case of variances), this enhances the risk that the results obtained from the use of standardised variables are sensitive to abnormal observations. The ECDF provides more robust results as it transforms the raw indicators based on location and dispersion measures (Hollo et al. (2012)). An ECDF is created by replacing the value of each indicator by its ranking number [r] scaled by the sample size [n]. For instance, if $x = (x_1, x_2, ..., x_n)$ denotes a dataset of a raw stress indicator x_t. The dataset is arranged in ascending order $(x_{[1]}, x_{[2]}, ..., x_{[n]})$ where $x_{[1]} \leq x_{[2]} \leq ... \leq x_{[n]}$ (i.e. $x_{[n]}$ represents that sample maximum and $x_{[1]}$ is the sample minimum) and [r] would be the ranking number assigned to a particular realisation of x_t. The ECDF $(F_n(x_t))$ for the stress indicator is then computed as

$$F_n(x_t) = \begin{cases} \frac{r}{n} \, for \, x_{[r]} \leq x_t < x_{r+1}, & \text{r=1,2,...,n-1} \\ 1, & \text{for } x_t \geq x_{[n]} \end{cases} \tag{2.3}$$

for t=1,2,...,n. It measures the fraction of observations of x_t not exceeding a specified value x^* (which equals the corresponding ranking number r^*). In this way, the ECDF transforms each raw stress indicator to lie in the range $[0,1]$, hence being unit-free. The ECDF is a non-decreasing function that jumps up by 1/n at each observed point. However, for purposes of construction of the SAFSI and to evaluate it efficacy in capturing stressful periods, we match the ECDF value of each observation to its original value in the dataset. The standardised stress indicators for the 17 selected indicators are shown in Figure A.1 in Appendix A.

2.3.2 Aggregation of indicators

This section is broken down into two parts. The first part outlines the method of aggregating individual stress indicators into the respective market sub-indices. The second part comprises the aggregation of these market sub-indices into a composite FSI for SA (SAFSI).

2.3.2.1 Construction of market sub-indices

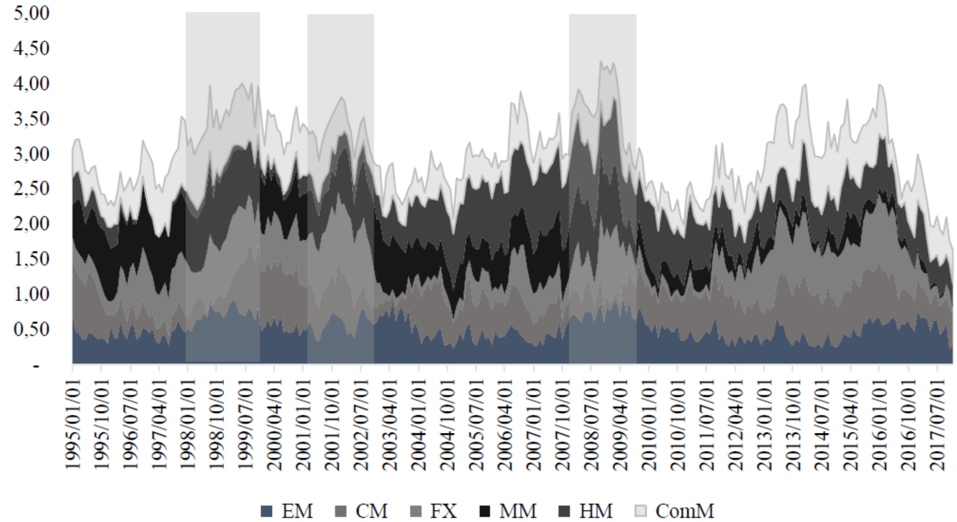
The market sub-indices ($S_{EM}, S_{CM}, S_{FX}, S_{MM}, S_{HM}, S_{ComM}$) are computed by taking the average of the individual stress indicators weighted by their information content which is captured by the pAUROC.[5] Thus, in a particular market sub-index, more weight is given to an individual stress measure that has better information content.

For instance, if one considers the equity market (EM) segment displayed in Table A.2 in Appendix A, the equity market sub-index is computed as

$$S_{EM} = \frac{\sum_{j=1}^{6} EM_{j,t} \times (pAUROC_j - 0.5)}{\sum_{j=1}^{6} (pAUROC_j - 0.5)} \tag{2.4}$$

[5]Subscripts EM, CM, FX, MM, HM, and ComM respectively denotes the equity market, credit market, foreign exchange market, money market, housing market, and commodity market.

Figure 2.2: Market sub-indices, January 1995 - December 2017



Notes: The six market sub-indices used for the construction of the SAFSI as depicted in the figure are constructed using Equation 2.4. Shaded regions are the identified periods of financial stress (see Section 2.3.1.2).

where $j = 1, 2, ..., 6$ denotes the six selected stress indicators, and $\text{EM}_{j,t}$ is the ECDF of the stress indicator j in the equity market segment. Applying this method of aggregation to each market segment yields the market sub-indices as shown in Figure 2.2. The shaded areas correspond to the stress periods as identified in Section 2.3.1.2. The equity market (EM), foreign exchange market (FX), money market (MM), and commodity market (ComM) are seen to be the main contributors to the increase of the overall stress in the financial system in all of three of the stress episodes identified.

2.3.2.2 Construction of the SAFSI by aggregating market sub-indices

The six market sub-indices are aggregated based on the application of standard portfolio theory that weights each sub-index by its cross-correlation with the others, since indicators capture similar element of risk.[6] Positive (negative) correlation across market sub-indices imply that overall financial stress index is larger (smaller) than the sum of its sub-components. Furthermore, time-

[6] The use of portfolio theory to aggregate market sub-indices into a comprehensive financial stress index was used by Hollo et al. (2012), Vermeulen et al. (2015), Louzis & Vouldis (2012), and Chatterjee et al. (2017) (see Section 2.2).

variation is allowed for in the cross-correlation structure between market sub-indices. As such, the SAFSI assigns more weight to situations in which several financial market segments experience high stress at the same time, thereby focusing on the systemic dimension of financial stress. According to Hollo et al. (2012), the stronger the co-movement across financial market segments, the more widespread is the state of financial instability. Therefore, the ability of the SAFSI to capture the co-movement across financial market segments will determine its effectiveness in detecting systemic stress episodes.

The SAFSI is computed according to Equation 2.5, inheriting all properties from its individual stress factors i.e. the SAFSI is a unit-free index bounded by the half-open interval (0,1]:

$$SAFSI_t = (w \times S_t)' \times C_t \times (w \times S_t) \tag{2.5}$$

where $S_t = (S_{EM,t}, S_{CM,t}, S_{FX,t}, S_{MM,t}, S_{HM,t}, S_{ComM,t})$ is a vector of the six standardised market sub-indices at each point in time; and $w = (w_{EM}, w_{CM}, w_{FX}, w_{MM}, w_{HM}, w_{ComM})$ is the vector of information weights that assigns more weight to those sub-indices that are more relevant for identifying episodes of financial stress. For instance, the weight for the equity market (EM) is computed as

$$w_{EM} = \frac{pAUROC_{EM} - 0.5}{\sum_m pAUROC_m - 0.5}, \quad \text{m=EM, CM, FX, MM, HM, ComM} \tag{2.6}$$

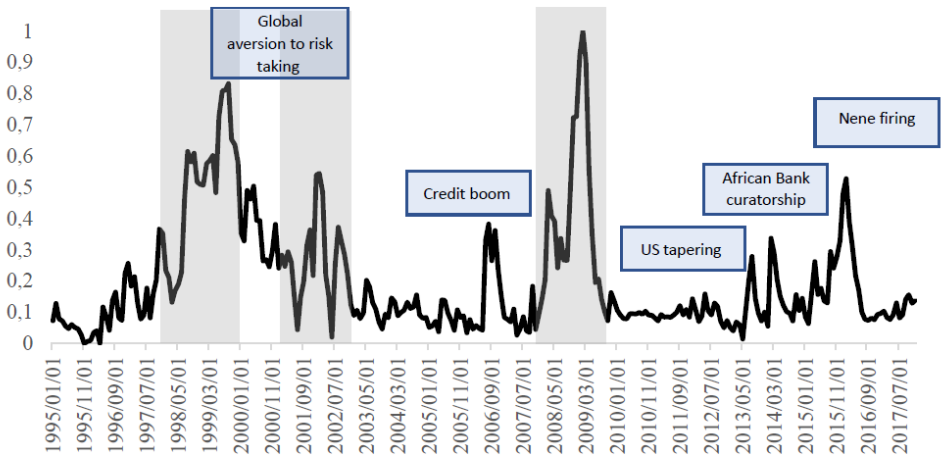
Note that the weights are computed using pAUROC - 0.5, since the measure is informative only if it is above 0.5. Lastly and most importantly, C_t in Equation 2.5 is the 6x6 matrix of time-varying cross-correlations $\rho_{m,m',t}$ (where $m \neq m'$) estimated by means of a multivariate GARCH, that emphasizes the extent of co-movement across different market segments at each point in time. The methodology employed to estimate the cross-correlations is elaborated in Appendix A. The resulting time-varying cross correlations between the market sub-indices are depicted by Figure A.2 in Appendix A. Most of the pair-wise cross correlations are shown to increase during the periods of financial stress, however to different extents. It should be emphasized that the cross-correlations do not serve as an economic predictor of correlation risk, but rather as an indicator of the similarity or dissimilarity of the historical ranking of the level of stress in two market segments at any point in time (Hollo et al. (2012)).

2.4 The SAFSI and evaluation of its strength

2.4.1 The South African Financial Stress Index (SAFSI)

Figure 2.3 displays the SAFSI over the period 1995 - 2017, with the shaded regions corresponding to the benchmark periods of financial stress as detailed in Section 2.3.1.2. The index identifies instabilities in the financial system of the country with values of 0.5 and greater indicative of stressful times. As can be seen from the figure, the constructed index spikes sharply during the key periods of financial stress. In addition to capturing the benchmark periods of financial stress, it is quite reassuring that the SAFSI captures other global and idiosyncratic risks that affect the financial markets in the country. The index picks up the stress in financial markets during the end of 2015 and beginning of 2016 which was mainly caused by the depreciation of the rand amid declining investor confidence, following the political turmoil that lead to the axing of former Finance Minister Nhlanhla Nene. In 2014, African Bank experienced liquidity stress and a sharp decline in the share price of its holding company, African Bank Investment Limited (ABIL), which generated risk in financial markets. The bank was put under curatorship by the South African Reserve Bank due to its inability to make sufficient provisions for bad debts and engaging in unsustainable lending. However, in the wake of central bank-led bailout of ABIL, at least 10 SA money market funds "broke the buck" significantly widening money market spreads. Financial contagion was however limited following the imposition of complementary interventions by authorities Havemann (2018). The SAFSI captures the vulnerability of the South African economy in 2013 following the announcement by the US Federal Reserve Bank of the possible tapering of its quantitative easing (QE) program. Following the announcement in May 2013 and in anticipation of the possible normalisation of monetary policy in the U.S., the South African economy experienced significant capital outflows together with a weakening currency. Financial stress captured by the SAFSI in

Figure 2.3: The SAFSI



Notes: Section 2.3 details the construction of the SAFSI. The shaded regions depict the benchmark episodes of financial stress in SA as outlined in Section 2.3.1.2.

2006 coincided with the higher rates of credit extension and consequently increased household indebtedness during that period, increasing the probability of higher default on loan repayment. Higher credit extension growth during this period was supported by lower interest rates (the tighter interest rate environment in the second half of 2006 had a lagged effect on credit extension growth) and the buoyancy of the housing market, as house prices continued to rise firmly throughout the first ten months of 2006, however, at a slowing pace. The National Credit Act, No. 34 of 2005 which became effective on 1 June 2006, and was implemented in three phases until 1 June 2007, aided in containing the growth in credit extension by regulating consumer credit. In addition, the constructed SAFSI captures the dampened investor confidence in the economy in the first half of 2000, as reflected by capital outflows and the depreciation of the rand. It is worth mentioning that during this period there was heightened global aversion to risk taking in emerging market economies in general.

The constructed SAFSI using Equation 2.5 as well as its counterpart without using correlation weights (i.e. implicitly assuming all sub-indices are perfectly correlated) are displayed in Figure A.3 in Appendix A. The SAFSI counterpart is a simple weighted average of the six sub-indices, such that only the vector $(w \times S_t)$ in Equation 2.5 is applicable. Visual inspection reveals that

SAFSI and its perfect correlation counterpart are relatively close to each other when correlations are high, especially during the stressful periods 1998-1999 and 2008-2009. Both the indicators peak at the same time (there is a 74% correlation between the two indicators), but the simple weighted average measure tends to demonstrate a relatively high level of financial stress even during normal times. The SAFSI that is constructed using both information weights and correlation weights, reduces the risk of combining informationally redundant data that would over-emphasize a given market segment, thus avoiding overstating the intensity of financial stress during normal times.

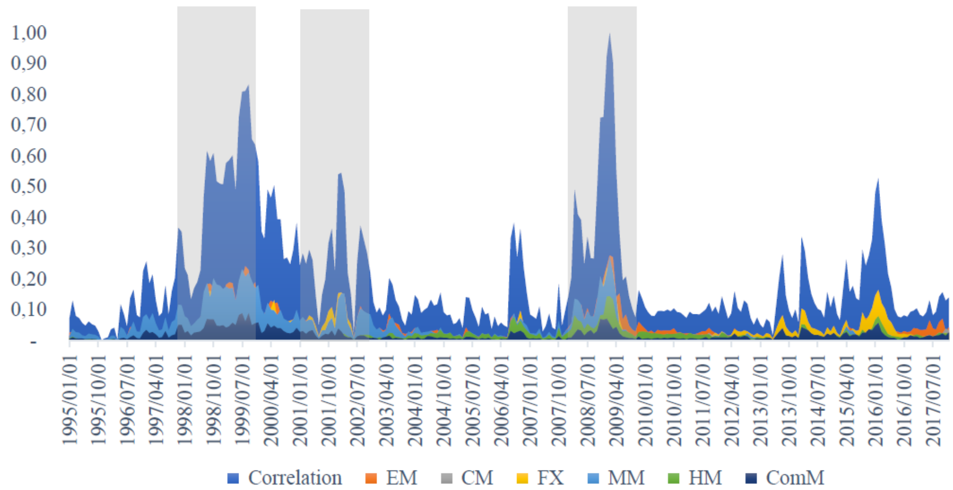
The comparison of these two indicators forms the basis for a decomposition of the SAFSI into contributions coming from each of the six market sub-indices (with information weights) and the overall contribution from the cross-correlations. Such a decomposition is useful for regulatory purposes, especially in terms of the financial stability surveillance functions carried out by macroprudential authorities. The decomposition is depicted in Figure 2.4 such that the SAFSI is a weighted average of the contributions from each sub-index and the cross-correlations between them. All the weights sum up to 1, and therefore at a given point in time, the contribution of a particular market to the SAFSI is simply the fraction of the SAFSI accounted for by that particular market sub-index. The residual component of the SAFSI unaccounted for by the six markets, reflects the contributions from the cross-market correlations described by the matrix C_t in Equation 2.5. The choice of aggregation method using time-varying cross-correlations is affirmed by the strength of the correlation components during periods of financial stress.

2.4.2 Comparison of SAFSI with alternative measures of financial stress

Figure A.4 in Appendix A compares the SAFSI constructed via Equation 2.5, with a financial stress index computed using principal component analysis (PCA) on the individual stress indices, and an alternative measure constructed by simply averaging the selected stress indicators (i.e. indicators are equally weighted).[7] Compared to the other stress measures, the figure shows that the

[7]PCA combines many variables into a few linear combinations or principal components. Various studies highlighted in the literature review (Section 2.2) use PCA analysis and can be referred to for the econometric methodology.

Figure 2.4: Decomposition of the SAFSI



Notes: The figure shows the decomposition of the SAFSI into contributions from each market sub-index (with information weights - pAUROC) and the overall contribution from the cross-correlations. 'EM', 'CM', 'FX', 'MM', 'HM', 'ComM' respectively denotes the equity market, credit market, foreign exchange market, housing market, and commodity market. Overall contribution from the cross-correlations is denoted by 'Correlation'. The shaded regions correspond to the benchmark periods of financial stress (see Section 2.3.1.2).

SAFSI does better in capturing the benchmark episodes of financial stress as well as other global and idiosyncratic risks that affect the financial markets in SA. Furthermore, the financial stress measures computed with PCA and equal weights seem to overstate the intensity of financial stress, particularly during normal times.

Further evidence in support of the SAFSI construction methodology is provided by the AUROC and partial AUROC values in Table 2.1, which captures the ability of the stress indices to match the benchmark episodes of financial stress in SA. The SAFSI has the largest AUROC and partial AUROC compared to the alternative financial stress indices which yields lower information content. Table 2.1 also shows that aggregating market sub-indices that have partial AUROC ranging from 0.625 to 0.917 yields overall financial stress indices with better information content (partial AUROC ranging from 0.856 to 0.933, depending on the method of aggregation). This suggests that a combination of the sub-indices yields an improvement over individual markets, even if the

The first principal component of the 17 selected stress indicators, which accounts for about 23 percent of the total variance, is chosen as the financial stress index employing PCA analysis. The equal-weights financial stress measure is simply the average of the 17 stress indicators that were selected using the procedure in Section 2.3.1.4.

equity market or money market on their own already provide good results.

Table 2.1: AUROC and partial AUROC of alternative stress measures and individual markets

		AUROC	pAUROC
Financial stress measures	SAFSI (Baseline)	0,865	0,933
	PCA (first principal component)	0,827	0,909
	Equal weights	0,792	0,856
Individual markets (information weights)	EM	0,859	0,917
	MM	0,816	0,883
	FX	0,775	0,825
	CM	0,665	0,708
	HM	0,638	0,694
	ComM	0,611	0,646
Individual markets (equal weights)	MM	0,816	0,883
	EM	0,813	0,882
	FX	0,775	0,825
	CM	0,672	0,732
	HM	0,638	0,694
	ComM	0,601	0,625

Notes: The table displays the AUROC and partial AUROC for the SAFSI and two alternatives (one computed using PCA and the other using equal weights of individual stress indicators). In addition, AUROC and partial AUROC values are shown for individual markets constructed with either information weights or equal weights. The individual markets are denoted by EM (equity market), CM (credit market), FX (foreign exchange market), MM (money market), HM (housing market), ComM (commodity market).

2.5 Financial regimes and real implications

In this section we use the newly constructed financial stress index (SAFSI) to study economic dynamics in the South African economy. There has been increasing attention by policy makers and academics, especially in the aftermath of the 2007-2009 global financial crisis, in studying the potential non-linearities between the financial sector and the real economy. Such studies have highlighted that the the economy responds differently to financial shocks during stressful financial times compared to normal times. We examine this conjecture for the South African economy by estimating a threshold vector autoregression (TVAR) model proposed by Alessandri & Mumtaz (2017) that examines the potential changes in economic dynamics during stressful and normal/tranquil periods. In this way we capture abrupt changes in regimes which are determined by the nature of the financial stress index, differing from Balcilar et al. (2016) who employ non-linear logistic smooth transition VAR in which regimes are determined by the interaction of all variables in the system.

2.5.1 Model specification and data

The TVAR model is specified as

$$Y_t = c_1 + \sum_{j=1}^{P} \beta_1 Y_{j,t-j} + v_t,\ VAR(v_t) = \omega_1\ if S_t \leq Y^*$$

$$Y_t = c_2 + \sum_{j=1}^{P} \beta_2 Y_{j,t-j} + v_t,\ VAR(v_t) = \omega_2\ if S_t > Y^*$$

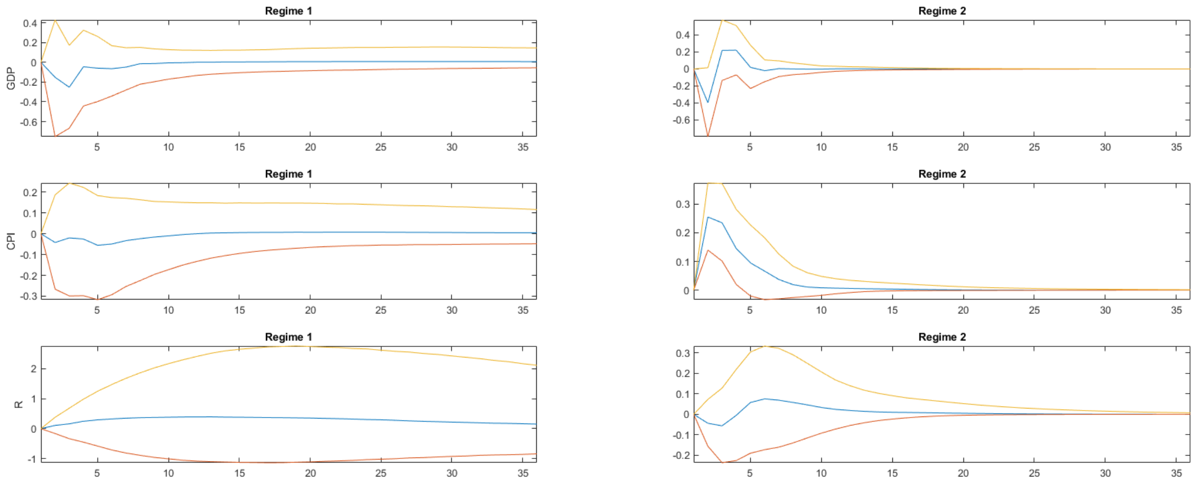
where Y_t is a matrix of endogenous variables which includes real gross domestic product growth (GDP), headline consumer price inflation (CPI), three-month treasury bill rate (R), and the constructed financial stress index (SAFSI). We use quarterly data over the period 1995-2017, as we would like to capture the dynamics of GDP (a measure of real economic activity). Our choice of economic variables allows us to capture the non-linear dynamics of a small open economy while maintaining a parsimonious model. We use 4 lags for the estimation, which is commonly adopted when working with quarterly data. $S_t = Y_{j,t-d}$ is the the threshold variable, which in our case is the lag of the financial stress index (where d reflects the threshold lag or the delay parameter, and Y^* is the threshold level. We assume that that economic agents take about one quarter to adjust to the financial shocks and set the delay parameter d to equal 1. The threshold variable allows regimes to switch endogenously and abruptly. The model separates the data into two regimes as decided by the data: A financial stress regime (Regime 2) occurs if and only if the SAFSI rises beyond an estimated threshold value, i.e. $S_t > Y^*$, and a financial sound regime (Regime 1) when $S_t \leq Y^*$. The estimated financially stressful regimes can be checked against the stressful periods identified in South African history in Section 2.3.1.2.

We follow the procedure of Alessandri & Mumtaz (2017) in estimating the model by employing Bayesian techniques using the Gibbs algorithm with a Metropolis Hastings step for drawing the threshold value from the random walk in each simulation. Appendix A provides further detail on the estimation procedure. Following Banbura et al. (2010), a natural conjugate prior for the VAR parameters in both regimes via dummy observations is imposed, to account for the short sample during stressful regimes. We set the overall tightness of the prior $\tau = 0.2$ and tightness of the prior on the constant $c = 10^5$, which are values that are typically used in macroeconomic literature as reported by Canova (2007).We run 100,000 iterations of the Gibbs sampler to ensure convergence and discard the first 80,000 as burn-in, using the last 20,000 for inference. Generalised impulse response functions as specified in Alessandri & Mumtaz (2017) are used to study the potential differences in the propagation of financial shocks under the specific regimes (see Appendix A for the definition of the impulse responses). The impulse responses fully account for abrupt endogenous changes in regimes during simulation. Consistent with empirical literature (for example Alessandri & Mumtaz (2017), Chatterjee et al. (2017), and Hubrich & Tetlow (2015)), we identify the structural shocks via Cholesky decomposition (in our case financial shocks) by ordering slower moving variables first followed by faster moving variables. In line with this, we order GDP first followed by CPI, R and then lastly SAFSI.

2.5.2 Empirical results

Figure A.5 in Appendix A shows the estimated threshold variable and the probability of regime 2. Regime 2 occurs when the estimated threshold variable goes beyond the estimated threshold value. As mentioned previously, the SAFSI is used as the threshold variable, which is a measure of financial stress in the South African financial sector. Note that in a TVAR framework, the change in regime is abrupt and as a result the economy is either in a stressful period (regime 2) or a normal period (regime 1). The estimated high stress periods shown in Figure A.5 are consistent with the identified episodes of high financial stress in South African history, which is summarised in Section 2.3.1.2. Regime 2 persisted during the late 1990s and early 2000s, as well as during the

Figure 2.5: Impulse responses to a financial shock



Notes: The figure shows the median responses of real economic activity (GDP), prices (CPI) and interest rate (R) to a one standard deviation financial shock (SAFSI) during stressful times (Regime 2) and tranquil times (Regime 1). The median responses are within 68% confidence bands

recent recession. It is also reassuring that the statistically estimated regimes capture the global and idiosyncratic risks, mentioned in Section 2.4.1 that affect local financial markets.

We now examine the potential change in macroeconomic dynamics during stressful and normal periods, following a one-standard deviation financial shock. Figure 2.5 reports the results depicted by impulse response functions. In our case, a financial shock is represented as a positive shock to the SAFSI. A financial shock in the high stress regime 2 has a larger impact on output and inflation, and to a lesser extent interest rates. Output falls by roughly twice as much if the economy is experiencing financially vulnerable times compared to normal times, clearly reflecting the disruptive effect of a financial shock during stressful times. Following a financial shock in the stressful/ financially vulnerable regime, output suffers a significant 0.4 percentage point decline and prices increase by about 0.25 percentage points after about one quarter, while the interest rate experiences a peak fall of only 0.1 percentage points at around two quarters. The higher price inflation in the stressful state is consistent with the findings of Hubrich & Tetlow (2015) and Balcilar et al. (2016). In this case, the stress event is interpreted as a negative supply shock that reduces real output and as a result puts upward pressure on prices, ceteris paribus (Hubrich & Tetlow (2015)). The interest rate response during the stress regime reflects monetary policy easing for about 2 quarters following the financial shock, and thereafter monetary policy tightening is implemented to contain inflation. However, the responses of the interest rate is rather small in magnitude, consistent with evidence provided by Coco & Viegi (2019) that monetary policy has become less active after the 2009 crisis due in part to the extension of the South African Reserve Bank's mandate to include financial stability. Interestingly, output increases beyond the first quarter to reach 0.2 percentage points after a year, before returning to its equilibrium level. This could suggest that economic agents adjust their expectations pertaining to the economy after one quarter following an unexpected financial shock. The left panel of Figure 2.5 shows that a financial shock during normal times has a negative but smaller effect on output growth, while the impact on prices and interest rates are negligible. In unreported results, we find that the results are similar following a larger financial shock i.e. three-standard deviation shock, suggesting that the impact of a financial shock on the economy does not depend on the size of the shock.

2.6 Conclusion

In this chapter, we develop a new technically improved financial stress index for the South African economy (SAFSI), covering the period January 1995 - December 2017. The index has the advantage of capturing the interconnectedness of six financial markets that are thought to be most significant for the South African economy, enabling an indicator to be assessed in terms of its systemic importance. We evaluate the performance of the SAFSI relative to alternative measures of financial stress and show that the index successfully captures the major financial events in the South African economy.

The SAFSI has important macroprudential and monetary policy implications. Firstly, the monthly frequency of the index allows for the real-time assessment of stress levels within the entire financial system, and the index can be easily updated to account for new observations as they become available. Secondly, the aggregation methodology ensures parsimony since each indicator is assessed in terms of its systemic importance and ranked according to its information content. As such, this approach may aid in analysing the usefulness of policy interventions from a monetary and macroprudential standpoint. Thirdly, the decomposition of the SAFSI into contributions from each market segment allows regulatory authorities to track how much each financial sector contributes to the build-up of stress at any given point in time. Knowledge of the sources of financial stress can guide the policymaker in choosing policy responses.

We use the estimated SAFSI to capture the abrupt change in financial regimes within a threshold vector autoregression model and find evidence of non-linearity in the transmission of a financial shock to real economy. Specifically, financial shocks are more detrimental to the real economy during stressful periods than normal times. An unexpected shock to financial stress conditions during financially vulnerable times is associated with a more prominent contraction in output and higher inflation. However, during normal times, the financial shock has a negligible impact on prices and interest rates, with a small output impact. These quantitative results suggest that policymakers in South Africa should acknowledge the non-linearities in the transmission of financial shocks and distinguish between the two states of the world.

Chapter 3

Financial market information as a predictor of economic conditions: A mixed-frequency approach

3.1 Introduction

Financial market disruptions are often cited as the main source of the prolonged economic downturn experienced by many advanced and developing economies during the period 2008-09. This has sparked interest in developing better measures to monitor instability in financial markets that could potentially serve as an early warning indicator of economic vulnerabilities. Given this backdrop, the objective of this chapter is to assess whether and the extent to which financial market information help in predicting economic conditions in South Africa. In particular, we evaluate whether a mixed-frequency specification enhances the predictive performance of financial information compared to traditional common-frequency specifications.

Although the South African literature on the topic is quite extensive (see Balcilar et al. (2018), Gumata et al. (2012), Thompson et al. (2015), and Kabundi & Mbelu (2017)), there is room for technical contribution. This chapter contributes empirically to the South African literature and emerging market literature in general in two ways. Firstly, we employ a newly constructed measure of financial stress outlined in Chapter 2, called $safsi$ here, that accounts for the potential interconnectedness of financial markets, allowing indicators to be assessed in terms of their systemic importance. Secondly, we assess the usefulness of financial market information (proxied by $safsi$) in predicting macroeconomic conditions by considering a mixed frequency approach. In particular, we consider the usefulness of a mixed frequency vector autoregression (MF-VAR) model in addition to a common frequency vector autoregression model (VAR) and threshold vector autoregression model (TVAR) in terms of comparing the forecasting performance of financial stress indicators across alternative model specifications. MF-VARs have recently been introduced by Schorfheide & Song (2015) and are still in their infancy in the forecasting literature, therefore much less is known about its predictive performance compared to its traditional common frequency counterparts. Furthermore, the use of MF-VARs in examining whether information from financial markets help in predicting economic activity is non-exist according to the best of our knowledge and therefore warrants this study. This chapter closes the information gap by evaluating the predictive performance of the MF-VAR model compared to the traditional single frequency VAR models (linear and non-linear) within the context of our objectives.

Bayesian methods are employed to estimate all vector autoregressive models mentioned above. Such methods have gained increasing popularity due to its efficiency in dealing with parameter uncertainty and improving forecast accuracy by using informative priors that shrink the unrestricted model towards a parsimonious naive benchmark (Banbura et al. (2010)). The models are estimated recursively over an expanding data window, and the forecasts from the models are evaluated with respect to point forecasts. Each specification includes two macroeconomic variables (i.e. real gross domestic product growth (gdp) and consumer price inflation (cpi)) and the financial stress indicator ($safsi$). Robustness checks are conducted by including the three-month treasury bill rate (r) as well as an alternative financial stress index constructed by Quantec. We judge the vector autoregressive model forecasts against the observed values for quarterly gdp and cpi. The evaluation sample is from 2011Q1 to 2017Q4 for the quarterly models (i.e. VAR and TVAR) and from 2011M1 to 2017M12 for the MF-VAR. With a training sample from 1995 to 2010 that captures the severe economic downturns of the 2008-2009 period, this gives us 28 out-of-sample forecasts for the quarterly models and 84 out-of-sample forecasts for the mixed-frequency specification. The out-of-sample forecasts from the MF-VAR are time-aggregated to obtain quarterly forecasts that are comparable with the quarterly models. Forecasts are examined for horizons of one to eight quarters ahead. All predictive densities are estimated following Alessandri & Mumtaz (2017), and the point forecasts are calculated as the arithmetic means of the predictive densities, and assessed by root mean-squared forecast errors (RMSFEs). We employ the McCracken (2007) test to formally assess whether any differences in forecast accuracy are statistically significant. In addition to the out-of-sample forecasting exercise that is recursively estimated, we also conduct an ex-ante forecasting exercise i.e. unlike recursive estimation of the models which involves updating the parameter estimates, we assume here that the future observations are not available for checking and therefore the parameter estimates are not updated. Using our benchmark financial stress index ($safsi$), this forecasting exercise is conducted over the period 2008Q1-2009Q4 and 2015Q1-2016Q4 to gauge the ability of the best performing model, selected based on out-of-sample forecast performance, in predicting the turning points in the macroeconomic variables of interest. We use these periods as they were the most recent periods within our sample that were clouded by economic vulnerabilities. Of particular interest to policymakers, is whether financial indicators provide valuable information to accurately predict economic downturns, and therefore serve as a basis for monetary policy formulation.

The remainder of the chapter is organised as follows. In Section 3.2 we review the literature on the predictive ability of financial stress indexes (FSIs). Section 3.3 and Section 3.4 cover the data employed in the study and the forecasting models, respectively. Section 3.5 outlines the forecast evaluations and Section 3.6 discusses the empirical results, while Section 3.7 concludes.

3.2 Literature review

Financial markets have long played a critical role in the facilitation of the flow of capital within and among economies worldwide, fostering economic activity among agents. As such, these markets have a direct influence on growth and activity in the real economy. The 2007-2009 global financial crisis is evidential that turmoil in these markets may have severe macroeconomic consequences. This has put forth increased focus on the development of measures to monitor instability in financial markets for the purpose of forecasting recessionary activity in the real economy and quantifying the extent to which financial market stress impacts the real economy. Such measures could inform policymakers in terms of formulating and implementing appropriate policy to deal with the macroeconomic consequences of increased stress in financial markets. However, the literature appears rather mixed in terms of the viability of financial stress measures as an early warning indicator of economic downturns, as no financial indicator seems to work 'too well for too long' (Stock & Watson (2003)). In this chapter, we focus on the forecasting performance of financial stress indexes (FSIs) in terms of predicting key macroeconomic variables.[1] Notwithstanding this, the literature review briefly highlights the economic theories that provide insight on how instability in financial markets affect the real economy. We discuss the latter first in order to provide some theoretical background and intuition on the linkage of the real economy and the financial sector.

Two prominent economic theories, which include the "real options" and "financial accelerator" framework provide insight on how instability in financial markets affects the real economy (Davig & Hakkio (2010)). The real options theory is based on a wait-and-see approach by agents that basically incorporates uncertainty into investment and consumption decisions i.e. a new irreversible investment is only made conditional on the uncertainty being resolved. This includes uncertainty pertaining to investor behaviour and the fundamental value of assets. The idea is that by postponing investments, firms are able to accumulate sufficient information pertaining to eco-

[1]No distinction between financial stress indexes (FSIs) and financial conditions indexes (FCIs) are made in this thesis, since the difference between them are relatively small. FCIs are aggregates of a variety of financial variables that aid in characterising the state of the financial markets. Similarly, FSIs monitor financial instability by looking at financial variables that indicate increased likelihood of a crisis.

nomic prospects which would validate a more informed decision regarding whether to undertake a particular investment. What the real options theory suggests is that financial stress will lead to less investment spending in the present, due to heightened financial market volatility and consequently greater uncertainty about the future state of the economy. Similarly, increased financial market volatility may impact negatively on households consumption spending as their future wealth is uncertain. To the extent that households and firms react in the same way, real economic activity will fall.

The financial accelerator framework shows how increased financial stress (i.e. deteriorating financial conditions) affects the real economy by allowing the cost of borrowing to be determined by the financial conditions of firms and consumers. Through this framework, for example, a deterioration in the financial conditions of firms (households) increases their cost of borrowing and thus reduces investment spending (consumption spending). This reduction in investment reduces profits, further dampening the financial prospects of firms, constraining their spending and depressing economic activity. Uncertainty pertaining to firm profitability determines the premium that the firm must pay to borrow funds (Bernanke et al. (1999)). Flights to quality, flights to liquidity, and increased asymmetry of information all have the effect of increasing the cost of credit for businesses and consumers. Both the theoretical frameworks, real options and financial accelerator, suggests that high financial stress, through heightened uncertainty, negatively affects economic activity.

Turning to the empirical side of the literature, there have been an increasing number of studies, especially in the aftermath of the global financial crisis, that examine the impact of financial stress on the economy, with some of the studies also evaluating the extent to which financial stress indicators can predict economic conditions (i.e. recessions). While such studies are extensive for advanced economies, it is limited for emerging market economies, due mainly to data limitations. Most of the studies have used FSIs that combine different quantities of financial variables into a single measure to proxy financial stress. In most cases, the FSI covers stress in the equity market, credit market, foreign exchange market, and money market, with a few accounting for stress in the commodities and housing market. The financial variables are aggregated using common methods which include principle component analysis (PCA), equal weights, variance-equal weights, dynamic factor modelling, and more recently portfolio theory and information weights.

Focusing on the predictive ability of financial stress measures, Hakkio & Keeton (2009) constructed the Kansas City FSI (PCA of 11 standardised financial indicators) during a time when the U.S. economy was experiencing significant financial stress. Employing vector autoregressive (VAR) analysis, they find that financial stress proxied by the constructed index can help predict economic activity, and that an increase in financial stress leads to persistent business cycle downturns. Similarly, Hatzius et al. (2010) investigates the link between financial conditions and economic activity using an alternative financial stress index constructed using PCA of 45 variables purged of macroeconomic influences. They allow for unbalanced panels and provide evidence that the index has better predictive power than existing indexes. Using the FSI developed by Hatzius et al. (2010) as well as two indexes constructed by the Basel Committee on Banking Supervision, Ng (2011) provide evidence that the financial stress indexes improve the forecasting accuracy of GDP growth in the U.S. at horizons of 2-4 quarters. More recently, Alessandri & Mumtaz (2017) employ linear and non-linear VAR models to examine the extent to which financial markets help in predicting macroeconomic outcomes in the United States. Their findings suggest that financial variables have significant predictive power over the Great Recession period, particularly if used within a threshold (non-linear) VAR model. However, the Great Recession is a unique event and thresholds do not yield reliable forecast improvements prior to 2008. Other international studies that have supported the use of FSIs as a reliable predictor of economic activity include, but is not limited to, Cevik, Dibooglu & Kenc (2013) and Koop & Korobilis (2014). On the contrary, Vermeulen et al. (2015) and Vašíček et al. (2017) suggest that policy makers should exercises caution in the use of FSIs as an early warning indicator of economic vulnerabilities as there appears to be a weak relationship between the index and the onset of the crisis.

In a recent South African study, Balcilar et al. (2018) compared the performance of alternative FCIs in forecasting output, inflation, and interest rates in a linear and non-linear context. These alternative FCIs were constructed using PCA, time-varying parameter factor augmented VAR model

(TVP-FAVAR) with dynamic model averaging (DMA), and TVP-VAR model with constant factor loading. The authors find that the non-linear logistic vector smooth transition regression (VSTAR) model outperforms linear models in forecasting output and inflation, while a semi-parametric (SP) model perform best in forecasting the interest rate. However, in the VSTAR framework, the lower and upper regimes are determined by the asymmetric and dynamic interactions of all the variables in the system, and not necessarily by the nature of the switching variable itself (Evgenidis & Tsagkanos (2017)). Other South African studies examining the ability of financial condition indexes to predict economic conditions include Gumata et al. (2012), Thompson et al. (2015), and Kabundi & Mbelu (2017). Utilising a FCI computed by PCA, Gumata et al. (2012) find evidence that the estimated FCI has strong predictive information for near-term growth, and the indicator outperforms the leading indicator of the South African Reserve Bank and individual financial variables. Improving on this measure, Thompson et al. (2015) construct an FCI using recursive PCA and postulate that the index is a good in-sample predictor of output growth and interest rates, but performs poorly in terms of predicting inflation. Kabundi & Mbelu (2017) find that the time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model outperforms the constant-loadings factor-augmented VAR model and the traditional VAR model in the out-of-sample forecasting of output (proxied by real gross domestic product) growth and the inflation rate.

This chapter fills the gap in the literature on assessing the predictive performance of financial information by considering the usefulness of a mixed frequency vector autoregression (MF-VAR) model in comparison to a common frequency vector autoregression model (VAR) and threshold vector autoregression model (TVAR). MF-VARs have recently been introduced by Schorfheide & Song (2015) and are still in their infancy in the forecasting literature, therefore much less is known about its predictive performance compared to its traditional common frequency counterparts.

3.3 Data

Monthly and quarterly frequency South African data covering the period from 1995 to 2017 is employed.[2] Data on real gross domestic product (gdp) and consumer price index (cpi) are sourced from Statistics South Africa, while data pertaining to the three-month treasury bill rate (r) is obtained from the South African Reserve Bank historical database. gdp and cpi enter the models in log first differences to obtain real GDP growth rates and CPI inflation, respectively. The interest rate and the financial stress indicators, outlined below, remain untransformed. We use the constructed FSI in Chapter 2, named the South African Financial Stress Index ($safsi$), as the benchmark measure to describe financial market stress in South Africa. This index was created by aggregating seventeen individual stress indicators selected from six major markets (including the equity market, credit market, foreign exchange market, money market, commodity market, and housing market) using information weights and time-varying cross-correlations between markets. As such, the $safsi$ represents an improvement over past measures of financial stress in that it captures the interconnectedness of financial markets by focusing on the systemic dimension of financial stress. The indicators included in the $safsi$ were selected based on their ability to signal the contemporaneous materialisation of key episodes of financial stress in South Africa.[3] Since the predictive power of many financial variables is known to be unstable over time, the use of broad indicators of financial stress reduce the risk of obtaining results that are heavily influenced by idiosyncratic behaviour of specific variables in specific sub-periods (Alessandri & Mumtaz (2017)).

As a robustness check, the analysis is replicated replacing $safsi$ with an alternative FSI constructed and updated by Quantec. The alternative financial stress indicator named in this article as $fsi\_quantec$, was constructed via a weighted-sum approach. Each of the components that constitute the Quantec financial conditions index (i.e. real interest rate, excess money supply growth,

[2] The quarterly data is obtained by simply averaging the monthly data in each quarter. Data on real gross domestic product is only observed at quarterly frequency. Monthly data spans the period January 1995 to December 2017. Likewise, the quarterly data for all the variables covers the period 1995Q1 - 2017Q4.

[3] The construction of the $safsi$ will not be covered in this chapter. Please refer to Chapter 2 for detail pertaining to the identification of the key periods of financial stress in the South African economy, selection and list of stress indicators that comprise the $safsi$, and the corresponding construction methodology.

real effective exchange rate, company earning yield, and yield spread) are regressed on manufacturing production and the resulting variable's coefficients are used to give an approximation of the relative weights attached to each component. $fsi\_quantec$ was chosen as an alternative because it is the only index that is regularly updated and as such data on the index was available for the sample period examined in this paper. [4] To allow for comparable results, the $safsi$ and $fsi\_quantec$ are each standardised by subtracting their sample mean from each observed value of the index and dividing by their standard deviation.

3.4 Forecasting models

Many studies have documented improvement in forecast accuracy through modelling structural change. Given this, we employ three alternative vector autoregressive (VAR) model specifications to assess whether financial market information help in predicting macroeconomic outcomes and whether model specification is a contributing factor. Bayesian methods are used to estimate the three alternative VAR model specifications, which include the common frequency VAR (VAR), threshold VAR ($TVAR$), and mixed frequency VAR ($MF-VAR$).[5] The use of Bayesian vector autoregressive methods is appropriate in the context of overcoming the properties of the data (i.e. non-stationarity) and the 'curse of dimensionality' (or over-parametrisation) and these methods which allow for the incorporation of informative priors have proved to be superior tools compared to frequentist vector autoregressive methods (Banbura et al. (2010)).[6] Such Bayesian methods have gained increasing popularity due to its efficiency in dealing with parameter uncertainty and

[4] For more detail on the construction of this alternative financial indicator, please refer to Luus (2007). The updated index was obtained via the Quantec online portal at https://www.easydata.co.za/. Note that since this index was constructed as a financial condition index (FCI), it is transformed into a financial stress index (FSI) for the purpose of this study by simply taking the negative of the FCI. This following basic intuition that when financial conditions deteriorate (improves), financial stress increases (decreases).

[5] We fully acknowledge use of the codes provided by Professor Haroon Mumtaz.

[6] Following the documented evidence of Doan et al. (1984) and Litterman (1986) pertaining to the improvement in forecast accuracy provided by Bayesian shrinkage in a small vector autogression (VAR), the use of Bayesian methods in forecasting economic variables has since gathered increasing popularity. Several others have also documented the superior performance of Bayesian methods over classical factor models, with examples including Koop (2013), and Carriero et al. (2011)

improving forecast accuracy by using informative priors that shrink the unrestricted model towards a parsimonious naive benchmark (Banbura et al. (2010)). The three models are outlined below.

3.4.1 VAR

The baseline model employed is the following linear common frequency quarterly Bayesian VAR (2) model

$$Y_t = c + \sum_{j=1}^{P} \beta_j Y_{t-j} + v_t,\ v_t \sim N(0, \sum)\ and\ t = 1, \ldots, T \tag{3.1}$$

Where β_j for $j = 1, \ldots, p$ are $N \times N$ matrices of coefficients with p denoting the lag order, c denotes a $N \times 1$ vector of constant terms, and the time-invariant $N \times N$ variance-covariance matrix is represented by $\sum$.[7] Y_t is the $N \times 1$ vector of endogenous variables which include growth in real gross domestic product (gdp), consumer price inflation (cpi), and alternative financial stress indexes as outlined in Section 3.3. As a robustness check, we re-estimate the model including the three-month treasury bill rate (r). All variables are sampled at quarterly frequency in this specification. Note that two versions of this model are used: the benchmark one (labelled $VAR\xi$) only contains the macroeconomic variables i.e. $Y_t = \{gdp, cpi\}$, while the expanded system (labelled VAR) adds the financial stress indicator to the benchmark specification i.e. $Y_t = \{gdp, cpi, fsi\}$ in order to examine the role played by financial information. $VAR\xi$ will also include r when we evaluate the robustness of the results. Based upon the benchmark model, we evaluate the forecast performance of three extensions that incorporate financial information (in the form of the alternative financial stress indexes), namely standard vector autoregression (VAR), regime-switching ($TVAR$), and mixed frequencies ($MF-VAR$).

We adopt the approach of Banbura et al. (2010) by implementing Normal-Inverse Wishart (NIW) conjugate priors for the model parameters via the following dummy or artificial observations that are appended to the data:

[7]The lag length was chosen in accordance with the Bayesian Information Criterion (BIC), which suggest the use of 2 lags to estimate the *VAR* and *TVAR* model.

$$
Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_1 \sigma_1 \ldots \gamma_N \sigma_N)}{\lambda} \\ 0_{N(p-1)\times N} \\ \cdots \\ diag(\sigma_1 \ldots \sigma_N) \\ \cdots \\ 0_{1\times N} \end{pmatrix}, \quad and\ X_{D,1} = \begin{pmatrix} \frac{J_p \otimes diag(\sigma_1 \ldots \sigma_N)}{\lambda} & 0_{Np\times 1} \\ \cdots & \cdots \\ 0_{N\times Np} & 0_{N\times 1} \\ \cdots & \cdots \\ 0_{1\times Np} & c \end{pmatrix} \tag{3.2}
$$

where the number of variables and the number of lags in the VAR are respectively denoted by N and p, γ_1 to γ_N are the prior means for the coefficients on the first lags of the dependent variables and $J_P = diag(1,\ldots,p)$. The hyperparameter λ controls the overall tightness of the prior on the VAR coefficients and c controls the tightness of the prior on the constant terms. In this study, the prior means are the OLS estimates of an AR(1) regression for each endogenous variable estimated over a training sample. σ_1 to σ_N are the standard deviation of error terms from these AR(1) regressions for each variable in the model. Following Canova (2007), we set $\lambda = 0.2$ a loose prior on the VAR coefficients and we choose a loose prior on the constant with $c = 10^5$. To incorporate the prior belief that the variables in the VAR can be represented by a process with unit roots, a prior on the sum of the lagged dependent variables is also introduced by adding the following dummy observations:[8]

$$
Y_{D,2} = \frac{diag(\gamma_1 \mu_1 \ldots \gamma_N \mu_N)}{\tau},\ X_{D,2} = \begin{pmatrix} \frac{(1_{1\times p}) \otimes diag(\gamma_1 \mu_1 \ldots \gamma_N \mu_N)}{\tau} & 0_{N\times 1} \end{pmatrix} \tag{3.3}
$$

where each variable's prior mean calculated using the training sample is represented by $\mu_i, i = 1,\ldots,N$, and the τ represents the hyperparameter that controls the degree of shrinkage i.e. we approach the case of exact differences as τ goes to 0, and the case of no shrinkage as τ goes to ∞. Following Banbura et al. (2010), we set the tightness of this sum-of-coefficients prior as $\tau = 10\lambda$. Given the artificial data and the natural conjugate prior, the conditional posterior distributions for

[8] Sims & Zha (1998), for example, provide evidence of improvement in forecasting performance following the imposition of additional priors that constrain the sum of coefficients.

the VAR parameters $B = vec([c, \beta_1; \beta_2 \ldots; \beta_j])$ and $\sum$ are given by

$$
\begin{aligned}
H(B|\sum, Y_t) \sim N(B^*, \sum \otimes (X^{*\prime} X^*)^{-1}), \\
H(\sum |B, Y_t) \sim IW(S^*, T^*)
\end{aligned}
\tag{3.4}
$$

where $B^* = (X^{*\prime} X^*)^{-1}(X^{*\prime} Y^*)$, $S^* = (Y^* - X^* B^*)'(Y^* - X^* B^*)$, $Y^* = [Y; Y_{D,1}; Y_{D,2}]$, $X^* = [X; X_{D,1}; X_{D,2}]$ with Y and X representing the regressands and regressors from the data, and T^* refers to the length of Y^*.

We use a Gibbs sampling algorithm, in accordance with Alessandri & Mumtaz (2017), to estimate this model and obtain the posterior parameter estimates for B and $\sum$. The model is estimated using 20,000 Gibbs draws and we discard the first 10,000 as burn-in. Once past the burn-in period we use the last 10,000 draws to produce the posterior predictive density given by

$$
p\left(Y_{T+1:T+h}|Y_{1-p:T}\right) = \int p(Y_{T+1:T+h}|Y_{1-p:T}, \theta) p(\theta|Y_{1-p:T}) d\theta \tag{3.5}
$$

where all the VAR parameters, i.e. B and $\sum$, are included in the vector θ, $h = 1, 2, \ldots, 8$, and the posterior distribution of the parameters and likelihood of future data is respectively represented by $p(\theta|Y_{1-p:T})$ and $p(Y_{T+1:T+h}|Y_{1-p:T}, \theta)$. These last two terms highlight how Bayesian forecasts account for parameter uncertainty as well as uncertainty regarding future developments. The forecast density can be easily obtained by simulating Y_t, h periods forward using the Gibbs draws for the VAR parameters.

3.4.2 TVAR

The threshold VAR, or *TVAR* model allows for the possibility of two regimes which switches abruptly and endogenously through the dynamics of the chosen threshold variable. Such a model is defined as

$$Y_t = \left[c_1 + \sum_{j=1}^{P} \beta_{1,j} Y_{t-j} + v_t \right] R_t + \left[c_2 + \sum_{j=1}^{P} \beta_{2,j} Y_{t-j} + v_t \right] (1 - R_t) \tag{3.6}$$

where $v_t \sim N(0, \sum_{R_t})$, $R_t = 1$ when $S_{t-d} \geq S^*$, $R_t = 0$ otherwise, and d represents the delay parameter which is also referred to as the threshold lag. In this application, the threshold variable is the d^{th} lag of the alternative financial stress indexes (fsi) described in Section 3.3. This is motivated by our interest in capturing changes in the transmission of financial shocks between good and bad times, consistent with the spirit of Alessandri & Mumtaz (2017), who show that the non-linear feature of this model can prove to be beneficial in terms of predicting recessions. We examine this conjecture here within a South African framework. In the above model specification $Y_t = \{gdp, cpi, fsi\}$, representing the vector of endogenous variables at quarterly frequency. As a robustness check, we re-estimate the *TVAR* model including the three-month treasury bill rate (r) i.e. in this case $Y_t = \{gdp, cpi, r, fsi\}$. We define $R_t = 1$ as the financial stress regime if and only if the d^{th} lag of the financial stress indicator S_{t-d} rises beyond an unobserved threshold value S^*, which we let the data decide. The delay d is freely estimated and found to be equal to 1 at the posterior mode.

Similar to the *VAR* model, a natural conjugate prior with dummy observations is imposed on the *TVAR* parameters in the two regimes motivated here by the fact that the sample can be relatively short in stressful regimes. The hyperparameters are specified as is in the *VAR* case. Following Alessandri & Mumtaz (2017), a normal fairly loose prior for the threshold value S^* is assumed where $S^* \sim N(\bar{S}, \bar{V})$ with $\bar{S}$ being the sample mean of the financial stress indicator and $\bar{V} = 10$. Given an initial value for the threshold level and threshold lag, the conditional posterior for the *TVAR* coefficients and covariances in the two regimes is given by the standard form as in the *VAR* case (Equation 3.4). A Gibbs sampling algorithm including a random walk Metropolis Hastings step is performed to sample S^* in each simulation (Alessandri & Mumtaz (2017)) i.e. $S^*_{new} = S^*_{old} + \phi^{1/2}\varepsilon$, where $\varepsilon \sim N(0,1)$ and $\phi^{1/2}$ is a scaling factor which is set so as to ensure that the acceptance rate lies in the 20-40% interval.[9] A Metropolis Hastings step is included due

[9] The acceptance probability is given by $\frac{f(Y_t|S^*_{new}, M)}{f(Y_t|S^*_{old}, M)}$ where $f(.)$ represents the posterior density and M denotes all

to the analytical intractability of the posterior distribution of S^*. The threshold lag is then sampled conditional on the threshold value. Chen & Lee (1995) show that the conditional posterior density of this delay parameter is a multinomial distribution with probability $\frac{L(Y_t)}{\sum^d L(Y_t)}$ where $L(.)$ is the likelihood function. As in the VAR case, we run 20,000 iterations of the Gibbs sampler and discard the first 10,000 as burn-in. The forecast density for the $TVAR$ is defined in the same way as in the VAR model (Equation 3.5), with the exception being that the vector including all the VAR parameters is now defined as $\theta = \{B_1, \sum_1, B_2, \sum_2, S^*, d\}$. Given the Gibbs draws for the parameters in θ, the forecast density can be easily computed by simulating Y_t, h periods in the future.

3.4.3 MF-VAR

We briefly outline the key elements of our $MF-VAR$. The model is cast in a state-space framework in order to accommodate the mixed frequency nature of the dataset i.e. to cope with missing observations.[10] In our application, the state-space comprises quarterly time series for growth in real gross domestic product (gdp) and monthly times series for the other variables which include consumer price index (cpi) and the financial stress index (fsi).[11] We also include the monthly three-month treasury bill rate (r) when we conduct a robustness analysis. The model is defined as is in the VAR case (Equation 3.1), however, at monthly frequency and hence the vector of endogenous variables is now partitioned as $Y_t = [Z_t, X_t]'$, where X_t is a $N \times 1$ vector that includes the variables that are observed at monthly frequency (in our case the variables cpi and fsi), and Z_t is a $N \times 1$ vector comprising the quarterly variables at monthly frequency (in our application, this is the variable gdp, which is gross domestic product that is only published quarterly). Since the quarterly variable gdp is only observed in the last month of each quarter (i.e. March, June, September, and December), Z_t contains missing observations for the first two months of each

other parameters in the model.

[10]For more extensive detail on state-space methods, see Durbin & Koopman (2001). For a more comprehensive treatment and detailed specification of the mixed frequency Bayesian vector autoregression (MF-VAR) employed in this chapter, see Schorfheide & Song (2015).

[11]Since gross domestic product is observed only at quarterly frequency, we treat the corresponding monthly or intra-quarterly values as unobserved or missing data and propose measurement and state-transition equations for the monthly VAR.

quarter. To construct the measurement equation, we adopt the latent approach used by Schorfheide & Song (2015) to get an expression for Z_t

$$Z_t = (\hat{Z}_t + \hat{Z}_{t-1} + \hat{Z}_{t-2}) \tag{3.7}$$

where Z_t is only observed every third month, whereas $\hat{Z}_t$ denotes the unobserved monthly data on Z_t. We then define the state vector as $s_t' = [Y_t', \ldots, Y_{t-p+1}']$, where $Y_t' = [\hat{Z}_t, X_t]'$ combines the unobserved with the observed monthly variables. The observation or measurement equation is written compactly as

$$Y_t = M_t s_t \tag{3.8}$$

where M_t represents a sequence of selection matrices that selects the time t variables that have been observed by period T and are part of the forecaster's information set.[12] We follow Durbin & Koopman (2001) and employ a vector of observables Y_t that is time-dependant and a time-varying matrix M_t, to replace the missing observations in s_t with estimated states. If an indicator exhibits a missing observation in period t, the corresponding entry in Y_t and the corresponding row of M_t are deleted.[13] Cast in state-space form, the transition equation of the $MF-VAR$, which stays fixed over time, is given by

$$s_t = \alpha + F s_{t-1} + u_t,\ u_t \sim N(0, \Omega(\sum)) \tag{3.9}$$

where α and F contain the constant terms and AR-coefficients, respectively. The singular variance-covariance matrix Ω equals $\sum$ at the upper left $N \times N$ sub-matrix, while all other elements are zero.

We impose natural conjugate priors for the model parameters via artificial observations, as

[12] Refer to Schorfheide & Song (2015) and Brave et al. (2016) for a more comprehensive description of the matrix M_t.

[13] The measurement equation for this model is subject to change over time, dependant on whether observations on Z_t are missing. The quarterly observed data for Z_t (i.e. in period 3, 6, 9 etc) is the sum of the unobserved monthly data.

implemented in the VAR case. The hyperparameters are set up in the same way as is in the VAR case. Unlike in the quarterly VAR and $TVAR$ model which uses 2 lags, we set the lag order at 3 for the $MF-VAR$ since at least three lags are required to disaggregate quarterly GDP into monthly GDP (Schorfheide & Song (2015)).[14] Given the artificial data and the natural conjugate prior, a Gibbs sampling algorithm which decomposes the posterior into two blocks of full conditional densities, described in Schorfheide & Song (2015) is applied to conduct inference for the $MF-VAR$ (see Appendix B for the steps of the Gibbs sampling algorithm). Basically, we set the priors for the $MF-VAR$ model via dummy observations and form an initial value of the state vector s_t (which is required by the Kalman filter), where an initial estimate of $\hat{Z}_t$ can be obtained by simple interpolation.[15] We use 20,000 Gibbs replications, using the last 10,000 for inference. Conditional on $\hat{Z}_t$, we use a Gibbs sampler to generate draws from the posterior distributions of the vector autoregression parameters in the transition equation ($\sum$ and $B = \{\alpha, F\}$) i.e.

$$
\begin{gathered}
H(B|\hat{Z}_t, \sum), \\
H(\sum|\hat{Z}_t, B)
\end{gathered}
\tag{3.10}
$$

Based on these draws, the state variable $\hat{Z}_t$ is drawn using the Carter and Kohn algorithm.[16] Future trajectories of Y_t are simulated so as to characterise the predictive distribution associated with the $MF-VAR$ and to compute forecasts. For each draw $(B, \sum, \hat{Z}_t)$ from the posterior distribution, we simulate a trajectory $s_{T+1:T+h}$ based on the state-transition equation. The simulated trajectories are time-aggregated since we are interested in evaluating forecasts of quarterly averages. After obtaining the simulated trajectories, point forecasts are approximated by computing means.

[14]The structure of the observation equation allows for a minimum of 3 lags. Furthermore, this keeps the computational feasibility of the $MF-VAR$ since each additional lag increases the number of parameters by $N \times N \times T$.

[15]The Kalman filter is a recursive filter that provides an estimate of the state variable given measurements observed over time Carter & Kohn (1994).

[16]This method was used by Schorfheide & Song (2015) and improves on computational efficiency due to the recursive nature of filtering techniques which allow to tackle the problem period by period. For a formal derivation of the Carter and Kohn algorithm and Kalman filter, see Carter & Kohn (1994).

3.5 Forecast evaluations

As a model validation procedure, the models described in Section 3.4 are estimated recursively over an expanding data window, and the forecasts from the models are evaluated with respect to point forecasts. We judge the vector autoregressive model forecasts against the observed values for quarterly growth of real GDP (gdp) and inflation rate (cpi). The evaluation sample is from 2011Q1 to 2017Q4 for the quarterly models (i.e. VAR and $TVAR$) and from 2011M1 to 2017M12 for the $MF-VAR$. Starting from the 1995Q1-2010Q4 sample for the quarterly models, this gives us a set of 28 out-of-sample forecasts. The training sample for the $MF-VAR$ is over the period 1995M1 to 2010M12, giving us 84 out-of-sample forecasts, which are time-aggregated to obtain quarterly forecasts that are comparable with the quarterly models. We choose the training sample i.e. 1995-2010 so as to capture the severe economic downturns experienced during the 2008-2009 period, and therefore train our models to better forecast future economic vulnerabilities. Forecasts are obtained recursively and we examine horizons of one to eight quarters. All predictive densities are estimated following Alessandri & Mumtaz (2017), and the point forecasts are calculated as the arithmetic means of the predictive densities, and assessed by root mean-squared forecast errors

$$RMSFE_i^h = \sqrt{\frac{1}{N}\sum(\hat{y}_{t+h}^i - y_{t+h}^i)^2}, \tag{3.11}$$

where i and h denote the variable and forecast horizon, respectively, for the forecast sample $t = 1,\ldots,N$. For ease of interpretation, we report the $RMSFEs$ as ratios relative to a benchmark model

$$relative\, RMSFE_{m,i}^h = \frac{RMSFE_{m,i}^h}{RMSFE_{b,i}^h}, \tag{3.12}$$

where$RMSFE_{b,i}^h$ refers to the $RMSFE$ of the benchmark $VAR\xi$ (which excludes a financial stress index), and $RMSFE_{m,i}^h$ is the $RMSFE$ of the comparative models which include the VAR, $TVAR$, and $MF-VAR$ as detailed in Section 3.4. Since the $RMSFE$ of the benchmark model is in the denominator, ratios below 1 indicate improvements in predictive accuracy with the relative models outlined above. The test developed by McCracken (2007) is applied to formally test whether the any differences in the forecasting ability between the restricted (benchmark model, *b*) and unrestricted models (alternative models, *m*, that include the financial stress index) are statistically significant. This test represents a variation of the Diebold & Mariano (1995) test, in that it provides asymptotically valid out-of-sample results that compare the predictive ability of two nested models. The Diebold & Mariano (1995) test of equal forecasting accuracy is valid only for non-nested models, and does not allow for the comparison of models that generated the forecasts. This test requires that the variance of the asymptotic distribution be positive to be valid, which is normally not the case with nested models. The McCracken (2007) test statistic that we use is represented as

$$MSE-F=\frac{(T-R-h+1)\times\bar{d}}{MS\hat{F}E_m} \tag{3.13}$$

where h is the forecast horizon, T is the total sample size (1995Q1-2017Q4), R represents the in-sample observations (1995Q1-2010Q4), and

$$\bar{d}=(T-R-h+1)^{-1}\sum_{t=R}^{T-h}(\hat{u}^2_{b,t+h}-\hat{u}^2_{m,t+h})=MS\hat{F}E_b-MS\hat{F}E_m$$

is the difference in mean squared forecast error (MSFE) of the restricted benchmark model (*b*) and the unrestricted alternative models (*m*). Lastly, $MS\hat{F}E_m=(T-R-h+1)^{-1}\sum_{t=R}^{T-h}(\hat{u}^2_{m,t+h})$ is the mean squared forecast error of the unrestricted alternative models (*m*). We compare the test statistic in Equation 3.13 with the asymptotically valid critical values from the F-distribution with degrees of freedom $\pi=P/R$ (ratio of out-of-sample forecasts (P) to the number of in-sample observations (R)) and k_2 (number of excess parameters) provided in McCracken (2007). The null hypothesis of equal predictive ability between the restricted and unrestricted model is only rejected if the calculated test statistic is larger than the critical values.

In addition to the recursively estimated out-of-sample forecasting exercise outlined above, we also conduct an ex-ante forecasting exercise i.e. assuming that the future observations are not available for checking and therefore not updating the estimates of the parameters based on recursive estimation of the models. Using our benchmark financial stress index ($safsi$), this forecasting exercise is conducted over the period 2008Q1-2009Q4 and 2015Q1-2016Q4 to gauge the ability of the best performing model, selected based on out-of-sample forecast performance, in predicting the turning points in the macroeconomic variables of interest (i.e. gdp and cpi). Of interest to policymakers, this exercise enables us to assess the performance of the selected model in terms of predicting economic downturns that were particularly evident during these recent periods and poses a challenge for existing models be it structural or non-structural.

3.6 Empirical results

Table 3.1 reports the average root mean square errors (RMSFE) generated by the models over the evaluation period, which runs from 2011Q1 to 2017Q4.[17] The RMSFE for the alternative specifications are reported as ratios relative to the benchmark model, as in e.g. Banbura et al. (2010). We adopt as benchmark a simple bivariate linear common frequency vector autoregression ($VAR\xi$) that includes growth in gross domestic product (gdp) and consumer price inflation (cpi). Using this model as a benchmark is convenient since it is the simplest model that produces predictions for the key macroeconomic variables of interest in this study. Moving across the table, the alternative vector autoregression specifications which include the financial indicator ($safsi$) are a linear common frequency model (VAR), threshold model with finance-driven regimes ($TVAR$), and a mixed-frequency model ($MF-VAR$). Ratios below 1 are indicative of improved forecasting performance relative to the benchmark model, and allows us to determine whether including financial information helps improve macroeconomic forecasts depending on model specification. The McCracken (2007) test is applied to formally test whether any differences in forecast accuracy are statistically significant.

Our results suggest that the $MF-VAR$ which includes financial information performs the best

[17] As mentioned previously, the sample begins in 1995Q1 and out-of-sample forecasts are calculated starting from 2011Q1 till the end of 2017. The RMSFE of the alternative models with the alternative financial stress indexes are reported in levels in Table B.2 in Appendix B.

at all horizons in terms of predicting gdp and cpi. The improvement is of the order of 32-39% for gdp and 41-42% for cpi. For gdp these differences in forecast accuracy relative to the benchmark are fairly stable and statistically significant at the 1% level only up to horizon 4, while being significant at the 5% level for horizon 5 and 6, and insignificant beyond horizon 6. Similar results are found for cpi, with the differences in forecast accuracy being statistically insignificant beyond horizon 6. This finding supports Schorfheide & Song (2015), who find that improvement in forecast accuracy with a mixed-frequency vector autoregression tempers off in the medium to long run. Looking at the VAR model results, the relative RMSFE for gdp and cpi are insignificant at all conventional levels and for all horizons (with the exception that the relative RMSFE for gdp is significant at the 5% level for only one-quarter ahead), which suggests that including financial information in this specification does not improve the forecast accuracy of these macroeconomic indicators. The $TVAR$ only performs marginally better than the benchmark in predicting gdp for horizons 1 to 3, while performing statistically significantly better in predicting cpi up to four quarters ahead. As a robustness check, we replicate the VAR, $TVAR$, and $MF-VAR$ models replacing $safsi$ with $fsi\_quantec$. The results are shown in Table B.1 in Appendix B. We ascertain that our main findings with respect to the superior forecasting performance of financial information within a mixed frequency VAR framework hold under this alternative specification. Including $fsi\_quantec$ within a VAR model results in marginally better forecasts for cpi only one-quarter ahead, while the $TVAR$ model performs poorly in forecasting both gdp and cpi. The RMSFE are tabulated in levels in Table B.2 for these alternative models including $safsi$ or $fsi\_quantec$.

We re-estimate all models (i.e. $VAR\xi$, VAR, $TVAR$, and $MF-VAR$ including the alternative financial stress indicators - $safsi$ or $fsi\_quantec$) by including the three-month treasury bill rate (r), to ascertain if our main results are consistent to the addition of another macroeconomic indicator. The relative RMSFEs of all models are displayed in Appendix B in Table B.3, while Table B.4 shows the RMSFEs in levels. While including the interest rate only marginally improves the forecast accuracy of cpi under the VAR and $TVAR$ for the alternative indicators of financial stress, the results for the $MF-VAR$ remains consistent with our previous findings excluding the interest

Table 3.1: Relative RMSFE of alternative specifications, 2011-2017

		VAR (safsi)	*TVAR (safsi)*	*MF-VAR (safsi)*
h = 1	gdp	0.969**	0.947***	0.646***
	cpi	1.006	0.828***	0.585***
h = 2	gdp	0.989	0.966*	0.678***
	cpi	1.001	0.880***	0.577***
h = 3	gdp	0.996	0.981*	0.640***
	cpi	1.001	0.838***	0.575***
h = 4	gdp	1.002	0.992	0.614***
	cpi	0.999	0.805**	0.584***
h = 5	gdp	1.001	0.997	0.605**
	cpi	1.000	0.771	0.573**
h = 6	gdp	1.000	0.994	0.604**
	cpi	1.000	0.740	0.560*
h = 7	gdp	1.000	0.994	0.602
	cpi	1.000	0.715	0.550
h = 8	gdp	1.000	0.995	0.599
	cpi	1.000	0.694	0.541

Notes: The table shows the average root mean square forecast errors (RMSFE) relative to the benchmark model ($VAR\xi$ - a linear common frequency vector autoregressive model containing only the macroeconomic variables - including gross domestic product growth (gdp) and consumer price inflation (cpi)) for gdp and cpi, for different forecast horizons h and different models which include the macroeconomic variables and financial market information captured by $safsi$. VAR, $TVAR$, and $MF-VAR$ are the alternative vector autoregressive models specified in linear common frequency, non-linear common frequency, and mixed-frequency, respectively. The McCracken (2007) test is carried out where differences in forecast accuracy are statistically significant at the 1% (***), 5% (**), or 10% (*) level.

rate.[18]

Table 3.2: RMSFE of MF-VAR (safsi) relative to MF-VAR excluding the financial indicator, 2011-2017

Horizon (h)	1	2	3	4	5	6	7	8
gdp	0.892***	0.950***	0.962***	0.970**	0.975*	0.975	0.977	0.983
cpi	0.682***	0.707***	0.721***	0.737***	0.746***	0.744***	0.748**	0.751*

Notes: The table shows the average root mean square forecast errors (RMSFE) of a mixed frequency VAR ($MF-VAR$) model including the financial stress indicator $sasfi$ relative to a $MF-VAR$ specification excluding $safsi$. The relative RMSFE are reported for gross domestic product growth (gdp) and consumer price inflation (cpi) for different forecast horizons h. The McCracken (2007) test is carried out where differences in forecast accuracy are statistically significant at the 1% (***), 5% (**), or 10% (*) level.

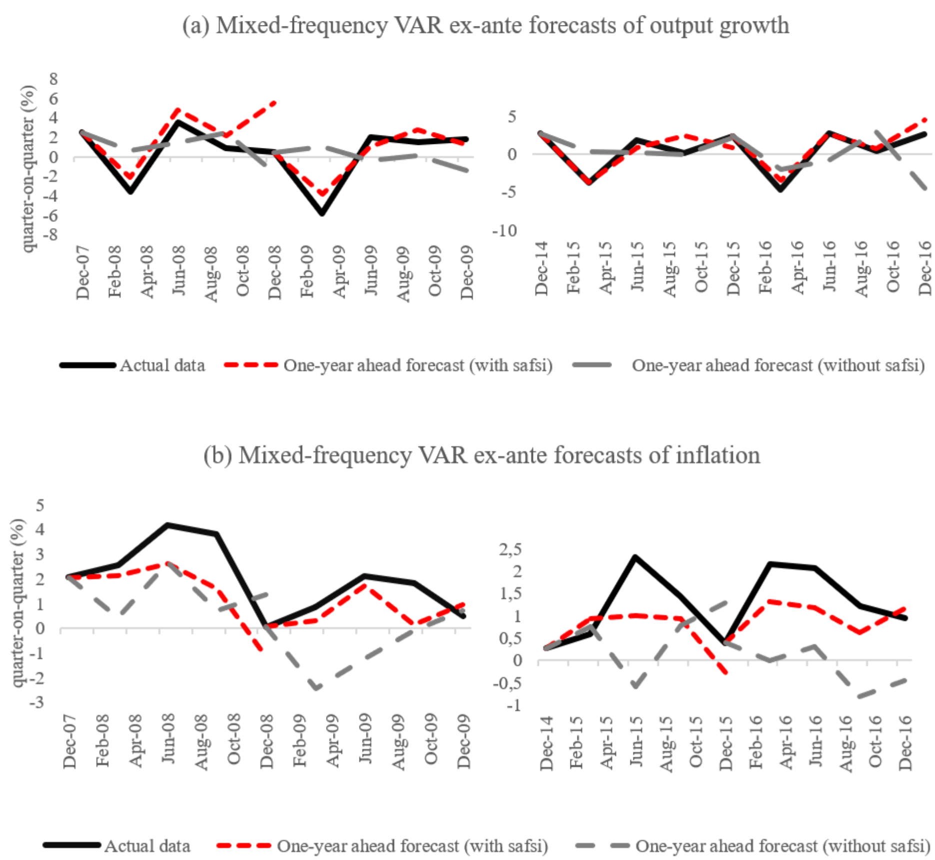
Table 3.2 provides the relative RMSFE of the $MF-VAR$ including financial information proxied by $safsi$ to the $MF-VAR$ estimated with only the two macroeconomic variables (gdp and cpi) excluding $safsi$.[19] The corresponding RMSFEs in levels are reported in Table B.6 in Appendix B. We find that including financial information in the $MF-VAR$ specification improves the forecasts of gdp and cpi. While the improvement in the forecast accuracy of gdp is marginal and statistically significant in the short-term, the improvement in cpi is larger in magnitude and statistically significant over the short to medium-term horizon. We find similar results when we replace $safs$i with $fsi\_quantec$ as shown in Table B.5 in Appendix B. Furthermore, the above results are robust to the inclusion of the three-month treasury bill rate (r) as reported in Table B.7 and Table B.8 in Appendix B. Overall, our main findings suggest that accounting for financial information via the inclusion of a financial stress index significantly improves the forecast accuracy of gdp and cpi when considered within a mixed-frequency specification. This reveals that accounting for intra-quarterly information improves the forecasting performance of financial information in terms of output and inflation, which are considered key macroeconomic indicators in formulating monetary policy decisions within a Taylor rule setting.

Figure 3.1 provides the ex-ante forecasts for real gross domestic product (output) growth and

[18] In unreported results, we find that the $TVAR$ model performs the best in forecasting the three-month treasury bill rate, reflecting the non-linear dynamics of interest rate, consistent with the findings of Baaziz et al. (2013) who document evidence of non-linearity in South Africa's monetary policy.

[19] The relative RMSFEs are computed as illustrated in Section 3.5, with the benchmark model now being replaced by the MF-VAR model estimated with only the two macroeconomic variables (gdp and cpi) excluding $safsi$.

Figure 3.1: Ex-ante forecasts of output growth and inflation



Notes: The figure displays actual data and one-year ahead ex-ante forecasts for gdp (panel (a)) and cpi (panel (b)) generated by the MF-VAR model including and excluding the benchmark financial stress index $safsi$ for the periods 2008-2009 and 2015-2016.

inflation generated by the best performing model according to RMSFE measures i.e. MF-VAR with financial information proxied by $safsi$, as outlined above. In addition, we also show the ex-ante forecasts generated by the mixed-frequency VAR model without the financial stress indicator $safsi$. The ex-ante forecasts obtained from the two models are shown for the periods 2008Q1-2009Q4 and 2015Q1-2016Q4. In this way, we are able to determine whether financial information provides valuable information in terms of forecasting economic downturns experienced during these recent periods. We generate one-year ahead ex-ante forecasts for these periods since the RMSFE measures provided in Table 3.1 suggest that the differences in forecast accuracy of the $MF-VAR$, in terms of gdp and cpi, relative to the benchmark $VAR\xi$ are statistically significant up to one-year ahead. Overall, Figure 3.1 shows that we obtain more accurate forecasts for both output growth and inflation when financial information is included in the MF-VAR model. In particular, the financial stress indicator performs better than expected in predicting the economic downturns experienced by the South African economy during the the recession periods of 2008-2009 and during the end of 2015 and beginning of 2016 which was clouded by political tension. Excluding the financial stress indicator $safsi$ from the MF-VAR specification results in more optimistic forecasts for both output growth and inflation, especially during the periods of economic downturn. This suggests that including financial information, as captured by $safsi$, within a mixed-frequency framework significantly improves the forecasts of key macroeconomic variables, and therefore could potentially serve as an early warning indicator of economic vulnerabilities within the South African economy.

3.7 Conclusion

In this chapter, we examine the predictive power of financial information with respect to output growth and inflation. Based on the information contained in a newly constructed financial stress index ($safsi$) in Chapter 2, we forecast the aforementioned macroeconomic variables using three vector autoregression specifications: a mixed-frequency ($MF-VAR$) specification which includes quarterly and monthly time series data, a standard linear quarterly frequency model (VAR), and a threshold (non-linear) quarterly frequency specification ($TVAR$). Our results reveal that accounting for information that becomes available within the quarter (i.e. modelling monthly dynamics) substantially improves the forecasting performance of financial information in terms of output growth and inflation, which are considered key economic indicators in formulating monetary policy decisions. This reflects the superiority of the mixed-frequency approach in forecasting low frequency events i.e. recessions. However, substantial gains in forecast accuracy within the mixed-frequency specification is more apparent for nowcasts and short-term forecasts, while the benefits from within-quarter information vanish over longer horizons. We find that financial information does have the potential to serve as early warning indicators of economic vulnerabilities, however, policymakers should be aware that model specification plays a fundamental role in the degree of forecast accuracy. Nonetheless, our results point to the valuable contribution of financial variables in predicting macroeconomic variables. The results from our study have important monetary policy implications, especially since financial market conditions are an important determinant of growth performance and as such has the potential to weaken or distort monetary policy transmission. In future research, it would be interesting to account for time-variation in the predictive power of financial information for output growth and inflation in the emerging market economy. This would be an interesting piece of research, especially following recent evidence on the G-7 countries provided by Kuosmanen & Vataja (2019), documenting that changing economic circumstances in these countries influence the forecasting content of financial variables for GDP growth.

Chapter 4

The Impact of Uncertainty Shocks: Role of Financial Regimes

4.1 Introduction

In 1964 (revisited in 1993) the late well-known Nobel Laureate in Economics, Milton Friedman, proposed the "guitar string" theory or better known "plucking model" for recessions, according to which he postulated that deep recessions are followed by rapid recoveries, just as a guitar string bounces right back after it is pulled and then released (Friedman (1964), Friedman (1993)). However, the economic performance in many economies since the Great Recession of 2008-09 has not followed that proposition, but instead economies globally experienced slow economic recovery. Many economists and policymakers, following the seminal work of Bloom (2009) have highlighted heightened economic uncertainty as the main source of this macroeconomic instability and anaemic recovery.[1] While traditionally, the transmission of uncertainty shocks have been linked to real frictions (Bernanke (1983); Bloom (2009)), recent studies have documented the crucial role of financial frictions in the transmission mechanism (Arellano et al. (2010); Gilchrist et al. (2014);

[1]In general, economic uncertainty refers to an environment in which the future state of the economy is unknown. Since uncertainty is a latent variable and presents quantification challenges, most of the measures of uncertainty have focused mainly on macroeconomic uncertainty which include the dispersion in economic forecasts, volatility of stock returns and the count of the term "economic uncertainty" in media.

Christiano et al. (2014); Caldara et al. (2016)). However, most of the studies examining the link between financial conditions and country-specific uncertainty have focused on advanced economies only. Against this backdrop and to narrow the gap in literature, this chapter examines the 'financial view' of the transmission of uncertainty shocks within a small open emerging market economy, in our case South Africa.

To examine this conjecture, we employ monthly data covering the period between January 1995 and December 2017 to estimate a nonlinear (threshold) vector autoregression (VAR) model with time-varying, stochastic volatilities and quantify the extent to which aggregate financial conditions influence the response of the South African economy to uncertainty shocks. Such a model proposed by Alessandri & Mumtaz (2019), allows the first moment dynamics of the system to be characterised by two distinct financial regimes (i.e. financially stressful versus tranquil/ normal periods) based on the financial stress indicator. The change in regime is abrupt and as a result the economy is either in a stressful period or a normal period. Particularly, the stress regime occurs when the estimated threshold variable (financial stress indicator) rises beyond an endogenously estimated threshold value. In this framework, uncertainty is treated as an unobservable state variable, and is estimated as the average volatility of the structural shocks in the economy. As such, this chapter contributes to the South African literature on the implications of uncertainty shocks, by estimating a model-based measure of uncertainty (unlike Redl (2018) and Hlatshwayo & Saxegaard (2016) that construct observable proxies for uncertainty) for the country within the framework of a non-linear stochastic volatility in mean VAR to quantify the impact of an uncertainty shock during stressful and tranquil financial periods.

Our estimates reveal that an uncertainty shock has different implications for the South African economy based on the state of financial markets. We find that the response of output is larger in normal times compared to periods characterised by high financial stress. In particular, the peaked contraction in output growth in the stress regime is roughly 5 times larger than the peaked contraction in the tranquil regime. Irrespective of the sign and magnitude of the volatility shock, the responses are much larger in the tranquil regime compared to the stress regime. This suggests that there is not enough room for financial uncertainty to increase further in the stress regime and hence the response of output is smaller, supporting Popescu & Rafael Smets (2010) that the impact of higher economic uncertainty is driven by its ability to increase financial uncertainty. Despite the smaller output response in the stress regime, the deterioration is more persistent than in the tranquil regime. Contrary to the aggregate demand effect, uncertainty shock is inflationary in both regimes with the impact being larger in the high stress regime, lending support to the the precautionary pricing effect following uncertain future demand and marginal costs. While our data reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices and interest rates. Variance decompositions show that the share of output variance explained by the volatility shocks in good financial times is more than double the share in bad times. Again, this is contrary to evidence provided for advanced economies, highlighting the differing dynamics in these economies compared to developing economies.

The rest of the chapter is organised as follows. Section 4.2 reviews the literature on the role of uncertainty in driving business cycle fluctuations, while Section 4.3 covers the data used in the model and Section 4.4 outlines the specification of the non-linear VAR model. Our empirical results are reported and discussed in Section 4.5 and Section 4.6 concludes.

4.2 Literature

The surge in research interest in economic uncertainty has been driven by its role in shaping the prolonged recession following the global financial crisis of 2007. Following the seminal work of Bloom (2009), there has been a growing number of empirical studies that have developed proxies for uncertainty to examine the transmission of uncertainty shocks to the real economy. The majority of these studies lend support to the negative channel in the transmission of uncertainty shocks, consistently proving that such innovations are linked to strong recessionary effects (Bloom (2014)). While traditionally, the transmission of these volatility shocks have been linked to real frictions (Bernanke (1983); Bloom (2009)), recent studies have documented the crucial role of financial frictions in the transmission mechanism (Arellano et al. (2010); Gilchrist et al. (2014); Christiano et al. (2014); Caldara et al. (2016)).

In general, the ‘real view’ of the transmission mechanism, commonly known as ‘real options’, is based on the “wait and see” approach by investors and firms in the face of high uncertainty pertaining to economic conditions. This view relies on important irreversible costs in firms’ hiring and investment decision, which puts pressure on agents to postpone these decisions, consequently dampening productivity and economic activity (Baker et al. (2016)). On the other hand, the ‘financial view’ of the transmission mechanism, or commonly known as the ‘risk-premium effect’, puts financial frictions in the form of credit aggregates and asset prices at the centre of the propagation of uncertainty shocks to the real economy. According to the view, high uncertainty which raises the probability of defaulting, results in an increase in risk premium or external finance, raising the cost of borrowing and negatively impacting firms’ investment. In this context, uncertainty works through its ability in amplifying financial stress. Consistent with the ‘financial view’, Gilchrist et al. (2014) suggests that innovations to uncertainty affect macroeconomic outcomes mainly via financial distortions, while Carrière-Swallow & Céspedes (2013) find evidence of strong correlation between economic dynamics and the depth of financial markets, in particular, United States (US) uncertainty shocks have a larger negative impact on emerging market economies with underdeveloped financial markets. Similarly, more recent studies including Gupta et al. (2020) and Bhattarai et al. (2019) document heterogeneity in the transmission of US uncertainty to emerging market economies dependent on country-specific factors including financial vulnerability and monetary policy stance, respectively. According to Caldara et al. (2016), the strong correlation between economic uncertainty and financial uncertainty makes it difficult to empirically discriminate between the two. To overcome this setback, these authors makes use of a penalty function and find evidence that the financial channel is crucial in the transmission of uncertainty shocks, while the uncertainty channel is negligible in the transmission of financial shocks. Similarly, Popescu & Rafael Smets (2010) find that once a measure of financial stress (i.e. credit spread) is included in a VAR framework, the independent role of uncertainty shocks (proxied by forecaster dispersion) becomes minimal.

Most of the studies examining the link between financial conditions and uncertainty have focused on advanced economies only (more so on the US), with the exception of Carrière-Swallow & Céspedes (2013), Gupta et al. (2020), and Bhattarai et al. (2019). However, these three studies have documented the importance of the financial channel in the international spillover of US uncertainty and not country-specific uncertainty shocks.[2] To narrow this gap in literature, we examine the 'financial view' of the transmission of uncertainty shocks within a small open emerging market economy, in our case South Africa. Specifically, we follow the approach by Alessandri & Mumtaz (2019) in estimating the state-dependent link between economic uncertainty and financial conditions in South Africa, within a non-linear VAR model.[3] In this way, we are able to examine whether the impact of uncertainty changes over time in relation to the state of South African financial markets. Previous South African studies, including Redl (2018), Hlatshwayo & Saxegaard (2016), and Kisten (2020) have provided evidence in support of the 'real view' of the transmission of uncertainty shocks, documenting the recessionary effects of uncertainty shocks. However, Redl (2018) does find that the estimated results are robust to the inclusion of a measure of financial stress. While Kisten (2020) does examine the time-varying transmission of uncertainty shocks, documenting that the impact of an uncertainty shock on key macroeconomic variables have declined systematically over time (supporting evidence for advanced economies by Mumtaz & Theodoridis (2018), Mumtaz (2016), and Beetsma & Giuliodori (2012)), the author does not consider the interdependence between financial conditions and uncertainty supported by the financial view of the transmission mechanism. Attempts in this regard are more evident, but considerably limited, for advanced economies (Lhuissier et al. (2016) and Alessandri & Mumtaz (2019) focus on the US). Employing a Markov-switching VAR, Lhuissier et al. (2016) find that uncertainty shocks (proxied by the VIX index) are more powerful during financial stress regimes

[2] Gupta et al. (2020) examines the relative importance of the exchange rate, trade and financial channel in the transmission of US uncertainty shocks on the dynamics of a panel of advanced economies and emerging market economies, and finds that in both cases the financial channel plays the most prominent role in the transmission mechanism.

[3] van Roye (2014), Aboura & van Roye (2017), Hubrich & Tetlow (2015), Hollo et al. (2012), Chatterjee et al. (2017), and Balcilar et al. (2016) have documented differing economic dynamics during stressful and normal times in the financial system, however, specifically examining the impact of financial shocks

than during tranquil regimes. Alessandri & Mumtaz (2019) find similar evidence, but make use of a non-linear VAR where economic uncertainty is approximated by the average volatility of the structural shocks in the economy, rather than being proxied by observable measures. In line with this, we contribute to the South African literature on the implications of uncertainty shocks, by estimating a model-based measure of uncertainty (unlike Redl (2018) and Hlatshwayo & Saxegaard (2016) that construct observable proxies for uncertainty) for the country within the framework of a non-linear stochastic volatility in mean VAR to quantify the impact of an uncertainty shock during stressful and tranquil financial periods.

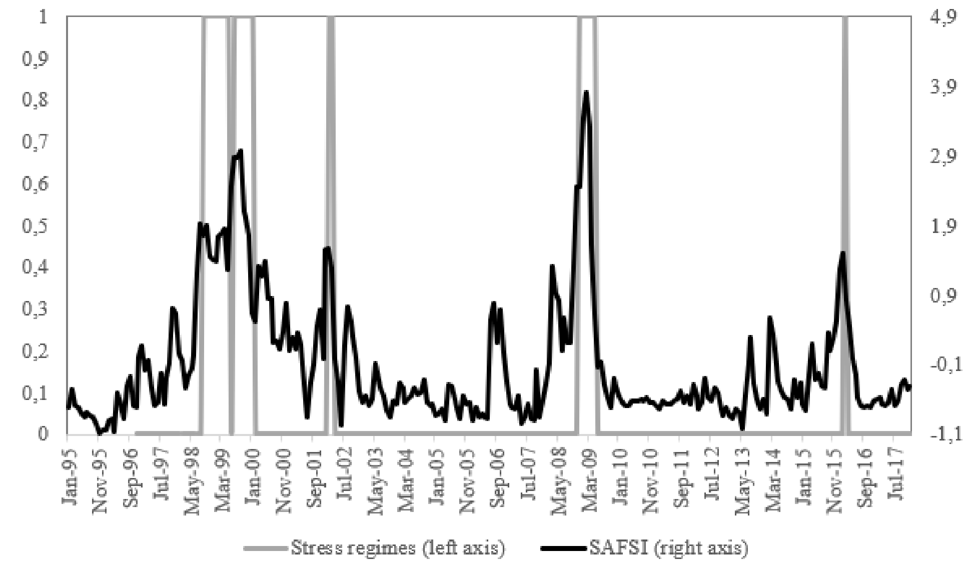
4.3 Data

Monthly data covering the period 1995 to 2017 is employed in our study. We obtain data on the industrial production index (IP) and the three-month treasury bill rate (R) from the South African Reserve Bank historical database, while data on headline consumer price index (CPI) is sourced from Statistics South Africa.[4] The estimation uses growth rates for industrial production and the price index, and therefore these variables enter our model as log first differences. Other variables, including the interest rate and the financial stress indicator, which is elaborated on below, remain untransformed.[5] We use the constructed financial stress index (called $SAFSI$) in Chapter to capture the state of financial markets. $SAFSI$ comprises seventeen financial indicators emanating from six major markets in South Africa (i.e. credit market, equity market, money market, housing market, foreign exchange market, and commodity market). These indicators were aggregated based on information weights and time-varying cross-correlations between market segments, representing a technical improvement over past measures (see Gumata et al. (2012), Thompson et al. (2015), Kasaï & Naraidoo (2013), and Kabundi & Mbelu (2017) that construct financial condition indexes

[4]The industrial production index covers real output in the manufacturing sector only.

[5]Note that the interest rate is non-stationary whereas the financial stress indicator is found to be stationary. However, the use of Bayesian vector autoregressive methods in our analysis overcomes the properties of the data, in our case non-stationarity, by allowing for the incorporation of informative priors (Banbura et al. (2010)).

Figure 4.1: The SAFSI and estimated stress regimes



Notes: The stress regimes are periods when the South African economy is estimated to have experienced high financial stress, which according to the threshold VAR model is defined as a state in which the index exceeds an estimated threshold. This threshold was estimated to be 1.38.

(FCIs) for South Africa).[6] As such, *SAFSI* has the advantage of capturing the interconnectedness of financial markets, allowing indicators to be assessed in terms of their systemic importance. Indicators included in the *SAFSI* were selected based on their ability to capture key episodes of stress in the South African financial system. The procedure in which the index is constructed reduces the risk of combining informationally redundant data that would over emphasise a given market segment at any point in time. The end result is a parsimonious index that captures the dynamics of a relevant set of financial indicators.

Figure 4.1 displays the *SAFSI* along with the estimated stress regimes over the period 1995 - 2017.[7] The stress regimes are defined as periods when the the threshold variable (which is the d_{th} lag of the financial stress index (*SAFSI*) denoted as Y_{t-d}) rises beyond an estimated critical

[6] We do not distinguish between financial condition indexes (FCIs) and financial stress indexes (FSIs) in this thesis, since the difference between them are negligible. While FCIs are aggregates of a variety of financial variables that aid in characterising the state of financial markets, FSIs similarly monitors financial instability by aggregating financial variables that indicate increased likelihood of a crisis.

[7] The construction of the *SAFSI* will not be covered in this chapter. Please refer to Chapter 2 for detail pertaining to the identification of the key periods of financial stress in the South African economy, selection and list of stress indicators that comprise the *SAFI*, and the corresponding construction methodology.

threshold value Y^*. Our model estimates the optimal delay parameter to be two months. The threshold VAR model is able to capture the main episodes of financial stress in South African history, as the estimated stress regimes are consistent with the benchmark episodes identified in Chapter 2. In particular, the estimated regimes captures the currency crisis experienced by the economy in 1998 following the East Asian financial crisis of 1997 and the Russian financial crisis of 1998; liquidity pressures experienced by smaller to mid-sized banks in 1999; the banking crisis of 2002 following the imposition of curatorship over Saambou Bank Limited (7th largest bank in SA) in February 2002 and the subsequent takeover of BOE Bank Limited by Nedbank Limited; the financial and economic impact of the 2008-2009 global financial crisis; and more recently the financial market turmoil at the beginning of 2016, following the political turmoil that lead to the axing of former Finance Minister Nhlanhla Nene.

4.4 Model specification

We quantify the impact of innovations to economic uncertainty on the South African economy during different financial states by estimating a Threshold VAR model with time-varying, stochastic volatilities.[8] Such a model proposed by Alessandri & Mumtaz (2019), which allows the first moment dynamics of the system to be characterised by two distinct financial regimes (i.e. financially stressful versus tranquil/ normal periods), is defined as

$$Y_t = \left[c_1 + \sum_{j=1}^{P} \beta_{1j} Y_{t-j} + \sum_{k=0}^{K} \theta_{1k} lnh_{t-k} + v_t \right] \tilde{R}_t + \left[c_2 + \sum_{j=1}^{P} \beta_{2j} Y_{t-j} + \sum_{k=0}^{K} \theta_{2k} lnh_{t-k} + v_t \right] (1 - \tilde{R}_t) \tag{4.1}$$

In our framework Y_t represents a $N \times 1$ vector of endogenous variables including industrial production growth (IP), consumer price inflation (CPI), three-month treasury bill rate (R), and the financial stress index ($SAFSI$). The parameters of the VAR system are represented by c_i, β_i, θ_i,

[8]Special thanks to Professor Mehmet Balcilar (Department of Economics, Eastern Mediterranean University, Famagusta, via Mersin 10, Northern Cyprus, Turkey) for assisting with the estimation of the model

and $v_t \sim N(0, \Omega_{it})$ for $i = 1, 2$, allowing us to capture the change in economic dynamics during stressful and tranquil financial conditions. In this setup, uncertainty is treated as an unobservable state variable, represented by h_t, and is estimated as the average volatility of the structural shocks in the economy. The inclusion of h_t in Equation 4.1 allows the economic variables (output, prices, and interest rates) to adjust endogenously to the different states of financial markets. As is common with monthly data, we set the number of lags of the endogenous variables in the system P to 2 based on the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC), and K which is the lag length of uncertainty is set to 1. $\tilde{R}_t$ allows for the possibility of two regimes which switches endogenously through the dynamics of some threshold variable. In our case, the threshold variable is the d_{th} lag of the financial stress index ($SAFSI$) denoted as Y_{t-d}. We define $\tilde{R}_t = 1$ ($\tilde{R}_t = 0$ otherwise) as the stress regime if and only if the threshold variable rises beyond an unobserved threshold value Y^*, which we let the data decide. Equation 4.1 shows all parameters are allowed to change across regimes. This is motivated by our interest in capturing changes in the transmission of uncertainty shocks between financially good and bad times, consistent with the spirit of Alessandri & Mumtaz (2019), but applied to the South African economy.

The covariance matrix of the error term v_t i.e. Ω_{it} has time-varying elements and is critical to our analysis. It is defined as $\Omega_{it} = A_i^{-1} H_t A_i^{-1'}$, depending on the economic regimes, $H_t = h_t S$ where $S = diag(s_1, \dots s_N)$, and A_i are lower triangular matrices with each non-zero element evolving as a random walk (Primiceri (2005)). The volatility process, which we take to represent economic uncertainty, evolves as an AR(1) process and is defined as

$$lnh_t = \alpha + F lnh_{t-1} + e_t,\ VAR(e_t) = Q \tag{4.2}$$

The above specification does not distinguish between the common and idiosyncratic component in volatility and h_t is a convolution of both components. Importantly, in estimating volatility h_t, all structural shocks implicitly carry the same weight. In this framework, a shock to volatility or uncertainty i.e. $e_t \geq 0$ raises h_t, shifting the covariance matrix of innovations v_t upwards, reducing the accuracy with which agents can predict future economic outcomes i.e. Y_{t+m}.

A natural conjugate prior with dummy observations, following Banbura et al. (2010), is imposed on the VAR parameters $B_i = c_i, \beta_{i_{i=1,2}}$ in the two regimes, given that the sample can be relatively short in the stress regime.[9] We estimate AR(1) regressions for each endogenous variable in the system using a pre-sample, and use the OLS coefficients as the prior means. Following Canova (2007), the hyperparameter that controls the overall tightness of the prior on the VAR coefficients τ is set to 0.2 a loose prior on the VAR coefficients and we choose a loose prior on the constant with $c = 10^5$. A normal fairly loose prior is assumed for the threshold value Y^* where $Y^* \sim N(\bar{Y}, \bar{V})$ with $\bar{Y}$ denoting the sample mean of the financial stress indicator and $\bar{V} = 10$. We assume a flat prior for the delay parameter d and limit its value between 1 and 2. The posterior distribution of the parameters and the state variable h_t are approximated using a Gibbs sampling algorithm.[10] In essence, given a draw of the state variable, the variables in the system are transformed to remove the heteroscedasticity, after which the model collapses to a standard threshold VAR and the conditional posterior distribution of the VAR parameters in both regimes, the delay parameter, and threshold are given by Alessandri & Mumtaz (2017).[11] In particular, the conditional distribution for the VAR coefficients is given by $N(B_i^*, \bar{\Omega}_i \otimes (X_i^{*'} X_i^*)^{-1})$ in each financial regime, where $B_i^* = (X_i^{*'} X_i^*)^{-1})(X_i^{*'} Y_i^*)$, Y_i^* and Y_i^* are the transformed data appended with dummy observations, and $\Omega_i = A_i^{-1} S A_i^{-1'}$. Given a draw for the VAR parameters, the threshold, and h_t, the conditional posterior distribution for A and the variance S is normal and inverse Gamma respectively. Given

[9]Technicalities pertaining to appending the data with dummy or artificial observations can be found in Banbura et al. (2010)

[10]See Alessandri & Mumtaz (2019) for detail regarding the implementation of each step in the algorithm. This is beyond the scope of this thesis, as we focus more on the results rather than the technicalities

[11]Due to the analytical intractability of the posterior distribution of Y^*, a random walk Metropolis Hastings step, following Chen & Lee (1995) is used to draw the threshold value in each simulation i.e. $Y^*_{new} = Y^*_{old} + \phi^{1/2}\varepsilon$, where $\varepsilon \sim N(0,1)$ and $\phi^{1/2}$ is a scaling factor which is set so as to ensure that the acceptance rate lies in the 20-40% interval. The acceptance probability is given by $\frac{f(Y_t|Y^*_{new},M)}{f(Y_t|Y^*_{old},M)}$ where $f(.)$ represents the posterior density and M denotes all other parameters in the model. The delay parameter d is then sampled conditional on the threshold value and its conditional posterior is a multinomial distribution with probability $\frac{L(Y_t)}{\Sigma^d L(Y_t)}$ where $L(.)$ is the likelihood function.

all of these parameters, the model takes on a non-linear state space framework, wherein the state variable h_t is drawn via a independence Metropolis Hastings algorithm for stochastic volatility models, following Jacquier et al. (2002).

We run 20,000 iterations of the Gibbs sampler to ensure convergence and discard the first 10,000 as burn-in, using the last 10,000 for inference. Generalised impulse response functions as specified in Koop et al. (1996) are used to study the potential differences in the propagation of uncertainty shocks under the specific financial regimes (i.e. tranquil versus stressful). The impulse responses are captured using Monte Carlo integration and defined as

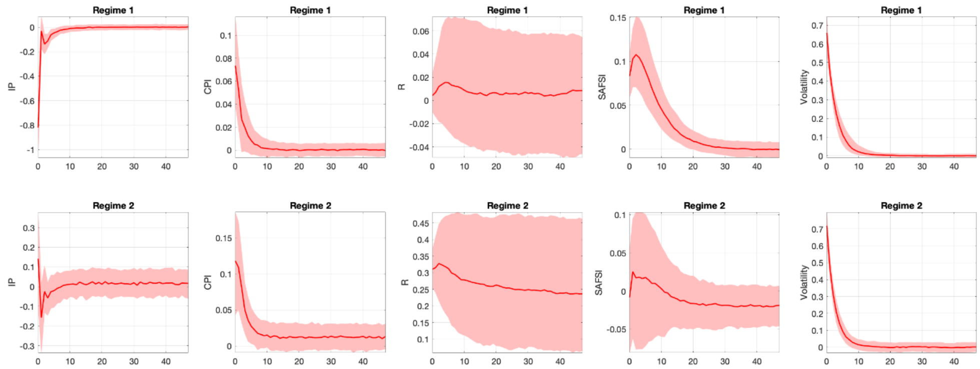
$$IRF_t^{\tilde{R}} = E(Y_{t+m}|\xi_t, Y_{t-1}^{\tilde{R}}, \mu) - E(Y_{t+m}|\xi_t, Y_{t-1}^{\tilde{R}}) \tag{4.3}$$

where ξ_t represents all the parameters and hyperparameters of the VAR model, m is the horizon under consideration, $\tilde{R} = 0,1$ denotes the regime and μ is the shock (i.e. increase in uncertainty or volatility, in our study). Equation 4.3 states that the impulse responses are computed as the difference between two conditional expectations: The first term is the forecast of the endogenous variables conditional on one of the structural shocks μ; the second term being the baseline forecast i.e. where the shock equals zero. The impulse responses fully account for abrupt endogenous changes in regimes and the conditional expectations are approximated via a stochastic simulation of the VAR model (Alessandri & Mumtaz (2017)).

4.5 Empirical results

In this section we report the change in macroeconomic and financial dynamics during good financial times (Regime 1) and bad financial times (Regime 2), following an exogenous increase in uncertainty. Regime 2 occurs when the estimated threshold variable goes beyond the estimated threshold value. As mentioned previously, the SAFSI is used as the threshold variable, which is a measure of financial stress in the South African financial sector. In our framework, the change in regime is abrupt and as a result the economy is either in a stressful period (Regime 2) or a normal

Figure 4.2: Impulse responses to a positive uncertainty shock



Notes: The figure shows the median responses of industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI to a positive one standard deviation model-based volatility (or uncertainty) shock during tranquil financial times or low stress regime (Regime 1) and stressful financial times or high stress regime (Regime 2). Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

period (Regime 1).

Figure 4.2 reports the impulse responses of the South African economy following an increase in uncertainty, represented as a positive one standard deviation shock to the volatility process h_t in Equation 4.2. In response to an uncertainty shock, there is an immediate deterioration in real output growth (IP)[12] and financial conditions, indicated by an immediate jump in our financial stress index SAFSI. We find a larger and statistically significant impact on output and financial conditions in the low stress Regime 1 compared to the high stress Regime 2. In particular, the peaked contraction in output growth in the tranquil regime is roughly 5 times larger than the peaked contraction in the stress regime. While there is an immediate short-lived positive impact on output in Regime 2, this impact is not evident once we impose a larger uncertainty shock, as is seen in Figure 4.3 below. Despite the smaller output response in the stress regime, the deterioration is more persistent than in the tranquil regime. In spite of this persistent impact, we do not find evidence of the amplification

[12] A similar sharp decline was also noted when we used the generalised stochastic volatility in mean VAR model of Mumtaz (2018), as reported by Figure C.4 in Appendix C. The variables contained in the model was industrial production growth (IP), consumer price inflation (CPI), and a measure of financial stress ($SAFSI$), and the uncertainty shock was identified using a Cholesky decomposition with the variables ordered as h_{1t}, h_{2t}, h_{3t}, $SAFSI$, IP, CPI.

impact of an uncertainty shock on economic activity during episodes of financial distress as predicted by the 'financial view' of the transmission mechanism (the crucial role of financial frictions in the transmission mechanism has been supported by Arellano et al. (2010); Gilchrist et al. (2014); Christiano et al. (2014); Caldara et al. (2016)); and more recently Alessandri & Mumtaz (2019) for advanced economies). One possible explanation for this contradictory evidence found when using South African data could be that there is not enough space for financial uncertainty to increase further in the high financial stress regime, and hence impact on output from economic uncertainty is smaller than the regime where financial uncertainty is low. Hence economic uncertainty increases financial uncertainty more in the low stress regime and depresses output more.[13]

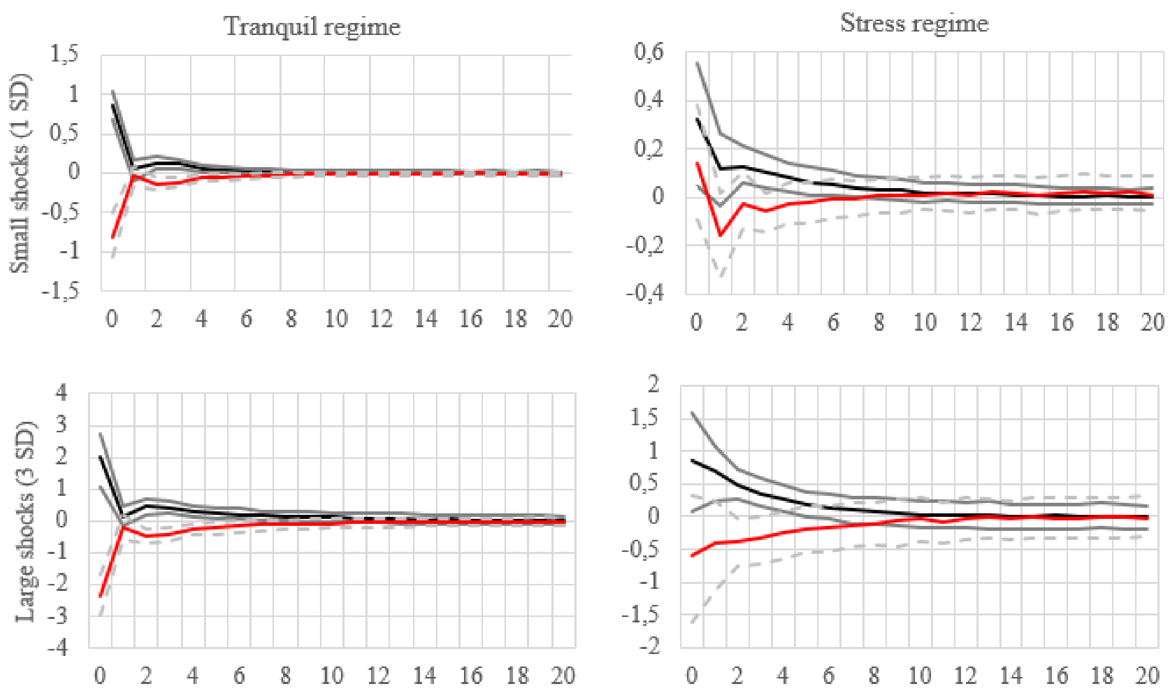
Since the stochastic volatility process is not regime-dependent, the volatility dynamics are identical across good and bad financial times as shown in the last column of Figure 4.2. Increases in uncertainty are generally associated with a negative demand shock in the economy i.e. reducing prices, interest rate, and output in accordance with the 'wait and see' behaviour of economic agents (Bloom (2009)). However, our estimation reveals that an uncertainty shock is inflationary in both regimes with the impact being larger in the high stress regime as illustrated in column 2. While this result contradicts the aggregate demand effect of an uncertainty shock, it lends support to the the precautionary pricing effect following uncertain future demand and marginal costs pointed out by Fernández-Villaverde et al. (2015), Mumtaz & Theodoridis (2015), and Redl (2018).[14] According to Klein (2011), price mark-ups are countercyclical in South Africa, in contrast to international experience, and therefore the recessionary effect of a positive uncertainty shock on production may translate to higher mark-ups introducing a rise in inflation.[15] Since price stability is one of the main goals of monetary policy in South Africa, the understanding of which propagation mechanism holds in the data is imperative. In line with this, we notice that although the short-term

[13] Popescu & Rafael Smets (2010) suggest that high uncertainty matters to the extent that it increases credit spreads and risk levels, otherwise its impact on the real economy relatively modest.

[14] Unlike in Alessandri & Mumtaz (2019), we do not find evidence of the aggregate demand effect on prices in the high stress regime as the precautionary mechanism appears to dominate in both regimes in the South African economy.

[15] Oh (2020) provides an in-depth theoretical explanation of firms' precautionary pricing motive within a standard New Keynesian model with Calvo-type price rigidities. In the Calvo model, output decreases and inflation rises following an uncertainty shock. By contrast, in a Rotemberg-type setup, only the aggregate demand effect is operative for firms as an uncertainty shock reduces both output and prices.

Figure 4.3: Output response following uncertainty shocks of different sizes and signs



Notes: The first row shows the responses of industrial production growth following a one standard deviation or small uncertainty shock during tranquil financial times (or Regime 1) and stressful financial times (or Regime 2). Median responses are reported within 68% confidence bands with the red solid line corresponding to positive uncertainty shocks and the black solid line to negative shocks. Similarly, the second row depicts the response of output growth to a three standard deviation (or large) uncertainty shock during the tranquil and stress regime. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

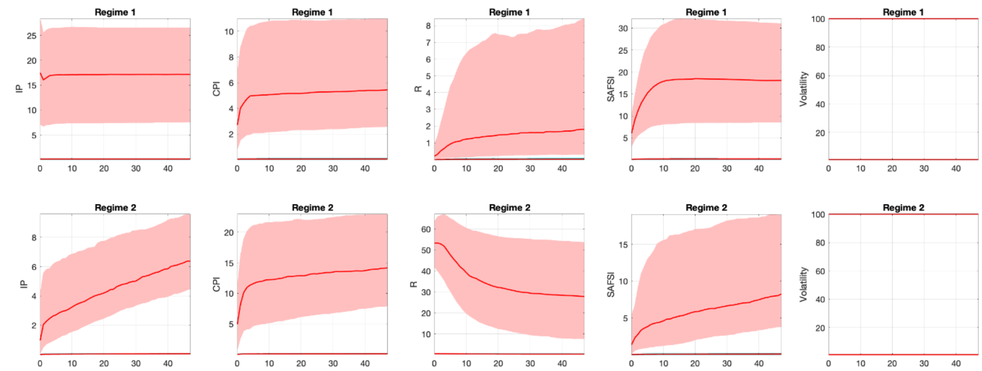
interest rates (R) does not respond significantly to the volatility shock, we nevertheless note that the immediate jump in interest rates in the high stress Regime 2 points to the procyclical behaviour of monetary policy as output falls but prices rise. While our data reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices and interest rates.

The real implications of a change in uncertainty might be dependent on the size and sign of the shock, given the non-linearity inherent in the model. Figure 4.3 compares the response of industrial production growth in good and bad financial times following uncertainty shocks of different magnitude (i.e. one and five standard deviation (SD) shocks) and sign (i.e. positive and negative volatility shocks). [16]The left column shows that the response of output in the tranquil regimes where financial conditions are loose are symmetrical in the size and sign of the shock. Irrespective of the sign and magnitude of the volatility shock, the responses are much larger in the tranquil regime compared to the stress regime in column 2. This is contrary to the findings of Alessandri & Mumtaz (2019) that financial frictions amplify the impact of uncertainty shocks, irrespective of its direction and size. However, we note that the responses of output are much more persistent in the stress regime. This suggests that an uncertainty shock in a tight credit environment has a more prolonged impact on the real economy, lasting for about six months, compared to the short-lived response in the tranquil regime. Interestingly, there is a sign asymmetry in the stress regime for both large and small shocks. Contrary to the evidence for the US economy provided by Alessandri & Mumtaz (2019), we find that for the South African economy a drop in volatility causes a larger change in output than a rise in volatility of equal magnitude. Our data reveals that volatility shocks in the stress regime matters more on the way down than on the way up, reaffirming our earlier assertion that there is not enough room for financial uncertainty to increase further in this regime and supporting Popescu & Rafael Smets (2010) that the impact of higher economic uncertainty is driven by its ability to increase financial uncertainty.

Variance decompositions shown in Figure 4.4 show the contribution of volatility shocks to the

[16]Responses of the other endogenous variables to uncertainty shocks of different sizes and signs are shown in Appendix C.

Figure 4.4: Forecast error variance decomposition



Notes: The figure shows the contribution of volatility shocks to the variance of each endogenous variable (i.e. industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI) as specified in the Threshold VAR outlined in Section 4.4. Regime 1 corresponds to tranquil financial times and Regime 2 to stressful financial times. The horizontal axis reports the forecast horizon which is measured in month.

variance of the endogenous variables in the Threshold VAR outlined in Section 4.4, allowing us to gauge the overall role of macroeconomic uncertainty in the business cycle. The Figure reveals that uncertainty shocks play a much more prominent role in the variance of output (column 1) and financial conditions (column 4) in the low stress Regime 1, accounting for more than double their variance in the high stress regime. This is contrary to evidence provided for the US economy by Alessandri & Mumtaz (2019), highlighting the differing dynamics in advanced and developing economies. However, for inflation and interest rate, uncertainty shocks are more relevant in stressful financial times.

4.6 Conclusion

In this chapter, we document the connection between economic uncertainty and financial market conditions, specifically that the macro-financial implications of an uncertainty shock differ across financial regimes. Using monthly South African data over the period 1995 to 2017, we estimate a non-linear VAR where uncertainty is captured by the average volatility of structural shocks in the economy. Regime shifts are abrupt and the economy shifts to a high stress regime characterised by tight financial condition when the financial stress indicator breaches an endogenously estimated threshold. We find that while the deterioration of output following an uncertainty shock is much more prominent during normal periods than during stressful periods, it is much more persistent during stressful financial times. Our findings support the proposition of Popescu & Rafael Smets (2010) that the impact of higher economic uncertainty is driven by its ability to increase financial uncertainty, and since there is not enough room for financial uncertainty to increase further in the stress regime, the response of output is smaller. Contrary to the aggregate demand effect and in support of the precautionary pricing effect, uncertainty shocks are inflationary in both regimes, with the impact being larger in the stress regime. Since price stability is one of the main goals of monetary policy in South Africa, the understanding of which propagation mechanism holds in the data is imperative. In line with this, we notice that although interest rates do not respond significantly to the volatility shock, we nevertheless note that the immediate jump in interest rates in the high stress regime points to the procyclical behaviour of monetary policy as output falls but prices rise. While our data reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices and interest rates. Our results suggest that policymakers could limit the propagation of uncertainty shocks by implementing appropriate macroprudential and monetary policy in line with the state of financial markets.

South Africa is a small open economy and hence is likely to be subjected to a variety of shocks from major global economies, as highlighted with regard to monetary policy shocks from the US recently by Meszaros & Olson (2020). Now given that, monetary policy shocks have been shown to generate significant macroeconomic uncertainty in the US (Mumtaz & Theodoridis (2019)), the possibility of spillover of US uncertainty to domestic uncertainty in South Africa via monetary policy shocks in the US (and other channels as outlined in Gupta et al. (2020)), cannot be ignored. Given this as part of future research, it would be interesting to analyze the role of foreign uncertainty, conditional on financial regimes, on macroeconomic variables of South Africa.

Chapter 5

Concluding Remarks

In this thesis, we develop a novel financial stress index for the South African economy (SAFSI) in Chapter 2, covering the period January 1995 - December 2017. The employed construction approach differs from previous studies in the South Africa literature in that it strikes a balance between efficacy and parsimony by selecting indicators based on their relevance in capturing key episodes of financial stress in South Africa. SAFSI has the advantage of capturing the interconnectedness of six financial markets that are thought to be most significant for the South African economy, enabling an indicator to be assessed in terms of its systemic importance. We evaluate the performance of the SAFSI relative to alternative measures of financial stress and show that the index successfully captures the major financial events in the South African economy.

The SAFSI has important macroprudential and monetary policy implications. Firstly, the monthly frequency of the index allows for the real-time assessment of stress levels within the entire financial system, and the index can be easily updated to account for new observations as they become available. Secondly, the aggregation methodology ensures parsimony since each indicator is assessed in terms of its systemic importance and ranked according to its information content. As such, this approach may aid in analysing the usefulness of policy interventions from a monetary and macroprudential standpoint. Thirdly, the decomposition of the SAFSI into contributions from each market segment allows regulatory authorities to track how much each financial sector contributes to the build-up of stress at any given point in time. Knowledge of the sources of financial stress can guide the policymaker in choosing policy responses.

We use the estimated SAFSI to capture the abrupt change in financial regimes within a threshold vector autoregression model and find evidence of non-linearity in the transmission of a financial shock to real economy. Specifically, financial shocks are more detrimental to the real economy during stressful periods than normal times. An unexpected shock to financial stress conditions during financially vulnerable times is associated with a more prominent contraction in output and higher inflation. However, during normal times, the financial shock has a negligible impact on prices and interest rates, with a small output impact. These quantitative results suggest that policymakers in South Africa should acknowledge the non-linearities in the transmission of financial shocks and distinguish between the two states of the world.

In Chapter 3, we examine the predictive power of SAFSI with respect to output growth and inflation. Based on the information contained in this financial stress index, we forecast the aforementioned macroeconomic variables using three vector autoregression specifications: a mixed-frequency specification which includes quarterly and monthly time series data, a standard linear quarterly frequency model, and a threshold (non-linear) quarterly frequency specification. Each model is estimated over an in-sample period that runs from 1995Q1 to 2010Q4, and then out-of-sample forecasts are generated recursively over an expanding data window until 2017Q4. Our out-of-sample forecasts results, which are assessed by root mean-squared forecast errors (RMSFEs) suggest that the mixed-frequency model including the financial stress indicator performs the best in forecasting both output growth and inflation. The McCracken (2007) test of equal predictive ability between models lends support to these findings for up to four quarters ahead.

In addition, we generate one-year ahead ex-ante forecasts from the mixed-frequency vector autoregression including and excluding the financial stress index for the periods 2008Q1-2009Q4 and 2015Q1-2016Q4. We conduct this exercises to determine whether financial information provides valuable information specifically in terms of forecasting economic downturns experienced during these recent periods. The ex-ante forecasts reveal that including financial information results in more accurate forecasts for both output growth and inflation. In particular, the financial stress indicator performs better than expected in predicting the economic downturns experienced by the South African economy during the recession periods of 2008-2009 and during the end of 2015 and beginning of 2016 which was clouded by political tension.

Our results reveal that accounting for information that becomes available within the quarter (i.e. modelling monthly dynamics) substantially improves the forecasting performance of financial information in terms of output growth and inflation, which are considered key economic indicators in formulating monetary policy decisions. Substantial gains in forecast accuracy within the mixed-frequency specification is more apparent for nowcasts and short-term forecasts, while the benefits from within-quarter information vanish over longer horizons. Financial information does have the potential to serve as early warning indicators of economic vulnerabilities, however, policymakers should be aware that model specification plays a fundamental role in the degree of forecast accuracy.

Finally, in Chapter 4, we document the connection between economic uncertainty and financial market conditions, specifically that the macro-financial implications of an uncertainty shock differ across financial regimes. Using monthly South African data over the period 1995 to 2017, we estimate a non-linear VAR where uncertainty is captured by the average volatility of structural shocks in the economy. Regime shifts are abrupt and the economy shifts to a high stress regime characterised by tight financial condition when the financial stress indicator breaches an endogenously estimated threshold. We find that while the deterioration of output following an uncertainty shock is much more prominent during normal periods than during stressful periods, it is much more persistent during stressful financial times. Our findings support the proposition of Popescu & Rafael Smets (2010) that the impact of higher economic uncertainty is driven by its ability to increase financial uncertainty, and since there is not enough room for financial uncertainty to increase further in the stress regime, the response of output is smaller. Contrary to the aggregate demand effect and in support of the precautionary pricing effect, uncertainty shocks are inflationary in both regimes, with the impact being larger in the stress regime. Since price stability is one of the main goals of monetary policy in South Africa, the understanding of which propagation mechanism holds in the data is imperative. In line with this, we notice that although interest rates do not respond significantly to the volatility shock, we nevertheless note that the immediate jump in interest rates in the high stress regime points to the procyclical behaviour of monetary policy as output falls but prices rise. While our data reveals that financial frictions do not amplify the impact of uncertainty on real output, it does increase the impact on prices and interest rates. Our results suggest that policymakers could limit the propagation of uncertainty shocks by implementing appropriate macroprudential and monetary policy in line with the state of financial markets.

South Africa is a small open economy and hence is likely to be subjected to a variety of shocks from major global economies, as highlighted with regard to monetary policy shocks from the US recently by Meszaros & Olson (2020). Now given that, monetary policy shocks have been shown to generate significant macroeconomic uncertainty in the US (Mumtaz & Theodoridis (2019)), the possibility of spillover of US uncertainty to domestic uncertainty in South Africa via monetary policy shocks in the US (and other channels as outlined in Gupta et al. (2020)), cannot be ignored. Given this as part of future research, it would be interesting to analyze the role of foreign uncertainty, conditional on financial regimes, on macroeconomic variables of South Africa.

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Appendix A

Derivation of the candidate indicators of financial stress

Since inflation rates in South Africa have varied substantially over time (as is the case in most countries), most of the indicators listed in Table A.1 are in real terms as they have been deflated by the headline consumer price index (CPI). Seven useful candidate indicators can possibly capture stress in the equity market; similarly, stress in the credit market, foreign exchange market, money market, housing market, and commodity market can possibly be captured by up to twelve, five, four, three, and six candidate indicators respectively. The formulae used to construct each of the indicators defined in Table A.1 are outlined below under their respective market segments.

Table A.1: Full list of indicators of financial stress

Market segment	Abbreviation	Stress indicators
Equity market (EM)	**ABS_rALSI**	Realised volatility in the stock price index
	CMax_rALSI	Cumulative maximum loss in the real stock price index over a two-year moving window
	ABS_rBPI	Realised volatility in the bank price index
	CMax_rBPI	Cumulative maximum loss in the real bank price index over a two-year moving window
	Diff_ALSI	Difference in stock returns over bank returns
	EBR	Excess bank returns over the broad stock index
	ABS_EBR	Realised volatility of excess bank returns over the broad stock index
Credit market (CM)	**G_PCE**	Monthly growth of real credit extention to the domestic private sector
	SSPR	Spread between SA 10-year government bond and US 10-year government bond yield (sovereign risk spread)
	CDiff_SSPR	Cumulative difference corresponding to the maximum increase of the sovereign risk spread
	ABS_rRGOV10t	Realised volatility in the 10-year government bond yield
	CMin_rRGOV10	Increase in the 10-year government bond yield compared to the minimum over a two-year rolling window
	Term_SPR	Term spread between the 10-year (long-term) government bond yield and 3-month treasury bill yield
	3_Term_SPR	Term spread between the 0-3 year government bond yield and 3-month treasury bill yield
	3_5Term_SPR	Term spread between the 3-5 year government bond yield and 3-month treasury bill yield
	5_10Term_SPR	Term spread between the 5-10 year government bond yield and 3-month treasury bill yield
	Corp_SPR	Spread between Eskom corporate bond yield and 10-year government bond yield
	CMin_Corp	Increase in the Eskom corporate bond yield compared to the minimum over a two-year rolling window
	ABS_Corpt	Realised volatility in the Eskom corporate bond
Foreign exchange market (FX)	CUMUL_REER	Cumulative change in the real effective exchange rate
	CUMUL_USD	Cumulative change in the bilateral exchange rate between the South African rand (ZAR) and the US dollar (USD)
	ABS_REER	Realised volatility of the real effective exchange rate
	ABS_USD	Realised volatility of the ZAR/USD exchange rate
	CMin_USD	ZAR/USD exchange rate compared with its highest level over a two-year rolling window
Money market (MM)	**IBS**	Spread between the 3-month interbank rate and the 3-month treasury bill rate (interbank spread)
	PRIME_SPR	Spread between the prime overdraft rate and the 3-month treasury bill rate (prime rate spread)
	CDIFF_IBS	Cumulative difference corresponding to the maximum increase of the interbank spread
	CDIFF_PRIME	Cumulative difference corresponding to the maximum increase of the prime rate spread
Housing market (HM)	CMax_HPI	Cumulative maximum loss in the real house price index over a two-year rolling window
	G_HPI	Monthly growth of the real house price index
	Afford_index	Affordability index expressed as the ratio of real house price index over real income per household
Commodity market (ComM)	G_GOLD	Monthly growth of the real gold price (US dollar)
	G_OIL	Monthly growth of the real oil price (US dollar-Brent crude)
	ABS_OIL	Realised volatility of real oil price
	ABS_GOLD	Realised volatility of real gold price
	CMax_GOLD	Cumulative maximum loss in the real gold price over a two-year rolling window
	CMin_OIL	Increase in the real oil price compared to its highest level over a two-year rolling window

Notes: The table briefly outlines all the candidate indicators being considered. Indicators highlighted in bold are those that have been selected for the construction of the SAFSI, based on the selection methodology outlined in Section 2.3.1.4.

Equity market (EM)

Realised volatility in the stock price index (ABS_rALSI) Asset return volatilities tend to be influenced by investors' uncertainty about future fundamentals and/or the sentiment and behaviour of other investors. The stock price index is expressed in real terms ($rALSI_t$) and is computed as $\frac{ALSI_t}{CPI_t} \times 100$. The realised volatility in the stock price index is computed by adjusting the absolute monthly log returns of the real stock price index ($lnALSI_t$) by their 5-year volatility (given data limitations) to account for the possibility of long-term changes in the volatility of the variable.

$$\begin{cases} \ln ALSI_t = \log\left(rALSI_t\right) - \log\left(rALSI_{t-1}\right) \\ ABS\_rALSI_t = \left|\frac{\ln ALSI_t}{\sigma \ln ALSI_{t,t-59}}\right| \end{cases}$$

Cumulative maximum loss in the real stock price index over a two-year moving window (CMax_rALSI) This indicator is computed as the cumulative maximum loss (CMax) that corresponds to the maximum loss compared to the highest level of the stock price index over two years. CMax is computed over a rolling window of 24 months.

$$CMax\_rALSI_t = 1 - \frac{rALSI_t}{\max_{i=0}^{23}(rALSI_{t-i})}$$

Realised volatility in the bank price index (ABS_rBPI) Similar to the realised volatility in the stock price index, the realised volatility in the bank price index is computed by adjusting the absolute monthly log returns of the real bank sector stock market index returns ($\ln BPI_t$) by their 5-year volatility. The bank price index is expressed in real terms ($rBPI_t$) and is computed as $\frac{BPI_t}{CPI_t} \times 100$.

$$\begin{cases} \ln BPI_t = \log\left(rBPI_t\right) - \log\left(rBPI_{t-1}\right) \\ ABS\_rBPI_t = \left|\frac{\ln BPI_t}{\sigma \ln BPI_{t,t-59}}\right| \end{cases}$$

Cumulative maximum loss in the real bank price index over a two-year moving window

(CMax_rBPI) Analogous to the computation of CMax_rALSI,

$$CMax\_rBPI_t = 1 - \frac{rBPI_t}{\max_{i=0}^{23}(rBPI_{t-i})}$$

Difference in stock returns over bank returns (Diff_ALSI)

$$Diff\_ALSI_t = (\log(rALSI_t) - \log(rALSI_{t-1})) - (\log(rBPI_t) - \log(rBPI_{t-1}))$$

Excess bank returns over the broad stock index (EBR) Excess bank returns are computed by regressing the monthly log returns of the real stock price index ($\ln ALSI_t$) over the monthly log returns of the real bank sector stock market index returns ($\ln BPI_t$). The residual term ε_t of the OLS regression is then considered as the excess returns of the bank sector stock market index.

$$\begin{cases} \ln ALSI_t = a + b \ln BPI_t + \varepsilon_t \\ EBR_t = \varepsilon_t \end{cases}$$

Realised volatility of excess bank returns over the broad stock index (ABS_EBR) This is simply the absolute value of the excess returns of the bank sector stock market index (i.e. the residual term from the OLS regression above).

$$ABS\_EBR_t = |\varepsilon_t|$$

Credit market (CM)

Monthly growth of real credit extension to the domestic private sector (G_PCE) This indicator is computed as the first log difference of real credit extended to the domestic private sector (deflated by the CPI).

$$G\_PCE_t = (\log(PCE_t) - \log(PCE_{t-1})) \times 100$$

Spread between SA 10-year government bond and US 10-year government bond yield

(SSPR) The SA and US 10-year government bond yields are expressed in real terms as deflated by the corresponding CPI. Real SA 10-year government bond yield (rRGOV10) and real US 10-year government bond yield (rRGOV10$_{US}$) are computed as shown below together with the resulting sovereign spread.

$$\begin{cases} rRGOV10_t = RGOV10_t - \left(\frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} \times 100\right) \\ rRGOV10_{US,t} = RGOV10_{US,t} - \left(\frac{CPI_{US,t} - CPI_{US,t-1}}{CPI_{US,t-1}} \times 100\right) \\ SSPR_t = rRGOV10_t - rRGOV10_{US,t} \end{cases}$$

Cumulative difference corresponding to the maximum increase of the sovereign risk spread (CDiff_SSPR) This measure is calculated over a two-year rolling window and serves to disentangles changes in risk profiles from changes in the proxy for the risk-free rate.

$$CDiff\_SSPR_t = rRGOV10_t - rRGOV10_{US,t} - \min_{i=0}^{23}(rRGOV10_{t-i} - rRGOV10_{US,t-i})$$

Realised volatility in the 10-year government bond yield (ABS_rRGOV10) The realised volatility is computed as the absolute monthly changes of the SA real 10-year government bond yield, adjusted by their 5-year volatility. Changes rather than growth rates are used to avoid excessively large variations that occur with very low yields.

$$\begin{cases} chrRGOV10_t = rRGOV10_t - rRGOV10_{t-1} \\ ABS\_rRGOV10_t = \left|\frac{chrRGOV10_t}{\sigma chrRGOV10_{t,t-59}}\right| \end{cases}$$

Increase in the 10-year government bond yield compared to the minimum over a two-year rolling window (CMin_rRGOV10)

$$CMin\_rRGOV10_t = \frac{rRGOV10_t}{\min_{i=0}^{23}(rRGOV10_{t-i})} - 1$$

Term spread between the 10-year (long-term) government bond yield and 3-month treasury bill yield (Term_SPR)

$$Term\_SPR_t = RGOV10_t - Tbill_t$$

Term spread between the 0-3 year government bond yield and 3-month treasury bill yield (3_Term_SPR)

$$3\_Term\_SPR_t = RGOV0\_3_t - Tbill_t$$

Term spread between the 3-5 year government bond yield and 3-month treasury bill yield (3_5Term_SPR)

$$3\_5Term\_SPR_t = RGOV3\_5_t - Tbill_t$$

Term spread between the 5-10 year government bond yield and 3-month treasury bill yield (5_10Term_SPR)

$$5\_10Term\_SPR_t = RGOV5\_10_t - Tbill_t$$

Spread between Eskom corporate bond yield and 10-year government bond yield (Corp_SPR) This indicator is computed as the difference in yield between an Eskom corporate bond (Corp) and a 10-year SA government bond.

$$Corp\_SPR_t = Corp_t - RGOV10_t$$

Increase in the Eskom corporate bond yield compared to the minimum over a two-year rolling window (CMin_Corp)

$$CMin\_Corp_t = \frac{Corp_t}{\min_{i=0}^{23}(Corp_{t-i})} - 1$$

Realised volatility in the Eskom corporate bond (ABS_Corp) The realised volatility is computed as the absolute monthly changes in the Eskom corporate bond yield, adjusted by their 5-year volatility to capture possible long-term changes in the volatility of yield.

$$\begin{cases} \ln Corp_t = \log\left(Corp_t\right) - \log\left(Corp_{t-1}\right) \\ ABS\_Corp_t = \left|\frac{\ln Corp_t}{\sigma \ln Corp_{t,t-59}}\right| \end{cases}$$

Foreign exchange market (FX)

Cumulative change in the real effective exchange rate (CUMUL_REER) The cumulative change (CUMUL) is computed over six months to capture longer-lasting changes in the real effective exchange rate (REER) which tend to be associated with more severe stress, as the real economy adjusts gradually over time. The REER is volatile around a changing rate if CUMUL>0.

$$CUMUL\_REER_t = [REER_t - REER_{t-6}]$$

Cumulative change in the bilateral exchange rate between the South African rand (ZAR) and the US dollar (USD) (CUMUL_USD) This is computed in a similar manner as the CUMUL_REER as longer-lasting changes in the bilateral exchange rate with a major trading partner, in this case the United States, would be associated with financial stress. A CUMUL>0 would imply that the US dollar is volatile around a changing rate.

$$CUMUL\_USD_t = [ZAR/USD_t - ZAR/USD_{t-6}]$$

Realised volatility of the real effective exchange rate (ABS_REER) Realised volatility again is computed as the absolute monthly changes in the REER, adjusted by their 5-year volatility to capture possible long-term changes in the volatility of the exchange rate.

$$\begin{cases} chREER_t = REER_t - REER_{t-1} \\ ABS\_REER_t = \left|\frac{chREER_t}{\sigma chREER_{t,t-59}}\right| \end{cases}$$

Realised volatility of the ZAR/USD exchange rate (ABS_USD)

$$\begin{cases} chUSD_t = ZAR/USD_t - ZAR/USD_{t-1} \\ ABS\_USD_t = \left| \frac{chUSD_t}{\sigma chUSD_{t,t-59}} \right| \end{cases}$$

ZAR/USD exchange rate compared with its highest level over a two-year rolling window (CMin_USD) This indicator captures financial stress associated with exchange rate depreciation.

$$CMin\_USD_t = \frac{ZAR/USD_t}{\min_{i=0}^{23}(ZAR/USD_{t-i})} - 1$$

Money market (MM)

Spread between the 3-month interbank rate and the 3-month treasury bill rate (interbank spread) (IBS) The interbank spread is an indicator of liquidity risks in the interbank market. The interbank rate is denoted by JIBAR (Johannesburg Interbank Average Rate).

$$IBS_t = JIBAR_t - Tbill_t$$

Spread between the prime overdraft rate and the 3-month treasury bill rate (prime rate spread) (PRIME_SPR) This indicator represents the risk premium on lending. PRIME denotes the prime overdraft interest rate.

$$PRIME\_SPR_t = PRIME_t - Tbill_t$$

Cumulative difference corresponding to the maximum increase of the interbank spread (CDiff_IBS)

$$CDiff\_IBS_t = JIBAR_t - Tbill_t - \min_{i=0}^{23}(JIBAR_{t-i} - Tbill_{t-i})$$

Cumulative difference corresponding to the maximum increase of the prime rate spread

(CDiff_PRIME)

$$CDiff\_PRIME_t = PRIME_t - Tbill_t - \min_{i=0}^{23}(PRIME_{t-i} - Tbill_{t-i})$$

Housing market (HM)

The ABSA house price index (HPI) is used to construct the HM indicators, however, since this index has been suspended from the end of 2016 due to methodological issues, I extrapolate the ABSA HPI from December 2016 using the year-on-year growth rate of FNB HPI (note that there is a 91.2% correlation between the year-on-year growth of ABSA HPI and FNB HPI, supporting extrapolation). The ABSA HPI indices are based on the total purchase price of homes in the 80-400 square meter size category, priced at R4.2 million or less in 2015 (including improvements), in respect of which mortgage loan applications were received and approved by ABSA. The ABSA HPI is expressed in real terms ($rHPI_t$) as deflated by the CPI.

Cumulative maximum loss in the real house price index over a two-year rolling window (CMax_HPI)

$$CMax\_HPI_t = 1 - \frac{rHPI_t}{\max_{i=0}^{23}(rHPI_{t-i})}$$

Monthly growth of the real house price index (G_HPI)

$$G\_HPI_t = (\log(rHPI_t) - \log(rHPI_{t-1})) \times 100$$

Affordability index expressed as the ratio of real house price index over real income per household (Afford_index) Interpolation is performed on quarterly frequency disposable income of households, sourced from the South African Reserve Bank (SARB), to get monthly estimates. The disposable income I_t is deflated by the CPI resulting in real disposable income of households rI_t.

$$Afford\_index_t = \frac{rHPI_t}{rI_t}$$

Commodity market (ComM)

Vulnerabilities in the commodity market is a possible source of financial stress in the South Africa given that the country is a resource-based and small open economy that depends on developments in international markets.

Monthly growth of the real gold price (US dollar) (G_GOLD) Since the gold price is expressed in USD dollar terms, it is deflated by the US CPI resulting in real gold price rGOLD.

$$G\_GOLD_t = (\log(rGOLD_t) - \log(rGOLD_{t-1})) \times 100$$

Monthly growth of the real oil price (US dollar-Brent crude) (G_OIL) Similar to the gold price, the oil price is deflated by the US CPI and the resultant real oil price rOIL is obtained.

$$G\_OIL_t = (\log(rOIL_t) - \log(rOIL_{t-1})) \times 100$$

Realised volatility of real oil price (ABS_OIL)

$$ABS\_OIL_t = \left| \frac{G\_OIL_t}{\sigma G\_OIL_{t,t-59}} \right|$$

Realised volatility of real gold price (ABS_GOLD)

$$ABS\_GOLD_t = \left| \frac{G\_GOLD_t}{\sigma G\_GOLD_{t,t-59}} \right|$$

Cumulative maximum loss in the real gold price over a two-year rolling window (CMax_GOLD)

$$CMax\_GOLD_t = 1 - \frac{rGOLD_t}{\max_{i=0}^{23}(rGOLD_{t-i})}$$

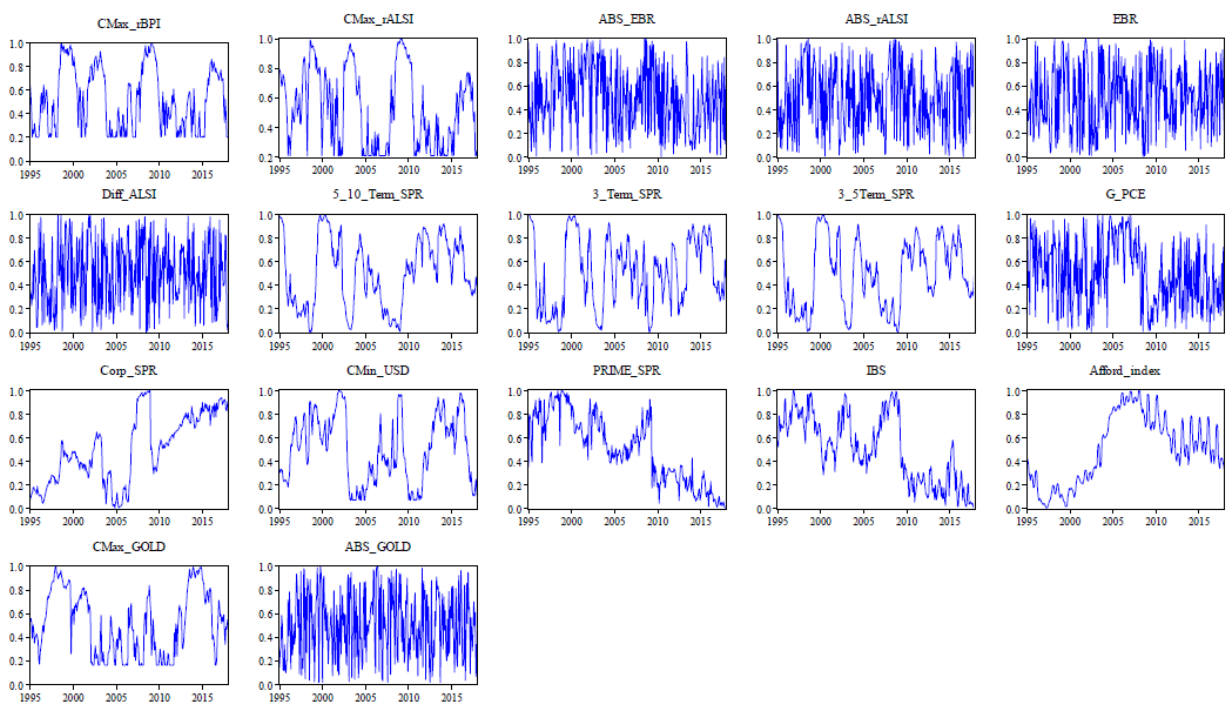
Increase in the real oil price compared to its highest level over a two-year rolling window

(CMin_OIL)

$$CMin\_OIL_t = \frac{rOIL_t}{\min_{i=0}^{23}(rOIL_{t-i})} - 1$$

Construction of SAFSI

Figure A.1: Standardised stress indicators, January 1995 - December 2017



Notes: The figure shows the empirical cumulative distribution function (ECDF) for each of the 17 indicators selected based on the selection procedure outlined above. Descriptions of the indicators are provided in Appendix A.

Table A.2: AUROC and partial AUROC of raw stress indicators

Market segment	Stress indicator	AUROC	pAUROC		
		of stress indicator	of stress indicator	of market segment	Incremental
Equity market (EM)	**CMax_rBPI**	**0,851**	**0,880**	**0,880**	**0,000**
	CMax_rALSI	**0,750**	**0,776**	**0,884**	**0,004**
	ABS_EBR	**0,686**	**0,724**	**0,901**	**0,017**
	ABS_rALSI	**0,632**	**0,640**	**0,905**	**0,003**
	EBR	**0,581**	**0,615**	**0,906**	**0,001**
	Diff_ALSI	**0,583**	**0,603**	**0,907**	**0,001**
	ABS_rBPI	0,552	0,557	0,871	-0,036
Credit market (CM)	**5_10_Term_SPR**	**0,650**	**0,675**	**0,675**	**0,000**
	3_Term_SPR	**0,635**	**0,668**	**0,687**	**0,011**
	Term_SPR	0,696	0,664	0,657	-0,030
	3_5Term_SPR	**0,625**	**0,645**	**0,695**	**0,009**
	ABS_rRGOV10	0,604	0,631	0,685	-0,010
	CMin_Corp	0,595	0,624	0,686	-0,010
	ABS_Corp	0,574	0,597	0,687	-0,008
	G_PCE	**0,593**	**0,596**	**0,702**	**0,006**
	Corp_SPR	**0,501**	**0,553**	**0,711**	**0,010**
	SSPR	0,568	0,285		
	CDiff_SSPR	0,552	0,280		
	CMin_rRGOV10	0,560	0,245		
Foreign exchange market (FX)	**CMin_USD**	**0,775**	**0,825**	**0,825**	**0,000**
	CUMUL_USD	0,573	0,596	0,692	-0,133
	CUMUL_REER	0,574	0,580	0,544	-0,281
	ABS_USD	0,550	0,571	0,541	-0,283
	ABS_REER	0,512	0,522	0,543	-0,281
Money market (MM)	**PRIME_SPR**	**0,815**	**0,878**	**0,878**	**0,000**
	IBS	**0,782**	**0,858**	**0,883**	**0,005**
	CDIFF_PRIME	0,691	0,727	0,863	-0,020
	CDIFF_IBS	0,637	0,666	0,859	-0,024
Housing market (HM)	**Afford_index**	**0,638**	**0,694**	**0,694**	**0,000**
	CMax_HPI	0,579	0,571	0,677	-0,016
	G_HPI	0,568	0,563	0,683	-0,011
Commodity market (ComM)	**CMax_GOLD**	**0,595**	**0,634**	**0,634**	**0,000**
	ABS_OIL	0,590	0,606	0,615	-0,019
	ABS_GOLD	**0,550**	**0,571**	**0,672**	**0,038**
	CMin_oil	0,558	0,547	0,654	-0,019
	G_GOLD	0,523	0,523	0,667	-0,005
	G_OIL	0,517	0,520	0,579	-0,093

Notes: This table lists 17 of the most useful stress indicators (highlighted in bold) selected based on the selection procedure outlined in Section 2.3.1.4. Descriptions of the indicators are provided in Appendix A. The indicators SSPR, CDiff_SSPR, and CMin_rRGOV10 are discarded in the selection procedure as they have pAUROC values less than 0.5.

Time-varying cross-correlations

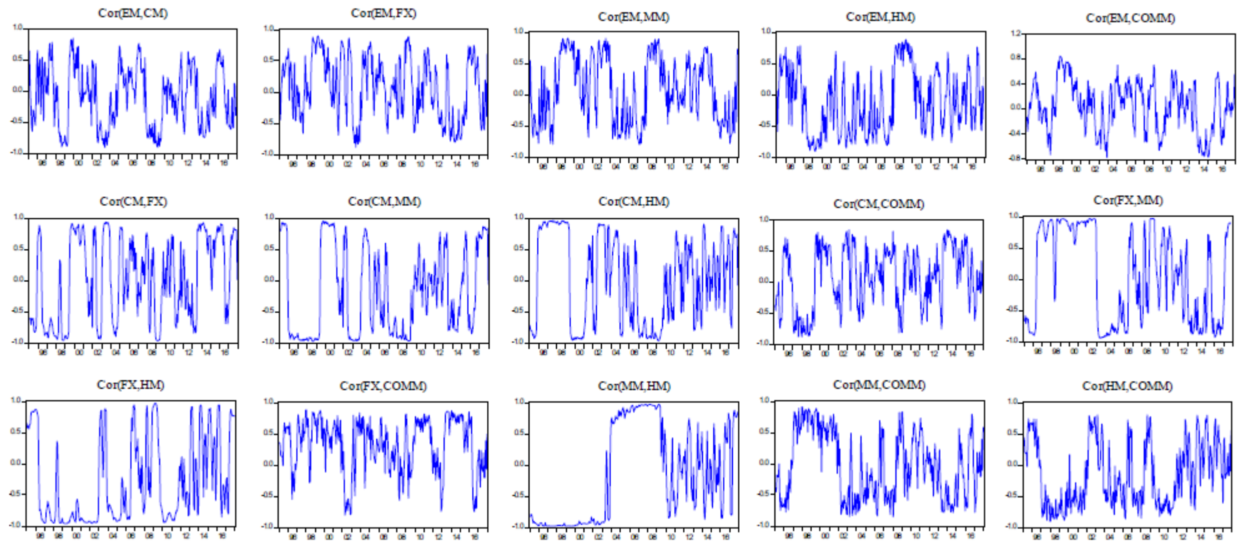
$$C_t = \begin{bmatrix} 1 & \rho_{EM,CM,t} & \rho_{EM,FX,t} & \rho_{EM,MM,t} & \rho_{EM,HM,t} & \rho_{EM,ComM,t} \\ \rho_{EM,CM,t} & 1 & \rho_{CM,FX,t} & \rho_{CM,MM,t} & \rho_{CM,HM,t} & \rho_{CM,ComM,t} \\ \rho_{EM,FX,t} & \rho_{CM,FX,t} & 1 & \rho_{FX,MM,t} & \rho_{FX,HM,t} & \rho_{FX,ComM,t} \\ \rho_{EM,MM,t} & \rho_{CM,MM,t} & \rho_{FX,MM,t} & 1 & \rho_{MM,HM,t} & \rho_{MM,ComM,t} \\ \rho_{EM,HM,t} & \rho_{CM,HM,t} & \rho_{FX,HM,t} & \rho_{MM,HM,t} & 1 & \rho_{HM,ComM,t} \\ \rho_{EM,ComM,t} & \rho_{CM,ComM,t} & \rho_{FX,ComM,t} & \rho_{MM,ComM,t} & \rho_{HM,ComM,t} & 1 \end{bmatrix}$$

The time-varying cross-correlations $\rho_{m,m',t}$ are estimated by means of a multivariate GARCH. This method is preferred as it data-driven (i.e. it uses the information provided by the data to estimate the parameters of the model), is able to capture abrupt changes in the correlation structure, and limits the risk of omitted variable bias given its multivariate nature Louzis & Vouldis (2012). The commonly used diagonal Baba, Engle, Kraft, and Kroner (BEKK) multivariate GARCH model introduced by Engle & Kroner (1995) is used in this chapter. The diagonal representation of the model assists in coping with the dimensionality problem (i.e. given the large number of parameters that have to be estimated). We use the diagonal BEKK multivariate GARCH (1,1) specification as in all cases this specification turns out to be the best model, in terms of the Schwarz criterion and Akaike information criterion, over models with more lags. This model is defined as

$$H_t = V_0 V_0' + A' \bar{S}_{t-1} \bar{S}_{t-1}' A + B' H_{t-1} B$$

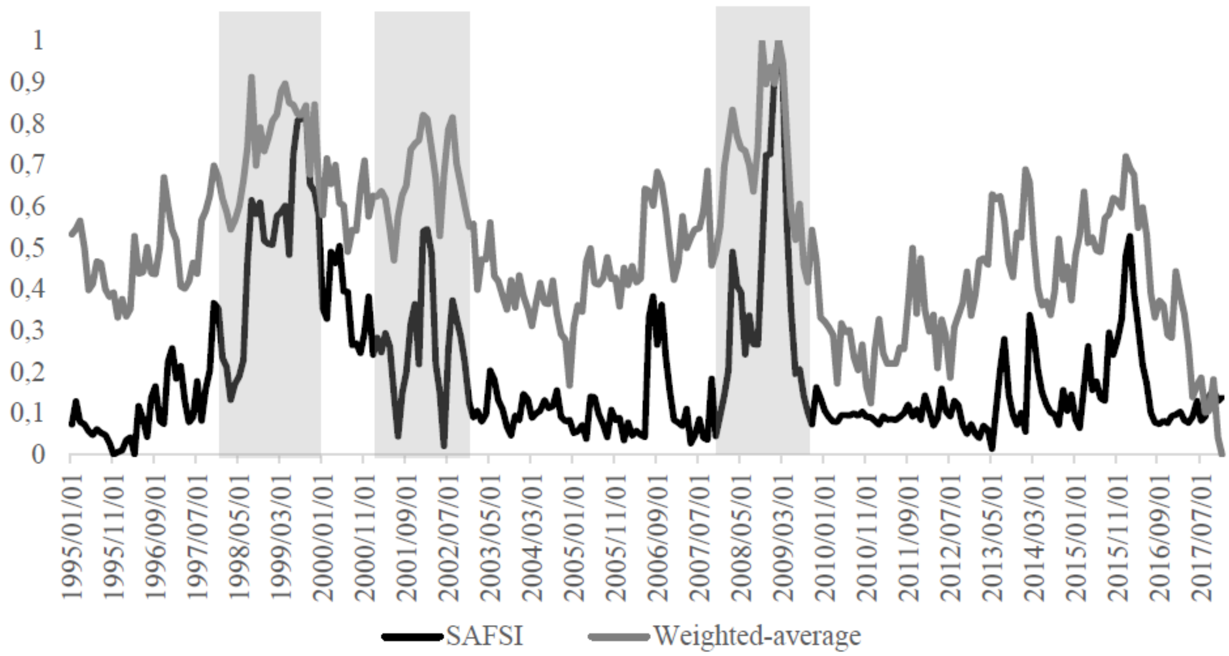
where V_0 is a 6x6 lower triangular matrix, A and B are 6x6 diagonal matrices; $\bar{S}_{t-1}$ is the vector of lagged demeaned normalised market sub-indices where $\bar{S}_t = S_t - 0.5$ because of the properties of the cumulative density function; and H_t is the 6x6 variance-covariance matrix of the demeaned normalised sub-indices. The constant term $V_0 V_0'$, which is the product of the two lower triangular matrices constant term, ensures the positive definiteness of the covariance matrices. Maximising the Gaussian likelihood function of the multivariate process determines the parameters of the model.

Figure A.2: Time-varying cross-correlations between market sub-indices, January 1995 - December 2017



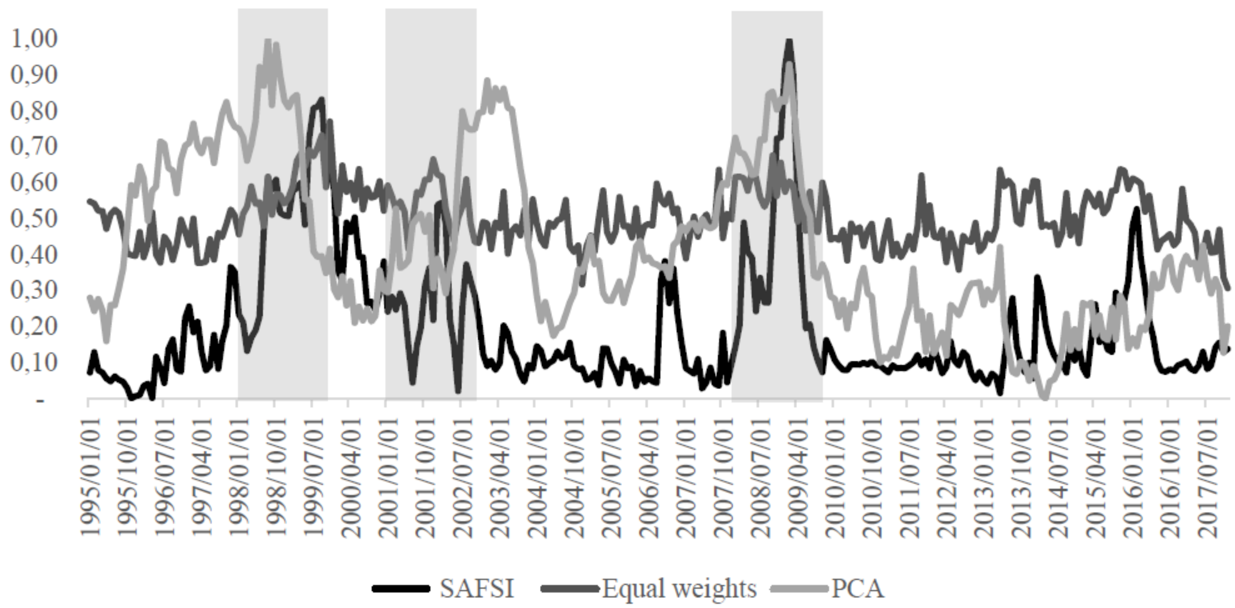
Notes: Pair-wise correlations are computed using a diagonal BEKK multivariate GARCH (1,1) model. ‘EM’, ‘CM’, ‘FX’, ‘MM’, ‘HM’, ‘ComM’ respectively denotes the equity market, credit market, foreign exchange market, housing market, and commodity market.

Figure A.3: SAFSI versus the simple weighted average of sub-indices ("perfect correlation")



Notes: The figure shows the comparison of the SAFSI (i.e. with information weights and correlation weights using Equation 2.4) with its perfect correlation counterpart using simple weighted average of market sub-indices (i.e. with information weights only) over the sample period (January 1995 - December 2017). The shaded regions correspond to the identified periods of financial stress (see Section 2.3.1.2).

Figure A.4: SAFSI and alternative measures



Notes: This figure compares the SAFSI with two alternative financial stress measures: one computed using PCA and the other constructed using equal-weights. The shaded regions depict the benchmark episodes of financial stress.

Threshold vector autoregression (TVAR)

Gibbs algorithm for TVAR with a Metropolis Hastings step

The following steps are followed to draw samples from the posterior distribution of the VAR parameters:

1. Set the priors for parameters. We make the assumption that $p(Y^*) \sim N(\bar{Y}^*, \sigma_{Y^*})$. A natural conjugate prior is imposed for the VAR parameters in both regimes via dummy observations (see Banbura et al. (2010). We set the initial value for Y^* as the mean of the threshold variable i.e. SAFSI.

2. The data is separated into two regimes i.e. tranquil regime (1) and financially stressful regime (2). The sample for the first regime $Y_{1,t}$ includes all observations where $S_(t) \leq Y^*$ and the sample for the second regime $Y_{2,t}$ includes all observations where $S_(t) > Y^*$.

3. The VAR parameters $b_r = \{c_r, \beta_r\}$ and ω_r are sampled in each regime $r = 1,2$. The conditional distribution of the VAR parameters is given by

$$H(b_r|\omega_r, Y_t, Y^*) \sim N(vec(B_r^*), \omega_r \otimes (X_r^{*\prime} X_r^*)^{-1}) H(\omega_r|b_r, Y_t, Y^*) \sim IW(S_r^*, T_r^*)$$

   where X denotes the right hand side variables of the VAR system, $y_r^* = [Y_{r,t}; Y_D]$ and $X_r^* = [X_{r,t}; Y_D]$ with Y_D, X_D the dummy observations that define the prior for the left and right hand side of the VAR respectively (see Banbura et al. (2010)) for further details on the construction of the dummy variables). Furthermore $B_r^* = (X_r^{*\prime} X_r^*)^{-1}(X_r^{*\prime} y_r^*)$ and $S_r^* = (y_r^* - X_r^* b)'(y_r^* - X_r^* b_r)$.

4. Since the posterior distribution of Y^* is not analytically tractable, we perform a random walk Metropolis Hastings step for sampling Y^* in each simulation i.e. $Y_{new}^* = Y_{old}^* + e$, where

$e \sim N(0,\Sigma)$ and Σ is a scaling factor which is chosen to ensure that the acceptance rate is in the 20-40% interval. The acceptance probability is computed as

$$\alpha = \frac{F(Y|b_r,\omega_r,Y^*_{new})p(Y^*_{new})}{F(Y|b_r,\omega_r,Y^*_{old})p(Y^*_{old})}$$

where $F(.)$ is the likelihood of the VAR computed as the product of the likelihoods in the two regimes.

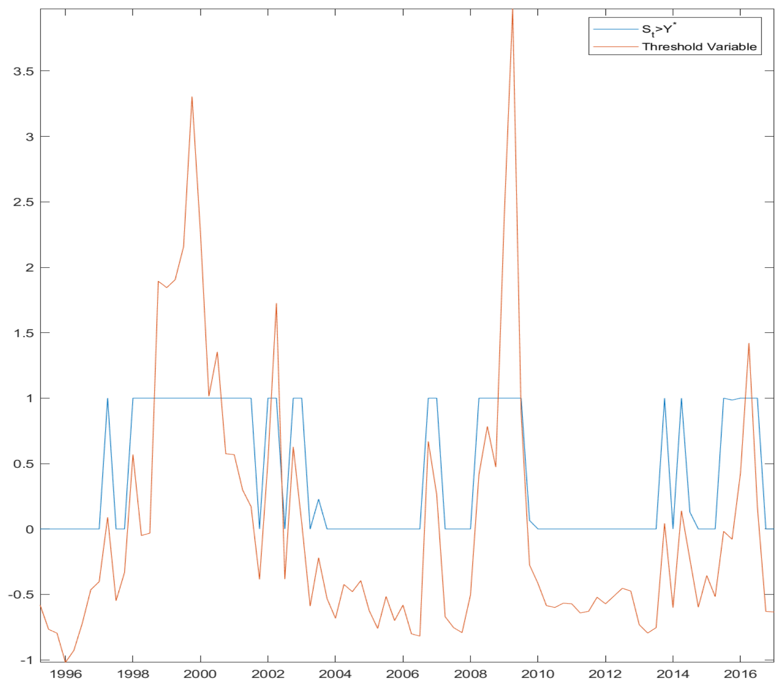
Impulse response definition and probability of regimes

Impulse responses are computed using monte-carlo integration and defined as

$$IRF^r_t = E(Y_{t+h}|\theta_t,Y^r_{t-1},\mu) - E(Y_{t+h}|\theta_t,Y^r_{t-1})$$

where θ_t represents all the parameters and hyperparameters of the VAR model, h is the horizon under consideration, $r = 1,2$ denotes the regime and μ is the shock. The above equation states that the impulse responses are computed as the difference between two conditional expectations: The first term is the forecast of the endogenous variables conditional on one of the structural shocks μ; the second term being the baseline forecast i.e. where the shock equals zero. The impulse responses are conditioned on observations in each regime and the conditional expectations are approximated via a stochastic simulation of the VAR model (Alessandri & Mumtaz (2017)).

Figure A.5: Probability of Regime 2



Notes: The figure shows the estimated threshold variable and the probability of the of stress regimes which occurs when the threshold variable is greater than the threshold value estimated by the model.

Appendix B

Gibbs sampling algorithm for the MF-VAR model

The following steps describe the Gibbs sampler for the MF-VAR:

1. Set priors and starting values. The prior for the VAR parameters α, F, and Ω are set using a Normal-Inverse Wishart (NIW) conjugate prior via dummy observations. Collecting the VAR coefficients in the matrix B i.e.$B = \{\alpha, F\}$, and the non-zero elements of the variance-covariance matrix Ω in the matrix $\sum = \begin{pmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} \\ \Omega_{12} & \Omega_{22} & \Omega_{23} \\ \Omega_{13} & \Omega_{23} & \Omega_{33} \end{pmatrix}$, this prior can be represented as $p(B) \sim N(B_0, A)$ and $p(\sum) \sim IW(\sum_0, V_0)$. The Kalman filter requires an initial value of the state vector $s_t = (\hat{Z}_t, X_t, \hat{Z}_{t-1}, X_{t-1}, \ldots, \hat{Z}_{t-p}, X_{t-p})'$. An initial estimate of $\hat{Z}_t$ is obtained by simple interpolation to fill in the months with missing data.

2. Conditional on $\hat{Z}_t$ and the error covariance matrix $\sum$, the posterior for the VAR coefficients B in vectorised form is normal and given as $H(B|\hat{Z}_t, \sum) \sim N(B^*, (A^{-1} + \sum^{-1} \otimes \bar{X}_t' \bar{X}_t)^{-1})$ where $B^* = (A^{-1} + \sum^{-1} \otimes \bar{X}_t' \bar{X}_t)^{-1}(A^{-1} vec(B_0) + \sum^{-1} \otimes \bar{X}_t' \bar{X}_t vec(\hat{B})), \bar{X}_t = \{\hat{Z}_{t-1}, X_{t-1}, \hat{Z}_{t-2}, X_{t-2}, \hat{Z}_{t-3}, X_{t-3}, 1\}$, and $\hat{B}$ is the OLS estimate of B using $\bar{Y}_t = \{\hat{Z}_t, X_t\}, \bar{X}_t$.

3. Conditional on $\hat{Z}_t$ and the VAR coefficients B, the error covariance $\sum$ has an inverse Wishart posterior with scale matrix $(\bar{Y}_t - \bar{X}_t B)'(\bar{Y}_t - \bar{X}_t B) + \sum_0)$ and degrees of freedom $(T + V_0)$.

4. This step refers to drawing the latent observations. Given a draw of the VAR parameters, the state variable $\hat{Z}_t$ is drawn using the Carter and Kohn algorithm with the Kalman filter. The

backward recursion needs a modification to account for the fact that the variance-covariance matrix Ω is singular (see Carter & Kohn (1994) for the implied modification). The backward recursion delivers a draw of $\hat{Z}'_T = (\hat{Z}_1, \hat{Z}_2, \ldots, \hat{Z}_T)$ from its conditional posterior distribution. Draws for $\hat{Z}_t$ are obtained by using the Carter and Kohn algorithm i.e. we run the Kalman filter from $t = 1, \ldots, T$ to obtain the mean $\hat{Z}_{T|T}$ as well as variance $P_{T|T}$ of the distribution $H(\hat{Z}_T|\tilde{Y}_T)$ (where $\tilde{Y}_T = [Y_1, \ldots, Y_T]$) and draw $\hat{Z}'_T$ from $N(\hat{Z}_{T|T}, P_{T|T})$. Subsequently, for $t = T-1, \ldots, 1$ we draw $\hat{Z}_t$ from $N(\hat{Z}_{t|t}, P_{t|t})$ by recursively updating $\hat{Z}_{t|t}$ and $P_{t|t}$.

Model results excluding three-month treasury bill rate (r)

Table B.1: Relative RMSFE of alternative specifications, 2011-2017

		VAR (fsi_quantec)	*TVAR (fsi_quantec)*	*MF-VAR (fsi_quantec)*
h = 1	gdp	1,041**	1,070**	0,666***
	cpi	0,966**	1,069**	0,586***
h = 2	gdp	1,020*	1,020*	0,684***
	cpi	1,024*	1,086***	0,589***
h = 3	gdp	1,009	1,002	0,645***
	cpi	1,059	1,048**	0,590***
h = 4	gdp	1,003	0,999	0,617***
	cpi	1,094	0,989	0,599***
h = 5	gdp	1,003	0,998	0,609**
	cpi	1,118	0,963	0,586*
h = 6	gdp	1,003	0,998	0,605*
	cpi	1,127	0,950	0,573*
h = 7	gdp	1,004	1,000	0,604
	cpi	1,134	0,940	0,561
h = 8	gdp	1,004	1,001	0,600
	cpi	1,138	0,922	0,550

Notes: The table reports the average root mean square forecast errors (RMSFE) relative to the benchmark model ($VAR\xi$ - a linear common frequency vector autoregressive model containing only the macroeconomic variables - refer to Section 3.4 for more detail) for gross domestic product growth (gdp) and consumer price inflation (cpi) for different forecast horizons h and different models which include the macroeconomic variables and financial market information captured by $fsi\_quantec$. VAR, $TVAR$, and $MF-VAR$ are the alternative vector autoregressive models specified in linear common frequency, non-linear common frequency, and mixed-frequency, respectively. The McCracken (2007) test is carried out where differences in forecast accuracy are statistically significant at the 1% (***), 5% (**), or 10% (*) level.

Table B.2: RMSFE of alternative models, 2011-2017

		VARξ	*VAR (safsi)*	*TVAR (safsi)*	*MF-VAR (safsi)*	*VAR (fsi_quantec)*	*TVAR (fsi_quantec)*	*MF-VAR (fsi_quantec)*
h = 1	gdp	1,788	1,733	1,694	1,155	1,861	1,913	1,192
	cpi	0,623	0,627	0,516	0,365	0,602	0,666	0,365
h = 2	gdp	2,197	2,172	2,123	1,489	2,242	2,24	1,502
	cpi	0,759	0,76	0,668	0,438	0,777	0,824	0,447
h = 3	gdp	2,452	2,443	2,406	1,57	2,475	2,457	1,582
	cpi	0,819	0,82	0,686	0,471	0,867	0,858	0,483
h = 4	gdp	2,606	2,61	2,584	1,6	2,614	2,603	1,608
	cpi	0,85	0,849	0,684	0,496	0,93	0,841	0,509
h = 5	gdp	2,617	2,666	2,655	1,613	2,672	2,658	1,621
	cpi	1,268	0,896	0,691	0,513	1,002	0,863	0,525
h = 6	gdp	2,688	2,688	2,673	1,622	2,697	2,683	1,626
	cpi	0,937	0,937	0,693	0,524	1,056	0,89	0,537
h = 7	gdp	2,71	2,711	2,695	1,632	2,72	2,71	1,636
	cpi	0,972	0,972	0,695	0,534	1,102	0,914	0,545
h = 8	gdp	2,739	2,74	2,726	1,64	2,75	2,741	1,644
	cpi	1,003	1,003	0,696	0,543	1,141	0,925	0,552

Notes: The table reports the average root mean square forecast errors (RMSFE) of the alternative models in levels for gross domestic product growth (gdp) and consumer price inflation (cpi) for different forecast horizons h and different models. $VAR\xi$ is the benchmark model (a linear common frequency vector autoregressive model containing only the two macroeconomic variables, while VAR, $TVAR$, and $MF-VAR$ are the alternative vector autoregressive models that includes the two macroeconomic variables as well as financial information (proxied by the financial stress indexes, $safsi$ or $fsi\_quantec$) specified in linear common frequency, non-linear common frequency, and mixed-frequency, respectively.

Robustness check including three-month treasury bill rate (r)

Table B.3: Relative RMSFE of alternative specifications, 2011-2017

		VAR (safsi)	*TVAR (safsi)*	*MF-VAR (safsi)*	*VAR (fsi_quantec)*	*TVAR (fsi_quantec)*	*MF-VAR (fsi_quantec)*
h = 1	gdp	0,973**	0,973**	0,632***	1,019*	1,038**	0,654***
	cpi	0,978**	0,852***	0,577***	0,913***	0,944***	0,583***
h = 2	gdp	0,989	0,981*	0,667***	0,983*	0,986	0,671***
	cpi	0,967**	0,873***	0,521***	0,862***	0,881***	0,516***
h = 3	gdp	0,997	0,991	0,643***	0,984*	0,986	0,645***
	cpi	0,958**	0,859***	0,502***	0,841***	0,842***	0,493***
h = 4	gdp	1,001	0,999	0,621***	0,985**	0,990	0,624**
	cpi	0,954**	0,855***	0,497***	0,836***	0,825***	0,486***
h = 5	gdp	1,000	0,997	0,607**	0,991	0,995	0,611**
	cpi	0,955**	0,853***	0,488***	0,835***	0,816**	0,477**
h = 6	gdp	1,000	0,998	0,605*	0,993	0,994	0,609*
	cpi	0,956*	0,853**	0,484**	0,844**	0,820	0,476
h = 7	gdp	1,000	0,998	0,603	0,993	0,993	0,608
	cpi	0,956	0,854	0,481*	0,849	0,818	0,472
h = 8	gdp	1,000	0,999	0,599	0,994	0,994	0,603
	cpi	0,957	0,853	0,478	0,852	0,811	0,468

Notes: The table reports the average root mean square forecast errors (RMSFE) relative to the benchmark model ($VAR\xi$ - a linear common frequency vector autoregressive model containing only the macroeconomic variables - including gross domestic product growth (gdp), consumer price inflation (cpi), as well as the three-month treasury bill rate (r)) for gdp and cpi for different forecast horizons h and different models which include the macroeconomic variables and financial market information captured by $safsi$ or $fsi\_quantec$. VAR, $TVAR$, and $MF-VAR$ are the alternative vector autoregressive models specified in linear common frequency, non-linear common frequency, and mixed-frequency, respectively. The McCracken (2007) test is carried out where differences in forecast accuracy are statistically significant at the 1% (***), 5% (**), or 10% (*) level.

Table B.4: RMSFE of alternative models, 2011-2017

		VARξ	*VAR (safsi)*	*TVAR (safsi)*	*MF-VAR (safsi)*	*VAR (fsi_quantec)*	*TVAR (fsi_quantec)*	*MF-VAR (fsi_quantec)*
h = 1	gdp	1,807	1,758	1,758	1,142	1,842	1,876	1,182
	cpi	0,588	0,575	0,501	0,339	0,537	0,555	0,343
h = 2	gdp	2,215	2,190	2,172	1,478	2,178	2,185	1,485
	cpi	0,747	0,722	0,652	0,389	0,644	0,658	0,386
h = 3	gdp	2,439	2,432	2,418	1,568	2,399	2,406	1,573
	cpi	0,804	0,770	0,691	0,404	0,676	0,677	0,397
h = 4	gdp	2,584	2,586	2,581	1,604	2,544	2,559	1,612
	cpi	0,829	0,791	0,709	0,412	0,693	0,684	0,403
h = 5	gdp	2,661	2,660	2,654	1,614	2,638	2,647	1,626
	cpi	0,851	0,813	0,726	0,415	0,711	0,694	0,406
h = 6	gdp	2,680	2,679	2,674	1,621	2,660	2,663	1,631
	cpi	0,860	0,822	0,734	0,416	0,726	0,705	0,409
h = 7	gdp	2,700	2,699	2,695	1,627	2,682	2,682	1,641
	cpi	0,870	0,832	0,743	0,419	0,739	0,712	0,411
h = 8	gdp	2,728	2,727	2,724	1,635	2,711	2,711	1,646
	cpi	0,879	0,841	0,750	0,420	0,749	0,713	0,411

Notes: The table reports the average root mean square forecast errors (RMSFE) relative to the benchmark model ($VAR\xi$ - a linear common frequency vector autoregressive model containing only the macroeconomic variables - including gross domestic product growth (gdp), consumer price inflation (cpi), as well as the three-month treasury bill rate (r)) for gdp and cpi for different forecast horizons h and different models which include the macroeconomic variables and financial market information captured by $safsi$ or $fsi\_quantec$. *VAR*, *TVAR*, and $MF-VAR$ are the alternative vector autoregressive models specified in linear common frequency, non-linear common frequency, and mixed-frequency, respectively. The McCracken (2007) test is carried out where differences in forecast accuracy are statistically significant at the 1% (***), 5% (**), or 10% (*) level.

Predictive performance gain of including a financial indicator in a MF-VAR

Excluding three-month treasury bill rate (r)

Table B.5: RMSFE of MF-VAR ($fsi\_quantec$) relative to MF-VAR excluding the financial indicator, 2011-2017

Horizon (h)	1	2	3	4	5	6	7	8
gdp	0,920***	0,959***	0,969**	0,976*	0,980	0,977	0,979	0,986
cpi	0,683***	0,721***	0,739***	0,757***	0,763***	0,762***	0,763**	0,763*

Notes: The table shows the average root mean square forecast errors (RMSFE) of a mixed frequency VAR ($MF-VAR$) model including the financial stress indicator $fsi\_quantec$ relative to a $MF-VAR$ specification excluding $fsi\_quantec$. The relative RMSFE are reported for gross domestic product growth (gdp) and consumer price inflation (cpi) for different forecast horizons h. The McCracken (2007) test is carried out where differences in forecast accuracy are statistically significant at the 1% (***), 5% (**), or 10% (*) level.

Table B.6: RMSFE of the alternative MF-VAR specifications, 2011-2017

		$MF-VAR\xi$	*MF-VAR (safsi)*	*MF-VAR (fsi_quantec)*
h = 1	gdp	1,295	1,155	1,192
	cpi	0,535	0,365	0,365
h = 2	gdp	1,567	1,489	1,502
	cpi	0,620	0,438	0,447
h = 3	gdp	1,632	1,570	1,582
	cpi	0,653	0,471	0,483
h = 4	gdp	1,649	1,600	1,608
	cpi	0,673	0,496	0,509
h = 5	gdp	1,655	1,613	1,621
	cpi	0,688	0,513	0,525
h = 6	gdp	1,664	1,622	1,626
	cpi	0,705	0,524	0,537
h = 7	gdp	1,670	1,632	1,636
	cpi	0,715	0,534	0,545
h = 8	gdp	1,667	1,640	1,644
	cpi	0,723	0,543	0,552

Notes: The table reports the average root mean square forecast errors (RMSFE) of the different $MF-VAR$ models in levels for gross domestic product growth (gdp) and consumer price inflation (cpi) for different forecast horizons h. $MF-VAR\xi$ is the benchmark bivariate mixed frequency VAR model containing only the macroeconomic variables (gross domestic product growth (gdp), consumer price inflation (cpi)). While $MF-VAR$ ($safsi$) and $MF-VAR$ ($fsi\_quantec$) are the mixed frequency VAR models that includes the two macroeconomic variables as well as financial information (proxied by the financial stress indexes, $safsi$ or $fsi\_quantec$).

Including three-month treasury bill rate (r)

Table B.7: Relative RMSFE of MF-VAR including financial indicator to MF-VAR without a financial stress indicator, 2011-2017

		MF-VAR (safsi)	*MF-VAR (fsi_quantec)*
h = 1	gdp	0,894***	0,926**
	cpi	0,676***	0,683***
h = 2	gdp	0,951**	0,956**
	cpi	0,702***	0,696***
h = 3	gdp	0,972**	0,975*
	cpi	0,712***	0,700***
h = 4	gdp	0,983*	0,988*
	cpi	0,721***	0,705***
h = 5	gdp	0,987	0,995
	cpi	0,722***	0,707***
h = 6	gdp	0,989	0,995
	cpi	0,714***	0,702***
h = 7	gdp	0,992	1,001
	cpi	0,709**	0,695**
h = 8	gdp	0,999	1,005
	cpi	0,706	0,690

Notes: The table shows the average root mean square forecast errors (RMSFE) of a mixed frequency VAR ($MF-VAR$) model including the financial stress indicator $safsi$ or $fsi\_quantec$ relative to a $MF-VAR$ specification without a financial stress indicator. The relative RMSFE are reported for gross domestic product growth (gdp) and consumer price inflation (cpi) for different forecast horizons h. The McCracken (2007) test is carried out where differences in forecast accuracy are statistically significant at the 1% (***), 5% (**), or 10% (*) level.

Table B.8: RMSFE of the alternative MF-VAR specifications, 2011-2017

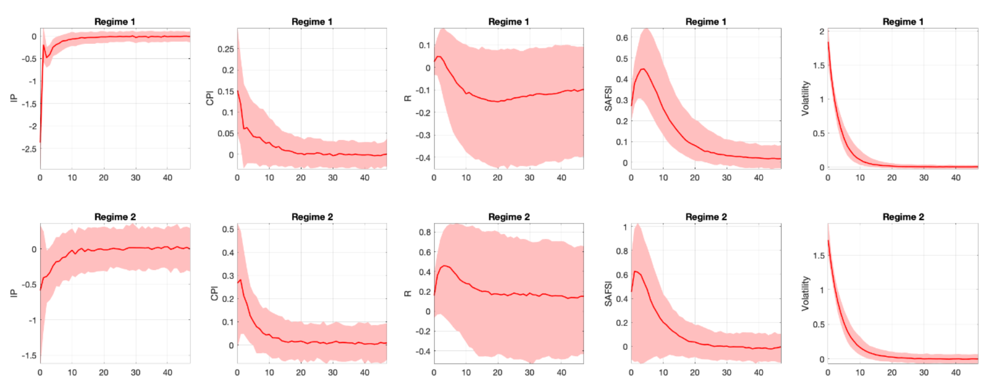
		$MF-VAR\xi$	*MF-VAR (safsi)*	*MF-VAR (fsi_quantec)*
h = 1	gdp	1,277	1,142	1,182
	cpi	0,502	0,339	0,343
h = 2	gdp	1,554	1,478	1,485
	cpi	0,554	0,389	0,386
h = 3	gdp	1,613	1,568	1,573
	cpi	0,567	0,404	0,397
h = 4	gdp	1,632	1,604	1,612
	cpi	0,571	0,412	0,403
h = 5	gdp	1,635	1,614	1,626
	cpi	0,575	0,415	0,406
h = 6	gdp	1,639	1,621	1,631
	cpi	0,583	0,416	0,409
h = 7	gdp	1,640	1,627	1,641
	cpi	0,591	0,419	0,411
h = 8	gdp	1,637	1,635	1,646
	cpi	0,596	0,420	0,411

Notes: The table reports the average root mean square forecast errors (RMSFE) of the different $MF-VAR$ models in levels for gross domestic product growth (gdp) and consumer price inflation (cpi) for different forecast horizons h. $MF-VAR\xi$ is the benchmark mixed frequency VAR model containing only the macroeconomic variables (gross domestic product growth (gdp), consumer price inflation (cpi), as well as the three-month treasury bill rate (r)). While $MF-VAR$ ($safsi$) and $MF-VAR$ ($fsi\_quantec$) are the mixed frequency VAR models that includes the three macroeconomic variables as well as financial information (proxied by the financial stress indexes, $safsi$ or $fsi\_quantec$).

Appendix C

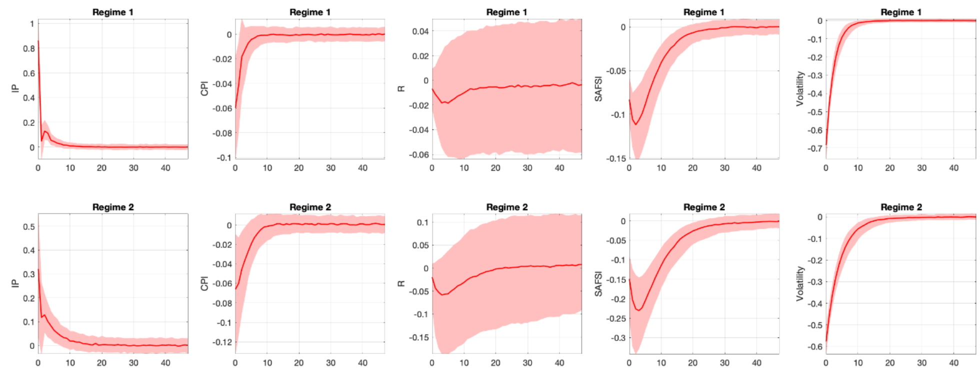
Impulse responses to uncertainty shocks of different sizes and signs

Figure C.1: Impulse responses to a large positive uncertainty shock



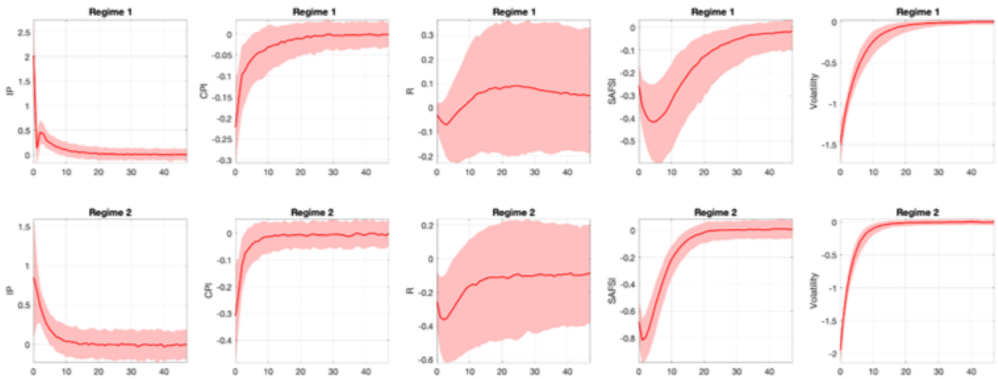
Notes: The figure shows the median responses of industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI to a positive three standard deviation model-based volatility (or uncertainty) shock during tranquil financial times or low stress regime (Regime 1) and stressful financial times or high stress regime (Regime 2). Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

Figure C.2: Impulse responses to a small negative uncertainty shock



Notes: The figure shows the median responses of industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI to a negative one standard deviation model-based volatility (or uncertainty) shock during tranquil financial times or low stress regime (Regime 1) and stressful financial times or high stress regime (Regime 2). Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

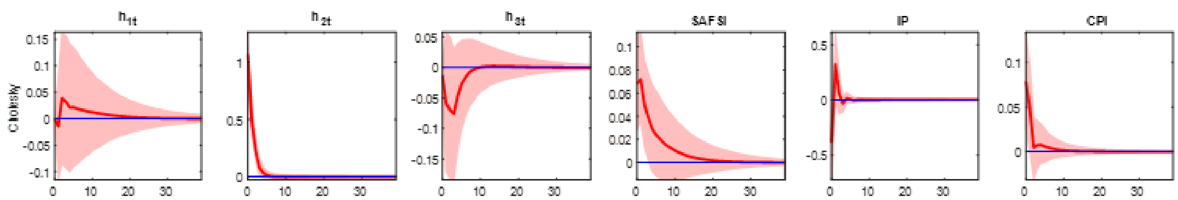
Figure C.3: Impulse responses to a large negative uncertainty shock



Notes: The figure shows the median responses of industrial production growth (IP), consumer price inflation (CPI), interest rate (R), and SAFSI to a negative three standard deviation model-based volatility (or uncertainty) shock during tranquil financial times or low stress regime (Regime 1) and stressful financial times or high stress regime (Regime 2). Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.

Impact of macro uncertainty shocks on the South African economy

Figure C.4: Impulse response to a output uncertainty shock



Notes: The figure reports the median responses of financial uncertainty (h_{1t}), output uncertainty (h_{2t}, inflation uncertainty (h_{3t}), SAFSI, industrial production growth (IP), and consumer price inflation (CPI) to a positive one standard deviation output uncertainty shock. Median responses are reported within 68% confidence bands. The estimation period is 1995M1-2017M12, and horizontal axis reports time which is measured in month.