Determinants of financial stress in South Africa

by

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DECLARATION

I, Siamisang Mmusi, hereby declare:

- That the content of this research is on my own, except whether otherwise indicated and acknowledged.

- Any work that is not my own has been duly referenced and the correct credit given to the author. The complete reference list can be found at the end of this document.

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ABSTRACT

With a globalised system, the credit crunch of 2007/2008 rippled through the global economy quickly and turned a global financial crisis into a global economic crisis, vulnerabilities in the economy surfaced when it hit and these still continue to plague South Africa today. According to the World Bank, South Africa's real GDP growth estimates are 0.8% in 2016/2017 and 1.1% in 2017/2018. Increasing uncertainty in global financial markets and banking systems, sharp declines in commodity prices, subdued global trade, currency pressure, as well as domestic constraints such as a current account deficit, a negative inflation outlook and high levels of unemployment, lead to increased financial stress in South Africa making the country more vulnerable in the event of an adverse scenario. Clearly, being cognizant of determinants of financial stress in South Africa is of paramount importance to policy makers as it allows them to assess potential risks to financial system stability and to consider timely and appropriate counteractions while maintaining a financial system that is resilient to systemic shocks. (South African Reserve Bank Financial Stability Review, 2016)

This study aims to construct a financial stress index using Principal Component Analysis to identify key determinants of financial stress in South Africa. Several variables that have been identified in standing literature as being able to capture certain symptoms of financial strain in emerging market economies are estimated then aggregated into an index using the principal component analysis method. The usefulness of the index in identifying past crises is then assessed, moreover its performance is contrasted against the financial stress index constructed by South African Reserve Bank as well as against a South African composite business cycle leading indicator. Finally, the ability of the index to predict economic activity is examined.

Table of Contents

1. INTRODUCTION

1.1 Motivation of study

Financial stress refers to episodes where economic agents are subjected to extreme uncertainty and varying expectations of loss in financial markets (Park & Mercado, 2014). South Africa has experienced several financial stress episodes in the post-apartheid era which have been clearly documented. The drivers of financial stress, their causal relationships and spill over effects are of prime substance to comprehend and scrutinise for the purposes of maintaining financial stability and competiveness of the country, as financial strain exacerbates the conditions in an already constrained economy (Park & Mercado, 2014). Further, the tension resulting from shakiness in the financial system can feed through to macroeconomic instabilities and lead to further deterioration in the solidity of the financial system. The key objective of this study is to observe drivers of stress in the South African financial system and then construct an index that has the ability to not only capture financial strain but also predict some level economic activity for South Africa.

1.1.1 Key Questions

- Is it optimal considering the ongoing episodes in the financial industry to create an index that captures known episodes of financial stress in South Africa by using a variation of variables that have been proven to capture stress in other emerging markets?
- If so, can this index's performance be compared to the South African Reserve Bank's index in capturing historic crisis events?
- How well does the South African financial stress index track the composite leading business cycle indicator?
- If the above questions are optimally answered, can the proposed financial stress index predict key indicators of economic activity within the South African domain?

The idea of financial stability, its predictability and causes is evolving. To date, as the literature review below reveals, it is still an open field for policy and research. It is upon this need that this study goes out to try and generate specific macro-financial indicators for South Africa to benchmark against those that are currently employed by the South African Reserve Bank (SARB). Principal Component Analysis is used to construct the South African Financial Stress Index (SAFSI), by employing a variation of variables that have empirically demonstrated the ability to encapsulate crucial aspects of financial strain in developing economies. These variables have been used with success in few emerging market studies including Turkey, Bulgaria, Czech Republic, Hungary, Poland, and Russia as explored by Cevik, Dibooglu, and Kenc (2013), Danninger, Tytell, Balakrishnan, and Elekdag (2009) and Cevik, Dibooglu, and Kutan (2013). They incorporate five essential elements: banking sector frailty, time varying stock market return volatility, external debt, sovereign debt and an exchange market pressure index. Because the nature of a recession in a particular country can be shaped by many factors, an examination is carried out to determine whether these pre-selected variables are applicable in a South African context. The examination focuses on the period of January 1997 – June 2016 with the intention that the South African stress index spans a decade earlier than the South African Reserve Bank's financial stress index (SARBFSI). Crisis events are rare therefore the wider the range of data, the bigger the bank of crisis events that can be used to test the viability of the newly constructed index and to assess its performance. The SARBFSI's period of observation is January 2006 – January 2015 therefore the SAFSI extends over a decade longer than the SARBFSI.

1.1.2 The benchmark

The Central Bank of South Africa is tasked with protecting and enhancing financial stability in the Republic of South Africa. The recent financial crisis made clear the significance of understanding and gauging systemic risks (South African Reserve Bank Financial Stability Review, 2016) this being so, there is a need to be aware of the factors that would precisely cause instability or any possible systemic risk in the financial system in South Africa.

To this end, SARB constructed a financial stress index (FSI) which uses five broad indicators as a base to create a general and simple index to quantify vulnerability in a financial system (South African Reserve Bank Financial Stability Review, 2016). The SARBFSI was formulated as an aggregated index that involves two-level construction processes that use variance-equal weight techniques across indicators It is derived from five financial markets (represented by a selection of variables) which are notable sources of funding for banks, namely the markets for credit, funding, equity, foreign exchange and real estate. The variables selected for calculation of the SARBFSI are as follows: Government bond spread, Interbank liquidity spread, Cost of borrowing , Treasury yield spread (Funding) ; CMAX60: All-share Index , VIX (Equity) ; US dollar/rand volatility index , Euro/rand volatility index; Sovereign bond spread (Foreign exchange) and CMAX: Absa House Price Index ,CMAX: Commercial real property prices (Real Estate) – a total of eleven variables. The performance of the SAFSI is compared to that of SARB's FSI with the purpose of determining which index captures stress events better.

1.1.3 Structure of thesis

Chapter one gives and introduction and motivation for the study while chapter two gives an overview of significant literature that has been published regarding this topic. Chapter three opens with a discussion about the methodology, which describes the broad underpinning of this study's chosen method - principal component analysis (PCA) and follows with a summary of how the Vector AutoRegression model will be applied along with Granger Causality hypothesis which will interpret results, it follows with motivation for the selection of proxies that are used to represent each pre-selected variable that encapsulate facets of financial strain and presents a preliminary assessment of data as well as details the aggregation of components that are used to construct the SAFSI. Chapter four gives empirical result and weighs up the performance of the SAFSI against the SARBFSI as well as against the composite leading business cycle indicator and explores the link between financial stress and economic activity is examined. To close, chapter five gives a conclusion and recommendation.

2. LITERATURE REVIEW

2.1 Financial stress indices

The literature on financial stress determinants is vast, the majority of this taking place in advanced economies. Vašíček et al. (2017) identified factors that have predictive power of financial stress for 25 Organisation for European Economic Co-operation and Development (OECD) countries; they then use the Bayesian model averaging (BMA) to identify leading indicators of stress. BMA is a procedure that allows a subset of the most useful leading indicators of financial stress to be selected from a set of all possible combinations of potential leading indicators. The authors use these indicators as explanatory variables in a panel model for all countries and in models at the individual country level. The result is that panel models barely accounts for FSI dynamics and a better outcome is achieved in country models. They also find that financial tension is hard to foresee out of sample despite reasonably good in-sample performance..

Hubrich and Tetlow (2015) built an FSI for the United States and studied its interactions with real activity, inflation and monetary policy using Markov-switching VAR model (MS-VAR model), estimated with Bayesian methods. Their results show when stress events come into the economy, they cause it havoc yet monetary policy is ineffectual for the duration of the financial turmoil.

The paper by Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) studies the interconnectedness between financial conditions and economic activity by constructing a new financial conditions index that features three key innovations besides interest rates and asset prices - a broad range of quantitative and survey-based indicators. Second, they make use of unbalanced panel estimation techniques results in a longer time series (back to 1970) than available for other indexes. Third, they control for past GDP growth and inflation and thus focus on the predictive power of financial conditions for future economic activity. The result is that their financial conditions index exhibits a stronger connection with future economic activity than existing indexes.

Lall, Cardarelli, and Elekdag (2009) construct a financial stress index in banking, securities and foreign exchange markets in 17 advanced economies over a period of 30 years referencing a bank of 113 financial stress episodes. They find that recessions that are followed a banking-sector related downturn are likely to continue for up to four times longer than otherwise and that cumulative losses that are incurred are up to three times more severe. The authors also find that arm's length financial systems have intensified the susceptibility of sharp contractions in economic activity if and when banking-related stress strikes but that arm's length financial systems are not necessarily more prone to stress. Additionally, signals that precede financial stress and also indicate that financial stress will lead to economic downturn include: a mounting aggregate credit, rising house prices, greater dependence on borrowing by non-financial corporations and size of financial imbalances in the household sector.

Oet, Eiben, Bianco, Gramlich, and Ong (2011) express a financial stress index for the United States based on daily public market data collected from four sectors of the financial markets – credit markets, foreign exchange markets, equity markets, and interbank markets. A dynamic weighting method is employed to capture changes in the relative importance of these four sectors as they occur. To boot, the design of the index allows the origin of the stress to be identified. The authors compare their index to alternative indexes using a detailed benchmarking methodology and show how their index can be applied to systemic stress monitoring and early warning system design.

Duca and Peltonen (2013) also developed an FSI that is able to identify the starting date of systemic financial crises. The index uses discrete choice models that combine both domestic and global indicators of macro-financial vulnerabilities to predict systemic financial crises. The author's analysis shows that combining indicators of domestic and global macro-financial vulnerabilities markedly improves the models' ability to forecast systemic financial crises. Our framework also displays a good out-of-sample performance in predicting the ongoing Global Financial Crisis.

Implementation of the correct intervention policy in time of crisis can ease the transition from a stressful period to a calmer period. That is why several studies are dedicated to the subject. In some developed economies, Central Banks increase money supply by printing notes and thus increasing the amount of currency in circulation. They then go into the market and entice commercial banks to sell their bonds at a high price which they willingly do because it gives them higher revenues, the bank will then use these revenues to issue debt thereby injecting liquidity, reducing interest rates and kick starting economic growth. This unconventional monetary policy is known as quantitative easing which the U.S. central bank, the Federal Reserve, implemented several rounds of following the global financial crisis of 2007-08. More recently, the Bank of Japan and the European Central Bank have implemented quantitative easing.

The SARB on the other hand has yet to face a crisis of comparable magnitude to the crisis of 2007-2008. In 1998 however, the contagion from turmoil in East Asia coupled with intense pressure on the rand resulted in an economic downturn that prompted the SARB to intervene, first the central bank borrowed foreign currency in the forward market and sold it in the spot market in an effort to halt pressure on the rand. As a result, the net open foreign position (i.e., net international reserves minus forward liabilities of the central bank) declined by $10 billion between April and September 1998. Second, by increasing interest rates by 7% in real terms as per Bhundia and Ricci (2005). However this action was ineffective and proved to be detrimental to investment and growth. In 2001, facing another economic downturn the SARB chose not to intervene which was a more successful strategy. Subsequently, the SARB adopted an inflation-targeting policy; its primary objective is to maintain price stability. The South African Central Bank's approach to financial stability maintenance places confidence in market forces to manage stability which means there is barely any intervention.

Li and St-Amant (2010), Baxa, Horváth, and Vašíček (2013) and Van Roye (2011) all direct their studies towards developed economies focusing on different crises and they all acknowledge the need for prescription measures that are different from usual as heightened levels of financial stress.

The financial crisis and the European sovereign debt crisis have shown that financial stress may be an important driver for economic activity. It is off the back of this, that Van Roye (2011) derives a financial stress index for Germany, using a dynamic approximate factor model that summarizes a stress component of various financial variables. Subsequently, the author analyses the effects of financial stress on economic activity in a threshold vector autoregressive model. The result is that that if the index exceeds a certain threshold, an increase in financial stress causes economic activity to decelerate significantly, whereas if it is below this threshold, economic activity remains nearly unaffected.

2.2 Transmission of financial stress

Financial stress transmission to economic variables has also been paid much attention to, Claessens, Köse, and Terrones (2008) study the connection between macroeconomic and financial indicators in times of recession and financial stress for 21 OECD countries; they take cycles of GDP as measures of economic activity and credit, house prices and equity prices as financial indicators. They conclude that in periods of low output levels/GDP, house and equity prices and the growth rate of credit disintegrate. Equity prices are the most volatile in terms of intensity and duration of degeneration and recessionary periods that the countries have in common are strongly related with those of the United States.

Vermeulen, Hoeberichts, Vašíček, Žigraiová, Šmídková & de Haan (2015) find that recessions that are a result of banking-related financial stress are more inclined to last at least twice as long as recessions which are not predicated by financial stress , not surprisingly Eichengreen and Arteta (2002) argue that in emerging market economies a banking related crisis could lead to a downturn as severe as the Great Depression of 1929. This is because banking crises are usually associated with systemic risk: "near perfect correlation of indices that is becomes difficult to diversify and hedge portfolios" an effect so destabilising it could lead to the collapse of financial markets.

Financial stress, defined as periods of impaired financial intermediation, is transmitted from advanced to emerging economies using a new financial stress index for emerging economies Balakrishnan, Danninger, Elekdag, and Tytell (2011). The authors show that a previous financial crisis in advanced economies passes through powerfully and quickly to emerging economies. The unprecedented spike in financial stress in advanced economies elevated stress across emerging economies above levels seen during the Asian crisis but with significant cross-country variation. The extent of spill over of financial stress is correlated to the depth of financial linkages between advanced and emerging economies.

2.3 Construction of a financial stress index

Cardarelli, Elekdag, and Lall (2011) use an equal variance weighted average technique to build their index to explore the reasons why financial stress occurrences result in economic recessions by studying the nature of explanatory variables at the onset of a decline in economic activity. Vermeulen et al. (2015) assembles a FSI which is an un-weighted sum of standardised variables for 28 OECD countries and tests its predictive power; the result is that there is an insubstantial link between the onset of a financial crisis and the FSI. Although the correlation between a crisis and sub-indices, markedly the banking crisis, is substantial it means that policymakers should bear in mind that a FSI has limited usefulness as a predictor of a crisis.

The aggregation of components and construction of the FSI is wide and varied. Illing and Liu (2006) developed an index to measure the degree of financial stress for the Canadian financial system using factor analysis, equal weights, economic weights and cumulative distribution functions. Vašíček et al. (2017) used the Bayesian model averaging (BMA) to identify leading indicators of stress. Hakkio and Keeton (2009) employed portfolio theory based aggregation schemes that take into account correlation structure of stress indicators in order to quantify the level of systemic stress. Cardarelli et al. (2011) constructed their index using a variance equal weighting procedure while Vermeulen et al. (2015) built a FSI which is an un-weighted sum of standardised variables.

The SARBFSI was formulated as an aggregated index that involves two-level construction processes that use variance-equal weight techniques across indicators. Variables are standardised before they are aggregated so that only deviations from the mean explain the movements in the SARBFSI. It is constructed for the period January 2006 – January 2015 on a monthly frequency and selects proxies of five dominants markets – credit, funding, equity, foreign exchange and real estate. Each market has an average of three proxies that serve as explanatory sub-indices for the main index.

It is clear that there has been a vast array of studies dedicated to financial turmoil in developed economies all aimed at alleviating its impact and counteracting its effects on the economy. Park and Mercado (2014) explore the conduits of financial transmission in emerging market economies from stress emanating in developed economies, their study highlights that globalisation and interconnectedness of financial systems implies that stress that emanates from regions outside of a of a particular country, can lead to local financial strain. They also give insight on the phenomena of spill over effects.

The criteria of which variables fort a part of the index is based on which features of financial stress that is explained by each variable, there is still a lot of are not vastly different between developed economies and emerging market economies. The study considers the uniqueness of developing markets and relies on variables that are have been empirically proven to have explanatory power to financial stress conditions in emerging markets, Cevik, Dibooglu, and Kutan (2013), Park and Mercado (2014), Danninger, M. S., Tytell, I., Balakrishnan, R., & Elekdag, S. (2009) and Cevik, Dibooglu, and Kenc (2013) use a variation of these to explain financial stress. Cevik, Dibooglu, and Kutan (2013) construct a financial stress index for Bulgaria, the Czech Republic, Hungary, Poland, Russia and Turkey amongst others in addition to that, they examine the association between financial stress and economic movement. These five key variables (banking sector frailty, time varying stock market return volatility, external debt, sovereign debt and an exchange market pressure index) seemingly capture key aspects of financial stress in sample countries. It is on the back of this as well as economic intuition that are the same variables are considered when the SAFSI is aggregated.

Cevik, Dibooglu, and Kenc (2013) create a financial stress index by utilising leading indicators of stress in Turkey. They constructed a Turkish FSI by considering a variation of the variable above moreover, they included 'trade credit' and 'credit stress' as additional sources of financial stress in their particular FSI because as they have influence in the Turkish economy. The outcome is that the FSI is quite accomplished in signalling cumulative economic activity and has explanatory power over all recessions in Turkey.

Hollo, Kremer, and Lo Duca (2012) observed that important financial stability variables for the European Central Bank emanate majorly from the core monetary policy factors including a measure of aggregate price levels, aggregate economic activity and aggregate short term interest rates. They find that the index Composite Indicator of Systemic Stress (European Central Bank's financial stress index) possesses explanatory power for standard macroeconomic variables like inflation, real GDP growth and monetary policy interest rates (in Euro area) This indicator has influenced other studies in the Euro-area such as Louzis and Vouldis (2013) particularly because its empirical results show that the index possess substantial and robust explanatory power for standard macroeconomic variables.

According to Hollo, D., Kremer, M., & Lo Duca, M. (2012) a FSI not only permits the real time monitoring and assessment of the stress level in the whole financial system, but it may also be used to gauge the impact of policy measures aimed at alleviating financial instability. The lesson from Bhundia and Ricci (2005) is that the South African Reserve Bank's policy response of increasing interest rates in response to pressure on the rand and borrowing foreign currency in the futures market and selling it in the spot market during the 1998 long term capital management (LTCM) crisis aggravated the crisis along with subsequent macroeconomic performance, while a lack of intervention during 2001 led to the crisis retreating faster which insinuates that even though there may be similarities in the birth of crises, policy behaviour and macroeconomic consequences can differ remarkably. South African authorities learnt from the 1998 mistake that an inflation-targeting framework successfully provided a more credible anchor for managing exchange rate fluctuations in South Africa.

Lastly, multivariate data analysis techniques can be used to model factors and responses and find the relationship that exists between all factors and responses and can extract useful information from multivariate data. There are varied techniques that can be used for the purpose of combing components and creating the FSI, however the PCA is employed in this study in contrast the SARB's variance-equal weight technique.

As the literature review reveals, there are varied approaches regarding the optimality of constructing a FSI - different methods and procedures are employed in empirical research in the selection the variables that should be included to construct FSIs. Yet the choice of the variables or raw stress indicators is of crucial importance for the construction of financial stress indices as they should represent key features of financial stress. It is therefore of critical interest for the current study to identify variables not yet considered in a South African context but would optimally capture key aspects of financial stress and hence will provide valuable information about the state of the economy and to fill the void in the literature.

3. RESEARCH METHODOLOGY

3.1 Methodology

Procedure of analysis towards uncovering the merits of this study is introduced here. The literature review in the preceding chapter offers a variety of methodology to build a FSI, a method that would statistically and scientifically isolate the most significant variables for building Financial Stress Index in South Africa is proposed. In this regard, literature repeatedly pointed at Principal Components Analysis (PCA), due to its tractability and wide application in such studies and practice.

3.1.1 Principal Component Analysis

PCA will be used to aggregate the relevant variables and then build an FSI for South Africa. The PCA method reflects a common factor, which is extracted from a group of financial indicators and captures the greatest common variation among them.

PCA defined as a multivariate technique that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables Abdi and Williams (2010). It is a statistical method that accounts for most of the original variability using a relatively small number of components by forming linear combinations of observed variables until data is reduced to a handful of measures that describe the overall population. The method analyses a data table representing observations described by several dependent variables, which are, in general, inter-correlated. Its goal is to extract the important information from the data table and to express this information as a set of new orthogonal variables called principal components. PCA is suitable when dealing with a lot of variables because incorporating all of them in a regression model can by definition lead to multicollinearity (the correlation amongst independent variables). The problem with regression analysis that occurs when two independent variables are highly correlated is that the relationship between dependent variable y and independent variable x is warped.

PCA principally allows a single series variable to be extracted which effectively captures the information in the background of all the factors that could otherwise co-move. It is presumed that each of these variables captures financial stress and hence all variables are likely to move together according to the level of financial stress in the economy Zhou, Xu, and Jiang (2017). This tendency of co-movement therefore would present a serious econometric error if put individually in an econometric model the outcome would be a spurious outcome. In the presence of multicollinearity, confidence intervals tend to be wide and t-statistics tend to be small even with a high R^2 value. To mitigate this risk, a single indicator or representation is more viable to speak of the entire risks presented by the variables. The single risk value should be a principal risk component as a proxy of the variables that could well explain financial stress.

An effective final model is expected to include variables which should explain more than 50% of total variance. The threshold is thus set at 50% for the purposes of this study. A drawback of PCA is that it does not allow for auto-correlation i.e. factor is constructed as a stationary variable with a zero mean thus it lacks a dynamic (autocorrelation) pattern. Abdi and Williams (2010) , it is not robust and is sensitive to outliers since it minuses squared distances from the multidimensional mean.

Given that episodes of financial stress are rare events, there will be difficulty in ascertaining whether an FSI is valuable. Nonetheless, the FSIs obtained using the PCA method will be compared to pre-determined benchmarks (the South African Central Bank's FSI and a composite business cycle leading indicator) and assessed from that standpoint. The idea is to test whether the SAFSI can capture stress better. The relationship between the SAFSI and key economic variables (aggregate price levels, aggregate economic activity and interest rates) is examined using the Vector Autoregressive model – i.e. looking at FSI and key variables to ascertain how these key variables impact FSI and test how these economic variables are affected when there is spill over from FSI (when there is stress)

3.1.2 Vector Autoregression

A Vector Autoregression model (an econometric model used to capture the linear interdependencies among multiple time series) will be best to demonstrate the relationship among the variables. Vector Autoregressive (VAR) models are natural tools for forecasting, they are setup is such that current values of a set of variables are partly explained by past values of the variables involved. The same model will be used to consider the links between financial tension and economic activity as well as the impact of shocks. Since the dynamic interactions between variables and vector autoregressive (VAR) models have best been described and interpreted by impulse response functions, there will be focus on impulse responses functions in order to assess the extent to which shocks in variables affect other variables and for how long (the magnitude and persistence of shocks)

3.1.3 Granger causality test

To study macro-financial links, Granger-causality test, a statistical hypothesis test for determining whether one time series is useful in forecasting another is employed. If a variable, or group of variables, c1 is found to be helpful for predicting another variable, or group of variables, c2 then c1 is said to Granger-cause c2; otherwise it is said to fail to Granger-cause c2.

Specifically, X is said to Granger-cause Y if previous values of X contain information that helps predict Y above and beyond that contained in past values of Y alone. The form of the Granger-causality equation is specified as

$$X_t = \sum_{j=1}^{p} a_l X_{t-l} + \sum_{l=1}^{p} b_l Y_{t-l} + u_t \qquad (3.1)$$

$$Y_t = \sum_{l=1}^{p} c_l X_{t-l} + \sum_{l=1}^{p} d_l Y_{t-l} + \omega_t, \qquad (3.2)$$

where p denotes the maximum lag length and u_t and ω_t are two uncorrelated white noise processes. Furthermore, Y is said to cause X when b_l is not equal to zero. Similarly, X causes Y when c_l is significantly different from zero; that is, if the p-value is less than 5%. When both statements hold, there is a feedback relationship between the two time series.

3.1.3 Financial stress measure

A financial stress index (FSI) measures the current state of stress in the financial system by combining several indicators of stress into a single statistic Park and Mercado (2014), a measure of performance of the stress indices is how well they measure and detect previous episodes of turmoil. An indicator is expected to rise considerably in stress periods in response to an occurrence that is known to have triggered a dysfunction in the stability of the financial system. Therefore, it is required that what counts as a 'considerable rise' is measurable. For the purposes of the study this is interpreted as follows: FSI > 1 financial stress and FSI < 1 no financial stress.

3.1.4 Selection of episodes of financial stress

Researchers follow different definitions when it comes to capturing a stress event, (Illing & Liu, 2006) defined financial stress as the force exerted on economic agents by uncertainty and changing expectations of losses in financial markets and institutions. Hakkio and Keeton (2009) describe financial stress as an interruption to the normal functioning of financial markets; they argue that episodes of financial stress must involve at least one of the following: (i) increased uncertainty about fundamental value of assets, (ii) increased asymmetry of information, (iii) decreased willingness to hold risky assets, and (iv) decreased willingness to hold illiquid assets.

Statistically type I errors (failure to report a high-stress event) can be reduced by not limiting stress identification of events to quantitative measures as these are likely to miss events that, for instance, are a result of a slow build-up of bad news rather than linked to a certain episode. (Hollo et al., 2012) Therefore for the study, episodes of financial turmoil will include known events: the East Asian crisis (1998), the 'dot.com' crisis (2000), the 9/11 events/rand (ZAR) crisis (2001) and global financial crisis (2008/2009). This list of events is drawn from South Africa's Industrial Development Corporation (IDC)'s department of research and information report published in December 2013. The report examines the South African post-apartheid economic landscape between 1994 and 2013. Established in 1940, the IDC is a national development finance institution set up to promote economic growth and industrial development. They are owned by the South African government under the supervision of the Economic Development Department. The bank of crisis events is selected from this report as the event's inclusion was based on them being explicitly identified as having had a significant impact on South African markets.

3.2 Construction of a financial stress index – theoretical analysis

There are few studies in literature that resemble an overall FSI for emerging market countries. Cevik, Dibooglu, and Kenc (2013) produce an FSI for Turkey focusing on the 1997-2010 period; the authors consider variables that have empirically been proven to capture key aspects of financial stress in emerging market economies. They incorporate: banking sector fragility, time varying stock market return volatility, an exchange market pressure index, external debt, sovereign debt spreads, trade credit and credit stress. The same variables are used to gauge financial stress in the South African economy. In addition, a variable that is a proxy for liquidity in financial markets is added as liquidity measures market risk and liquidity with implications for monetary policy, financial stability and economic activity, thus a total of eight variables are considered for design the SAFSI. The selection of proxies for each variable relied on their relevance and availability of data, the discussion from here onwards relates to the justification of selection of proxies.

3.2.1 Banking sector fragility

The South African economy is dominated by the banking sector which accounts for approximately 22% of GDP growth steadily increasing from 17% in 1994, therefore the stability of the banking sector is of paramount importance to include in the SAFSI. Anything that worsens a bank's balance sheet could qualify as a measure of the sector's fragility; nonetheless in this context the study makes use of the TED spread which is the spread between the 3-month interbank lending rate and the 91-day Treasury Bill rate for South Africa - the wider the spread, the riskier the banking sector is. The spread reflects the risk associated with lending to banks versus lending to the South African government. Therefore, an increase in the spread is indicative of counterparty risk (risk of default of interbank loans) increasing and consequently a weakening of the banking sector. Banking sector index takes into account the variability of banking sector returns in relation to the whole market and thus an alternative proxy for banking sector volatility will be obtained using the GARCH (1, 1) model. A decomposition of the GARCH model is detailed in the empirical analysis section.

3.2.2 Securities market risk

Securities markets become more volatile in periods of high financial stress and the volatility of securities market is essential in pricing derivatives and hedging evidence. The Johannesburg Stock Exchange all-share index (FTSE/JSE Africa Bank Index), which is a representation of market capitalisation weighted index is used to extract time varying stock market volatility using the GARCH (1, 1) model and employed to measure stock market securities risk, higher volatility captures heightened uncertainty.

3.2.3 Currency risk

The exchange rate relative to the most traded currency in the world (US $) is an indication of a country's economic performance. An appreciating local currency shows an investor's willingness to invest in a country; on the other hand, an exchange rate that excessively appreciates could be an indication of currency overvaluation.

Currency risk will be derived by applying the GARCH (1, 1) model on monthly change of real effective exchange rate which reflects investor's uncertainty about the fundamental value of the currency. REER (real effective exchange rate) is defined as "the weighted average of a country's currency relative to an index or basket of other major currencies, adjusted for the effects of inflation." A decrease in REER indicates a depreciation of local currency against the weighted basket of currencies of its trading partners. A REER coefficient which is less than 1 means that the home currency is worth less than the imported currency and vice versa. Alternatively, a monthly index of the EMPI (Exchange

Market Pressure Index) as proposed by Cevik, Dibooglu, and Kenc (2013) which incorporates exchange rate change, international reserves change and the overnight local interest rate change relative to the US interest rate will be used to measure currency risk as follows:

$$EMPI = \frac{\Delta e_t - \mu\Delta e}{\sigma\Delta e} - \frac{\Delta RES_t - \mu\Delta RES}{\sigma\Delta RES} + \frac{\Delta(i_t - iUS_t)}{\sigma\Delta\,(i_t - iUS_t)} \tag{3.3}$$

where Δe_t and ΔRES_t are 12-month changes in the exchange rate and total reserves minus gold and μ plus σ represent mean and deviation of the exchange rate and total international reserves respectively and i_t and iUS_t represent the overnight interest rate for South Africa and the US, respectively. Similarly σ_x denotes the standard deviation of variable x (x = the changes in the exchange rate, total reserves, and overnight interest rate).

3.2.4 External debt

Although debt is pertinent to sustainable growth in emerging markets, unsustainable debt levels lead to liquidity and solvency issues. Extreme increases in debt lead not only to questions around its sustainability but also tend to yield negative growth results for African countries as per Muhanji and Ojah (2011). There is a strong linkage between sustainable debt levels and the ability of open African economies to survive external shocks as the authors found, ineffective management of external shocks are part of the reason that Africa's external debt problems have persisted. A debt crisis arises from the inability of a nation to service its foreign debt obligation therefore the 12-month growth rate of total external debt is used as part of SAFSI.

3.2.5 Sovereign risk

A decline of investor sentiment of South African economy tends to reflect recessionary conditions as it underpins capital flows into the country, interest rate spreads between South Africa and the US are used as gages for sovereign risk which is computed by taking the difference between South Africa's current government 10-year index and US Treasury 10-year yield. The sovereign spread indicates risk of the government's funding ability in the capital markets; a rising spread is a sign of increased default risk.

3.2.6 Trade finance

In a small, open economy like South Africa the balance of payments reflects the disequilibrium in the economy; if domestic savings are not enough to cover domestic investment or if there is a trade deficit then the country needs either a high level of reserves or net capital inflows to bridge the gap. Although South Africa has profited from increasing global investor interest in global markets it is characterised by a structural trade deficit because of its tendency to import high value and export low value. This makes the country more vulnerable to adverse effects of mismanagement of trade financing, effects such as increased foreign ownership of domestic assets.

Trade finance is another important component of financial stress for emerging markets, without adequate trade finance, opportunities for growth and development are missed yet a country that relies less on external funding is less vulnerable to external factors and makes it more resilient. Cevik, Dibooglu, and Kenc (2013) use financial account balance, a component of the balance of payments (BoP) that covers claims on or liabilities to non-residents as a proxy for trade finance. Equally, the South Africa BoP financial account balance is a proxy of trade finance.

3.2.7 Credit stress

Credit provision to the private sector is one of the ways that South Africa has liberalised its financial system in order to develop it, though there is merit to this strategy credit stress has a negative impact and is of prime importance in a developing economy such as South Africa, the growth rate of the claims on the private sector as a percentage of broad money to represent credit stress is utilised.

3.2.8 Liquidity

Financial markets in developing nations such as South Africa have evolved since the 1980s by progressing in ways such as establishing and deepening stock exchanges, privatisation of owned entities and opening up bank ownership to foreigners; creating financial markets that should enable sustainable economic growth. Andrianaivo and Yartey (2009) Liquidity facilitates price discovery and is a key indicator of financial market development. Because of a lack of data for the bid-ask spread for the period of observation, stock market capitalisation scaled by GDP is used as a proxy for liquidity.

3.3 Data and preliminary observations

The preceding discussion uses an array of macroeconomic variables which are described in section 3.2 titled construction of a financial stress index. The study focuses on the post-apartheid era of 1995 to 2016; the range of data is based on availability baring in mind the more crises events that the index can be tested against, the better the assessment of its performance. The study uses data obtained from Bloomberg, Bank for International Settlements (BIS), International Monetary Fund (IMF) and Federal Reserve Economic Data (FRED) database, on a frequency of data that is monthly, see Appendix A for a record summary of data collected.

3.3.1 Banking sector fragility

The raw banking sector index data in figure 3.1 represents South Africa's banking sector index - FTSE/JSE Africa Bank Index for South Africa - as obtained from Bloomberg for January 1997 – June 2016. It is observed that the index is at its lowest until 2005 thereafter there is steady escalation of the index with peaks in 2007-2008 and again in 2014-2015. Banking sector index was at its most volatile in 1998.

Figure 3.1 shows that banking sector returns exhibits volatility clustering, which is confirmed by the statistical significance ARCH-LM test as reported in Table 4.1 presented on page 36. One of the underlying assumptions of the error term u_t of the classic linear regression model $y = \propto + \beta x_t + u_t$ is that the variance of all error terms is constant and finite over all values of x_t i.e. $var(u_{t)=}\ \sigma^2 < \infty$.

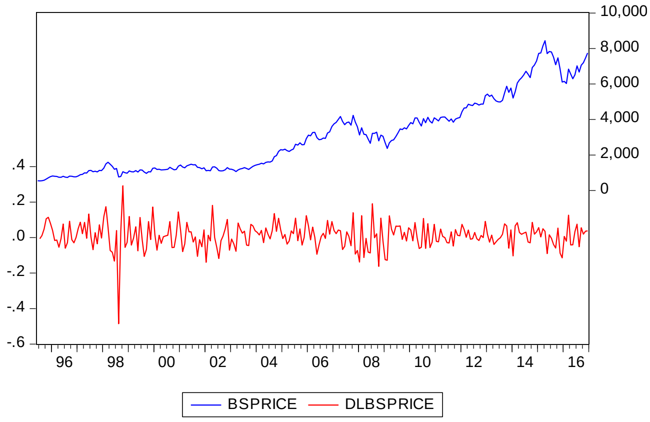


Figure 3.1 Banking sector index (DLBSPRICE)

The TED spread (T_Spread) as per figure 3.2 below, is computed by taking the difference between the 3-month interbank lending rate and the 91-day TB rate - the wider the spread, the more fragile the banking sector. The expectation is that banking sector fragility will have a negative coefficient that is statistically significant for both the GARCH model and the TED spread. In terms of the spread, the period where it is widest is 1998 followed by 1996 then 2008/2009 and to a milder extent 2002, this signifies that investors preferred to invest in the safer 91-day TB during these periods. This exhibition of flight to quality and liquidity is considered a hint of a presence of financial stress.

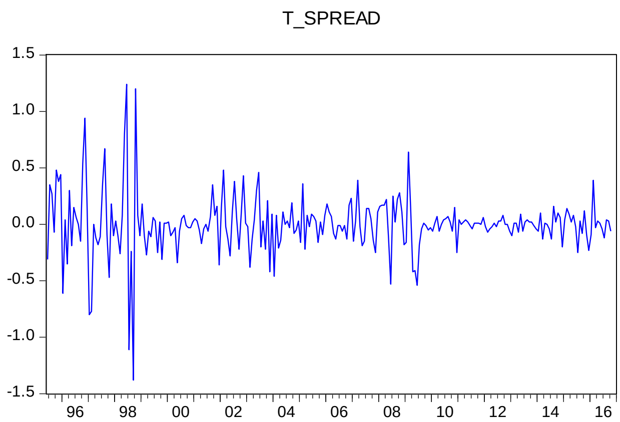


Figure 3.2 TED Spread

3.3.2 Security market risk

Once again results of the ARCH-LM test tabled in table 4.1 confirm that there are ARCH effects present in the securities market data set therefore there is a need to apply GARCH models in order to treat the problem of heteroskedasticity. Time varying volatility stock market volatility was obtained using the GARCH (1, 1) model, using FTSE/JSE All Share Index data was gleaned from Bloomberg. The raw series shows stagnation up until 2005 and then steady growth up until 2016. The most significant peak was in the 2006- 2008 period while volatility is most prevalent in 1998; 2001/2002 and 2008.

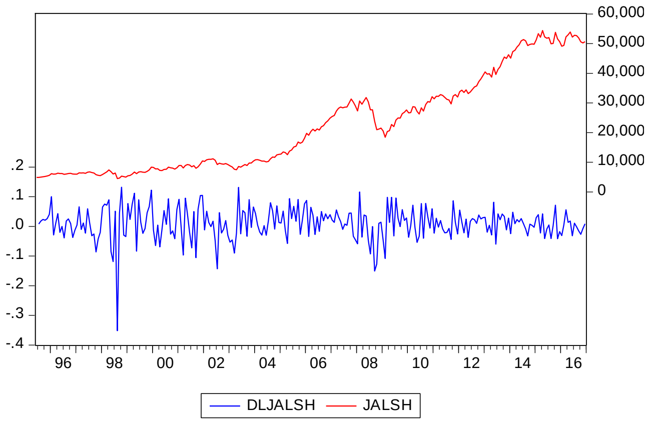


Figure 3.3 Securities market index (DLJALSH)

3.3.3 Currency risk

Figure 3.4 signals that local currency was under strain in 1998, 2001, 2008 and 2015, a sharp increase in the USD/ZAR rate can be observed in these periods (i.e. depreciation of ZAR) while periods of 2003-2006 and 2009-2010 give an idea about a better performing ZAR relative to the US dollar. The ZAR depreciated in nominal terms against the US dollar (USD) by 28 % (April 1998 – August 1998); 26 %(September 2001- December 2001 (Bhundia & Ricci, 2005) 39 % (July 2008 – January 2009) and 25% (January 2015 – December 2015). Notably, a REER a depreciation of the ZAR is depicted by a trough and an appreciation by a peak in figure 3.5. The loss in currency value on a real effective basis during these periods signifies that carrying the rand was riskier over the same periods as the depreciation in nominal terms (1998, 2001, 2008 and 2015).

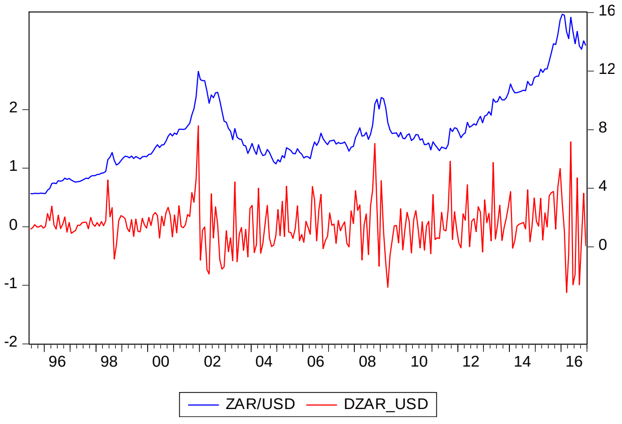


Figure 3.4 ZAR/USD exchange

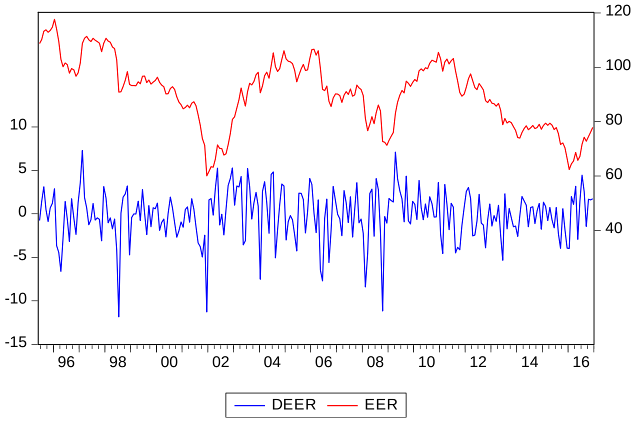


Figure 3.5 Real effective exchange rates (REER) for 1995 -2016

GARCH (1,1) was once again be used to model the variance depicted in figure 3.5 above, from the raw data it is clear that exchange rates had the most variability in 1998, 2002 and 2008. Results are recorded in table 4.1 page 36.

The overall market pressures (intensity and duration) will be evaluated using the EMPI which takes into account movements in the exchange rate and foreign exchange reserves (Cevik, Dibooglu, & Kenc, 2013) EMPI is computed as follows:

$$EMPI = \frac{\Delta e_t - \mu\Delta e}{\sigma\Delta e} - \frac{\Delta RES_t - \mu\Delta RES}{\sigma\Delta RES} + \frac{\Delta(i_t - iUS_t)}{\sigma\Delta\,(i_t - iUS_t)} \qquad (3.4)$$

EMPI increases as the exchange rate depreciates or as international reserves decline, in figure 3.6 depicts added currency pressure in 1998, 2001 and 2008.

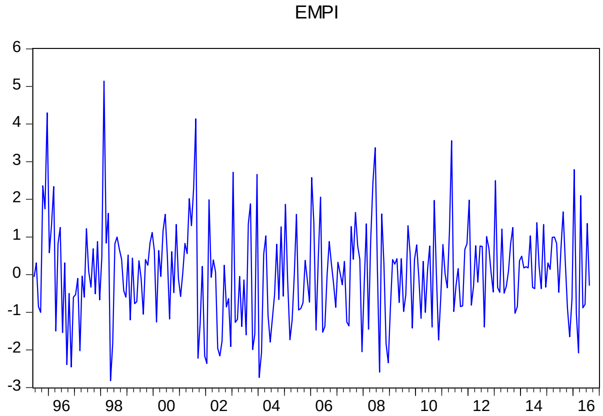


Figure 3.6 Exchange market pressure index (EMPI)

3.3.4 External debt

The country's outstanding foreign debt that is distinguishable between short and longer term is only available from 2002. Due to this, the South Africa debt to GDP ratio obtained from Bloomberg (SABTGDIQ Index) is extracted for the period of isolation and then transformed by multiplying it with GDP. Because both debt to GDP ratios and GDP levels are reported in quarterly frequency, data is subsequently transformed from low to high frequency using the quadratic match average method which performs a proprietary local quadratic interpolation of the low frequency data to fill in the high observations. The graphic illustration of the transformed data reveals troughs in 2002, 2006 and 2007 followed by an upward trajectory that saw levels being reinstated to around 50% by the end of 2016.

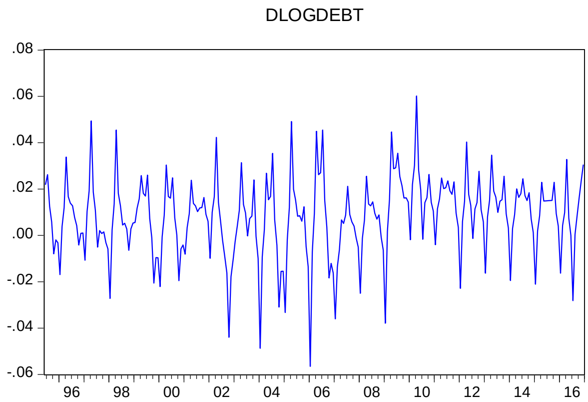


Figure 3.7 South African Debt (DLOGDEBT)

3.3.5 Sovereign risk

South Africa's current government 10-year index (CTZAR10YR) is available from 1998 while the US Treasury 10-year yield (USGG10YR) is obtained from 1995. A dynamic back casting in the software programme eViews, is used to estimate the missing South Africa's current government 10-year index data before the original observation range. That is, a random walk model for the 1998 – 2016 series is built and then back casted for the missing values 1995 – 1998 using the exponential smoothing technique.

Sovereign spread (S_SPREAD1) is taken as the difference between USGG10YR and the logged difference of CTZAR10YR – LDCTZAR10YR, because the US Treasury yield is taken to be the risk free rate it is subtracted from South Africa's current government 10 year index. The spread should widen when there is strain on the South African financial system as this would signify flight to quality and liquidity.

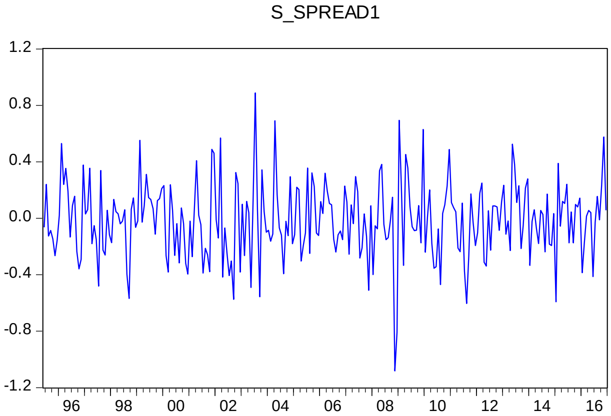


Figure 3.8. S_Spread

Since 2014 South Africa's ratings downgraded by most rating agencies has been looming. Poor growth prospects and rising government debt as well as high deficits on the current account are cited as reasons for the possible downgrade. The spread is widest during 1998/1999 and 2003.

3.3.6 Trade finance

Balance of payments series (SABPFABL from Bloomberg) is reported on a quarterly basis as a result, the data is converted to a monthly frequency using the quadratic match average method. South Africa has a long record of trade deficits which is characterised by a high appetite for imports. Quarter three 2016 data is missing for this index and so, the average of quarter two 2016 and four 2016 was used and that figure as quarter three's value. Data was then de-trended to take seasonality out resulting in variable DLBOP. In recent times, weak global demand impacted exports and the weaker currency has offset to some extent the highly adverse trends in commodity prices.

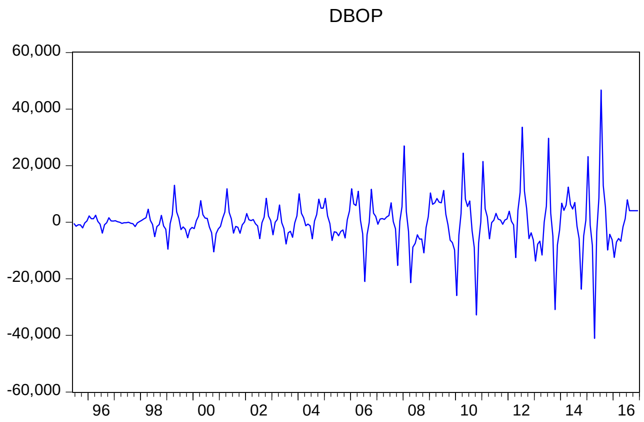


Figure 3.9 BOP Balance of payments (DDLBOP)

3.3.7 Credit stress

IMF's South Africa claims on private sector annual growth as a percentage of broad money is depicted in figure 3.10 below. Claims on private sector include gross credit from the financial system to individuals, enterprises, nonfinancial public entities not included under net domestic credit, and financial institutions not included elsewhere. There is a monumentally razor-sharp dip in the proxy in 2001 followed by a strong recovery a few months later, the most notable variation since then is the reduction in rate from 2007 to 2008 likely caused by the banking sector cutting back on lending to the private sector as they were seeking to reduce risk by deleveraging. The rate of expansion has been uneventful ever since; weak credit growth goes in hand with the subdued outlook for SA consumption, thus, there is an expectation that the coefficient for credit stress to be insignificant and positive in sign.

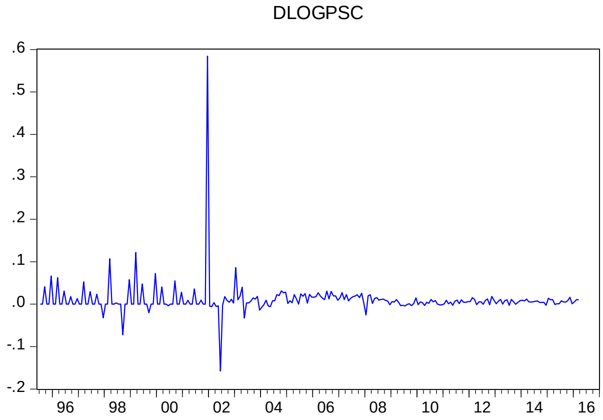


Figure 3.10 Claims on private sector (DLOGPSG)

3.3.8 Liquidity

An index volume represents the trading activity in of all securities that are covered by a particular index; therefore the volume and price from the JALSH index is used to compute market capitalisation then it is scaled by GDP. Again, the constant match sum method was used to transform GDP data from low to high frequency. Figure 3.11 shows a significant upside in stock market activity per GDP during 1998 followed by periods of heightened activity in 2001/2002. It's clear from the pattern in figure 3.11 that each time the market turns after a trough, there are gains within a short period of time which signals to the market being relatively efficient.

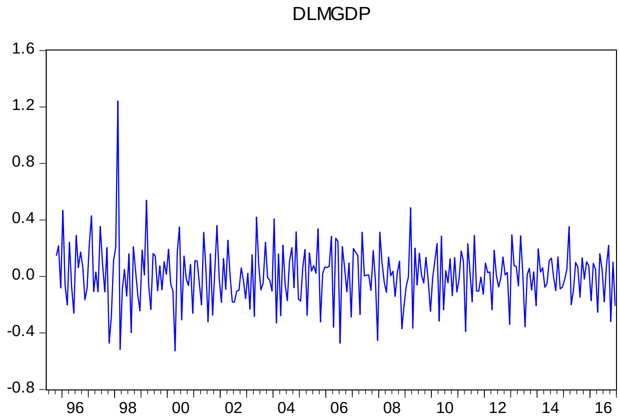


Figure 3.11 Market capitalisation scaled by GDP (DLMGDP)

Because of the assumed relation between stock market liquidity and economic growth, the coefficient for this proxy should be positive; as in the more developed and liquid the JSE is, the less financial stress there is.

3.4 Descriptive Statistics

Table 3.4 shows summary descriptive statistics of all the proxies for the pre-determined variables. EMPI shows the highest mean while the standard deviation is highest for REER; both are representatives of currency risk. The mean and median of REER are comparatively not close to each other, this indicates that the midpoint of data is not close to the mean therefore currency risk is loosely clustered against the mean. The proxies generally do follow the standard risk-return trade-off where high standard deviation is expected to be accompanied by high returns with the exception of DLBOP the proxy for trade finance; its standard deviation is very high relative to its mean which means that the proxy possesses a lot of risk. The Jarque-Bera statistic strongly rejects the null hypothesis of normality in all the return distributions. The skewness and kurtosis confirm that distributions are not normal as the kurtosis is greater than 3 for all variables meaning that all distribution is leptokurtic plus a normal distribution has a skewness of 0, a value that none of the variables have.

Table 3.4 Summary descriptive statistics of log returns

	DLBSPRICE	T_SPREAD	DLJALSH	REER	EMPI	DLOGDEBT	DLBOP	S_SPREAD1	DLOGPSC	DLMGDP
Mean	0.010	0.001	0.009	-0.196	0.062	0.008	0.009	-0.018	0.011	0.013
Median	0.010	0.010	0.011	-0.095	0.080	0.010	0.003	-0.021	0.005	0.018
Maximum	0.292	1.240	0.132	7.280	5.140	0.060	18.542	0.889	0.584	1.242
Minimum	-0.485	-1.380	-0.351	-11.850	-2.820	-0.057	-18.677	-1.081	-0.158	-0.527
Std. Dev.	0.074	0.266	0.056	2.887	1.315	0.017	5.093	0.271	0.042	0.210
Skewness	-0.942	0.069	-1.222	-0.804	0.467	-0.479	0.188	-0.023	10.121	0.627
Kurtosis	10.999	10.602	9.564	5.049	3.821	4.642	9.878	3.972	140.700	7.089
Jarque-Bera	692.273	592.597	502.855	69.559	15.869	37.200	488.305	9.700	198554.100	187.510
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	0.000
Sum	2.469	0.130	2.321	-48.280	15.240	2.006	2.133	-4.395	2.633	3.155
Sum Sq. Dev.	1.330	17.383	0.755	2041.400	423.676	0.069	6381.189	17.949	0.438	10.809
Observations	*234*	*234*	*234*	*234*	*234*	*234*	*234*	*234*	*234*	*234*

Notes: The table reports the summary statistics for the log returns of the proxies at monthly frequency from January 1997 to June 2016

Appendix B shows the pairwise correlation coefficients. There is mostly low correlation meaning that the variables capture different dimensions of financial stress. .The correlation ranges from -0.154 to 0.66, which indicates weak co-movement of the variables. The low correlations also suggest that each variable can be treated as free explanatory variable. The highest correlation (and the most statistically significant as denoted by a t-statistic of greater than 5) is between the JSE All Share (DLJALSH) and the banking sector index (DLBSPRICE) likely because the South African banking sector dominates the stock exchange. The two variables with the least correlation are external debt (DLOGDEBT) and trade finance (DLBOP) this could mean that internal debt is a bigger source of trade finance rather than external debt.

4. EMPERICAL ANALYSIS

4.1 Results interpretation of stationarity test

A stationary series is defined as one with a constant mean, constant variance and constant autocovariances for each given lag (weak stationarity) A series that is not stationary has the following consequences: shocks do not decay; a spurious regression and statistical inference will be wrong (t-stats and standard errors will be wrong, distributions assumed will be invalid) Two tests are undertaken to confirm that returns are stationary (since the dlog of stock prices is used) the Augmented Dickey Fuller (ADF) test and the Phillips Perron (PP) test. ADF's objective is to examine the null hypothesis that $\varphi = 1$ in $yt = \varphi yt - 1 + ut$ against the one-sided alternative $\varphi < 1$ thus H0: series contains a unit root versus H1: series is stationary.

The test results recorded in Table 4.1 indicate that all the transformed series have a unit root process at levels and are integrated of the order I(1). PP is non-parametric and builds on the ADF test with its robustness with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation.

4.2 Generalised AutoRegressive Conditional Heteroskedasticity(GARCH)

One of the underlying assumptions of classic linear regression model is that the variance of the error terms is constant and finite over all values of x_t

$$var\ (u_{t)=}\ \sigma^2 < \infty \qquad (4.1)$$

an assumption that denotes homeskedasticity, however when the assumption is violated and error terms are not constant and finite over all values of x_t the time series suffers from heteroskedasticity, that is, there is volatility clustering. According to Engle (2001), volatility clustering is a phenomenon where good or bad information filters into the market in clusters, then an econometric model using classic linear regression becomes hard to interpret.

The GARCH model for variance is designed to model volatility clustering, it is specified as follows:

$$h_{t+1} = \omega \ + \alpha \, (r_t - \ n_t)^2 + \ \beta \, h_t \ = \omega \ + \alpha \, h \, , \varepsilon_t^2 + \beta \, h_t \tag{4.3}$$

$$\omega \ > 0 \, , \alpha \ \geq 0, \text{and } \beta \geq 0$$

4.3 Results interpretation of ARCH-LM test

With regards to the series that exhibited volatility clustering and needed to be modelled using GARCH, the null hypothesis that there is no ARCH up to order in the residuals is tested by running the regression:

$$e_t^2 = \ \alpha_0 + \ \left(\sum_{\theta=1}^{q} \alpha_{\theta t}^{e^2} - \ \theta\right) + \ u_t \tag{4.4}$$

ARCH-LM test of order of 10 strongly rejects the null hypothesis of homoskedasticity in the individual series which makes it valid to employ GARCH models for the conditional variance of the returns for DLBSPRICE, REER and DLJALSH. *p*-values are less than 0.5 (significant) at 10 lags for each series which confirms justification for implying the GARCH (1,1) model. Please refer to Appendix E for autocorrelation functions (ACF)/correlograms.

Following the employment of the GARCH (1, 1) model, the standardised variables examination for autocorrelation, ARCH-LM results confirm the absence of ARCH-effects in the individual series because *p*-values are now greater than 0.5 meaning it can be accepted that the hypothesis of "no residual ARCH" is true. The variance equation is also recorded in table 4.1 where it is clear that the AR and MA terms are statistically significant for DLBSPRICE and DLJALSH however the AR (1) term is not statistically significant for REER. Parameter estimates from GARCH (1, 1) models for the conditional variance are reported in the second panel of the table. They indicate that the GARCH model captures the high volatility persistence in the variables and is correctly specified.

The sum of the ARCH and GARCH coefficients,$\alpha_1 + \beta_1$, indicates that shocks to volatility have a persistent effect on the conditional variance.

In other words, periods of high volatility in the prices will last for a long time (Engle, 2001).

Table 4.1 Estimation Results of ARMA (p,q)-GARCH(p,q) Models

	DLBSPRICE	DLJALSH	REER
PANEL A: MEAN MODEL			
C	1.329	0.0117	-0.2158
	[0.000]	***[0.000]***	***[0.2974]***
AR (1)	0.8505	-0.62909	-0.29046
	[0.000]	***[0.000]***	***[0.0089]***
AR(2)		-0.801	
		[0.000]	
MA(1)	-0.8909	0.5682	0.5872
	[0.000]	***[0.000]***	***[0.0001]***
MA(2)		*0.8329*	
		[0.000]	
Notes: p values are recorded in parentheses			
PANEL B: GARCH MODEL			
	DLBSPRICE	**DLJALSH**	**REER**
Constant	3.3719	0.0001	1.0407
	[0.132]	***[0.21]***	***[0.0350]***
ARCH	0.207	0.285	0.1333
	[0.006]	***[0.0002]***	***[0.0471]***
GARCH	0.7478	0.7073	0.7356
	[0.000]	***[0.000]***	***[0.000]***
Notes: p values are recorded in parentheses			

4.3.1 Banking sector fragility result

The results of the ARCH-LM test recorded in table 4.1 above show that there are ARCH effects present in this data set (high volatility is followed by high volatility and low volatility is followed by low volatility) therefore there is a need to apply GARCH models in order to treat the problem of heteroskedasticity.

4.4 Lag order selection

The Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC) are used to select optimal lag lengths for all the variables, the result show that the smallest AIC and BIC values correspond to an ARMA (2,2) model for DLJALSH and an AMRA (1,1) model for DLSPRICE and REER. To test for autocorrelation, the Ljung box test is applied to the residuals after formulating appropriate ARMA (*p,q*) model for each of the variables. The Box-Ljung test null hypothesis *HO* is: model does not exhibit a lack of fit while the alternate hypothesis *H1* is: the model exhibits lack of fit. As per table 3.6, the p-values are significant at 36 lags for all the variables; thus the null hypothesis is rejected and table 4.2 beneath depicts the results.

Table 4.2 ADF and PP results

	PP	ADF	*p*
DLBSPRICE	I[0] $^{\times}$	I[0] $^{\times}$	0.000
T_SPREAD	I[0] $^{\times}$	I[0] $^{\times}$	0.000
DLJALSH	I[0] $^{\times}$	I[0] $^{\times}$	0.000
REER	I[0] $^{\times}$	I[0] $^{\times}$	0.000
EMPI	I[0] $^{\times}$	I[0] $^{\times}$	0.000
DLOGDEBT	I[0] $^{\times}$	I[0] $^{\times}$	0.000
DLBOP	I[0] $^{\times}$	I[0] $^{\times}$	0.000
S_SPREAD1	I[0] $^{\times}$	I[0] $^{\times}$	0.000
DLOGPSC	I[0] $^{\times}$	I[0] $^{\times}$	0.000
DLMGDP	I[0] $^{\times}$	I[0] $^{\times}$	0.000
Notes: $^{\times}$ ***indicates statistical significance at 5% and 10%.***			

4.5 Aggregation of components

The proxies above still possess a variety of distributions, this makes developing an aggregation scheme that preserves the interpretation of each indicator difficult. Therefore, it is useful to transform every indicator to ensure compatibility before aggregation, subject to several considerations. PCA accounts for most of the original variability using a relatively small number of components. By forming linear combinations of observed variables, data reduction is achieved by creating a handful of measures that describe the overall population. The new linear combination can is expressed as:

$$p1 = \beta 11x1 + \beta 12x2 + \cdot\cdot\cdot + \beta 1k\, xk \quad (4.5)$$

$$p2 = \beta 21x1 + \beta 22x2 + \cdot\cdot\cdot + \beta 2k\, xk \quad (4.6)$$

where βij are coefficients to be calculated, representing the coefficient on the j the explanatory variable in the i th principal component. These coefficients are also known as factor loadings. Points with the largest variation will have the most influence on principal components as components are ranked in terms of the amount of variance that they explain for this reason, data is normalised before it is aggregated into the components in order to reduce the risk of having variables with the biggest variance overwhelm the PCA. There is no consensus on how to best scale the data for PCA, in this regard the study uses a normalising procedure from the eViews software that converts proxies to mean-reverting with minimum variance.

Aggregation of an index should reflect the relative importance of the various variables hence the PCA methodology is selected, it is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components.

When looking to tell a story using several independent variables, PCA assists with deducing which linear combination of these variables matters the most. It constructs a new property by summarising data and keeping the best possible characteristics of the data. It creates a new property that is linearly combined and reflects both common and unique variance (Abdi & Williams, 2010).

4.6 Results and Findings

A principal component analysis was performed for the purpose of this study to identify key drivers of financial stress. The study used E-views statistical software package to enter and compute the measurements of the model.

The initial grouping included all 10 proxies and the first four components (representatives of trade finance, liquidity, external debt, credit stress and currency risk respectively) account for 53% of all variability. The first step is to remove T_Spread and

EMPI variables from the grouping since the correlation coefficients of the alternate proxies for banking sector fragility and security markets risk DLBSPRICE and REER respectively are higher. What remains is banking sector volatility obtained from a GARCH (1, 1) model as a proxy for the banking sector and the REER as a proxy for securities market risk.

Table 4.3 Principal Component Analysis results

Eigenvalues: (Sum = 8, Average = 1)					
				Cumulative	Cumulative
Number	Value	Difference	Proportion	Value	Proportion
1	1.60575	0.241585	0.2007	1.60575	0.2007
2	1.364166	0.229109	0.1705	2.969916	0.3712
3	1.135057	0.132587	0.1419	4.104973	0.5131
4	1.00247	0.050441	0.1253	5.107442	0.6384
5	0.952029	0.134909	0.119	6.059471	0.7574
6	0.81712	0.197798	0.1021	6.876592	0.8596
7	0.619322	0.115235	0.0774	7.495913	0.937
8	0.504087	---	0.063	8	1

Eigenvectors (loadings):								
Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8
DLBSPRICE	0.411619	0.499951	0.042733	-0.044058	0.25835	0.171243	-0.678716	0.141868
DLJALSH	-0.453772	0.515638	0.186407	-0.146368	0.12097	0.056374	0.045583	-0.67242
DLBOP	0.016489	0.104548	0.069156	0.972042	0.161765	-0.005604	0.069611	-0.090022
DLMGDP	0.319592	0.425085	-0.483613	-0.092083	0.239536	0.130441	0.625947	0.09274
DLOGDEBT	0.021579	-0.307247	0.480234	-0.121304	0.69122	0.369921	0.197648	0.078126
DLOGPSC	0.256583	0.190718	0.485186	0.030512	-0.595207	0.499343	0.234885	0.051667
REER	-0.574301	0.36653	0.151325	0.016747	0.019378	-0.074613	0.066822	0.708693
S_SPREAD1	0.355145	0.165591	0.485627	-0.085812	0.051423	-0.747462	0.204719	0.001085

With this change, eight proxies for the eight variables that are crucial measures for emerging markets stress remain. 63% of variation is accounted for by the first four variables. Table 4.3 shows results of a PCA computed on a correlation matrix. The first section provides a summary of the eigenvalues and the second section shows the corresponding eigenvectors. The principal component explains 20% of the variation; the second principal component explains an additional 17% of the overall variation. The proportion that the remainder of the variables add individually is close to 10% each, in fact each component following the first two principal components adds between 7% and 13% additional variation, this signifies that each variable makes a decent contribution towards explaining the overall variance in the data.

PCA reports eigenvalues and eigenvectors, eigenvalues explain the scale of the principal components while eigenvectors explain the direction of the principal components. When eigenvector is multiplied by the square root of the eigenvalue the result is a factor loading:

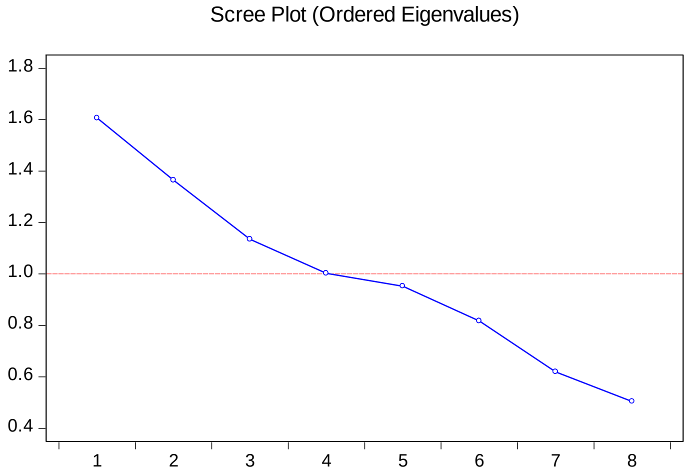
$$Factor\ loading = eigenvector \times \sqrt{eigenvalue} \tag{4.7}$$

Factor loadings help to interpret principal components because they provide information about the load and direction of a principal value within the stress index. In other words, from the above principal component analysis, it is clear that principal component one accounts for 20% of total variance of the FSI and has positive loadings for all components except DLJALSH and REER. The first four principal components have eigenvalues of more than 1. The contribution of variable κ to component S is derived as follows:

$$c_{\kappa,\mathrm{S}} = \frac{\int_{\kappa,\mathrm{S}}^{2}}{\sum_{\kappa} \int_{\kappa,\mathrm{S}}^{2}} = \frac{\int_{\kappa,\mathrm{S}}^{2}}{\partial_{\kappa}} \tag{4.8}$$

Where ∂_{κ} is the eigenvalue of the κth factor. Eigenvalues that are greater than 1 is one way of identifying the number of components to retain for a PCA based on a correlation matrix, the scree plot is a graphical way of making the same decision.

Figure 4.1 Scree Plot



Correlations across sub-indices recorded in table 4.4 below are weak which means the state of financial instability will not be so widespread in the event of a stress episode.

Table 4.4 Ordinary correlations of principal components

Ordinary correlations:								
	DLBSPRICE	DLJALSH	DLBOP	DLMGDP	DLOGDEBT	DLOGPSC	REER	S_SPREAD1
DLBSPRICE	1							
DLJALSH	0.037649	1						
DLBOP	0.045929	-0.015619	1					
DLMGDP	0.302448	-0.002839	0.000466	1				
DLOGDEBT	-0.022355	-0.036694	-0.014023	-0.14218	1			
DLOGPSC	0.150288	-0.011052	0.015642	-0.015919	-0.020245	1		
REER	-0.10609	0.466309	0.039313	-0.111288	-0.066788	-0.070653	1	
S_SPREAD1	0.1971	-0.050051	0.00764	0.031097	0.051054	0.149908	-0.107361	1

Figure 4.2 plots orthonormal loadings biplot where eigenvector coefficients and loadings between principal components can be observed. The analysis is of components with eigenvalues of more than 1 and component scores are displayed as circles and factor loadings are displayed as lines. The further each coefficient is from zero, the greater the contribution that variable makes to that component.

The first graph of figure 4.2 plots principal 1 on the x axis and principal component 2 on the y axis. DLJALSH and REER have negative coefficients which means they reduce they reduce the SAFSI. Although DLOGDEBT and DLBOP have negative coefficients, it is not significantly so. The variables that contribute positively to financial stress are DLBSPRICE, S_SPREAD, DLMGDP and DLOGPSC in order of their loadings. That is, security market and currency risk do not pose as much as of a threat as banking sector fragility, illiquidity, sovereign risk and trade finance respectively. The second graph plots principal 1 on the x axis and principal component 3 on the y axis. DLJALSH and REER still have negative coefficients and DLSBSPRICE still dominates followed closely by DLMGDP and S_SPREAD.

Judging by the Orthonormal loadings biplot figure, it is clear that of all the variables with a positive coefficient, DLBSPRICE has the highest factor loading followed by S_SPREAD and DLMGPD. REER and DLJALSH have negative coefficients and high factor loadings. In other words, banking sector fragility, illiquidity, sovereign risk, security market risk and exchange risk are the biggest drivers of financial stress from pre-selected variables.

As stated in the preliminary assessment, banking sector fragility would likely dominate because of its huge contribution to South African GPD. It cost the South African Reserve Bank approximately 9 billion to bailout the country's fifth bank in market size, African Bank Limited, arguably to maintain financial stability. Variability in the banking sector causes an immense strain on South Africa's financial system. What is not expected to dominate is the illiquidity proxy, mainly because it is not one of the original variables suggested by Cevik, Dibooglu, and Kenc (2013) to capture stress in emerging markets.

Sovereign spread measured by macroeconomic fundamentals, such as interest rate spreads between a home country and the United States can be used as a measure of risk perception In the short run, it is the degree of political risk, corruption, and financial stability in a country that plays the key role in the valuation of sovereign debt. Bellas, Papaioannou, and Petrova (2010), that is to say investor's risk perceptions drive short term capital flows. For South Africa, the risk of the country being downgraded to a junk status means the cost of borrowing will swell and make the country an unattractive investment prospect.

In summary, an increase in the SAFSI is signal of a severe economic downturn. As sovereign spreads widen, exchange markets come under pressure (and thus a slowdown in capital flows), lending in banks falter as they attempt to deleverage and ineffective financial markets deter investors consequently, financial stability of the country is compromised by these conditions.

In some literature, it is common to select at least five principal components before constructing an index. It is important to examine components (variables) and make sure that those that are retained provide an interpretable result. To this unrotated factor loadings are employed to test whether the same variables dominate as under PCA as per figure 4.2. Right off the bat, it is clear that just as PCA selects four principal components, there are four retained factors (F1- F4) according to factor loadings and the variance that they account for by is approximately 63% (5.107/8) of total variance. In other words, four variables have greater explanatory power of overall variability in the index than others.

Factor loadings represent variation between components and the original variable, table 4.5 shows that DLBSPRICE, DLJALSH, DLMGDP, DLOGDEBT and REER load on the second factor (F2) while S_SPREAD loads on F3 and the rest load on F2. Factor 1 (F1) has the most correlation with variables with a cumulative loading of 31% followed by Factor 2 (F2) with 27% , Factor 3 (F3) at 22% and Factor 4 (F4) at 19%.

Figure 4.2 Orthonormal Loadings Biplot

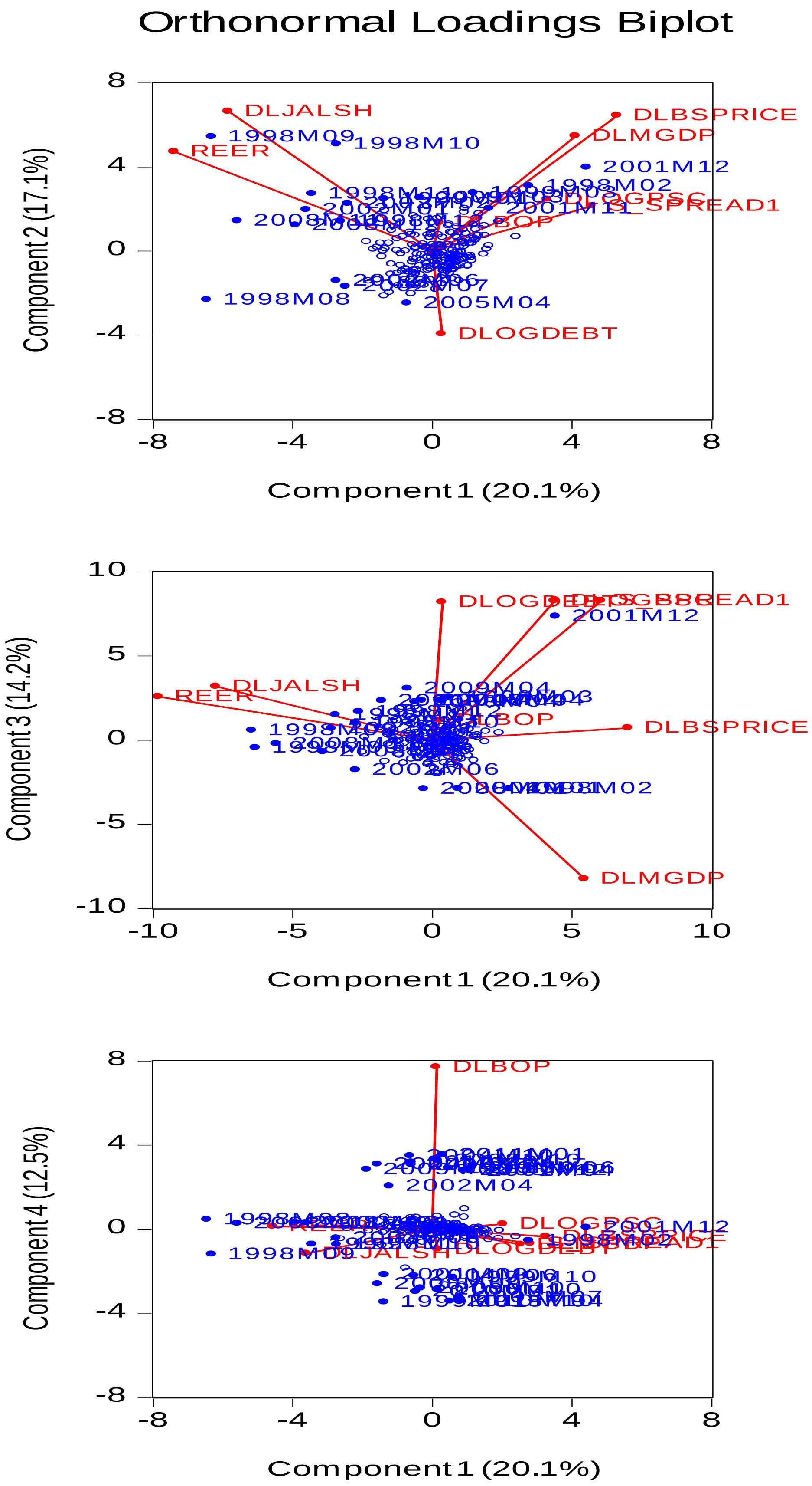


Table 4.5 Unrotated loadings

Unrotated Loadings

	F1	F2	F3	F4	Communality	Uniqueness
DLBSPRICE	0.521596	0.58393	0.045527	-0.044112	0.617056	0.382944
DLJALSH	-0.575012	0.602252	0.198596	-0.146549	0.754263	0.245737
DLBOP	0.020895	0.122109	0.073678	**0.973242**	0.967975	0.032025
DLMGDP	0.404981	0.496489	-0.515236	-0.092197	0.68448	0.31552
DLOGDEBT	0.027344	-0.358857	0.511636	-0.121454	0.406049	0.593951
DLOGPSC	0.325137	0.222754	0.516913	0.03055	0.423466	0.576534
REER	-0.727744	0.428098	0.16122	0.016767	0.739153	0.260847
S_SPREAD1	0.450033	0.193406	0.517382	-0.085918	0.515001	0.484999

Factor	Variance	Cumulative	Difference	Proportion	Cumulative
F1	1.60575	1.60575	0.241585	0.314394	0.314394
F2	1.364166	2.969916	0.229109	0.267094	0.581488
F3	1.135057	4.104973	0.132587	0.222236	0.803724
F4	1.00247	5.107442	---	0.196276	1
Total	**5.107442**	**5.107442**		1	

Next, the factors are rotated using a varimax method to minimise the number of variables that have high loadings on each factor, a method developed by (Kaiser, 1958) For varimax a simple solution means that each component has a smallnumber of large loadings and a large number of zero (or small) loadings. (Abdi & Williams, 2010) This implies simple interpretation (presented in table 4.5 below) is because, after a varimax rotation, each original variable tends to be associated with one (or a small number) of components, and each component represents only a small number of variables. As a general rule, rotated loadings of above 0.7 are considered important. Thus DLBOP, DLJALSH, REER, DLMGDP and S_SPREAD are considered the important to the SAFSI.

Table 4.6 Rotated factor loadings

Rotated loadings: L * inv(T)'				
	F1	F2	F3	F4
DLBSPRICE	-0.006644	0.552688	0.558139	0.005345
DLJALSH	**0.860574**	0.071254	0.060855	-0.069957
DLBOP	-0.002389	0.022947	0.044207	**0.982593**
DLMGDP	-0.104377	**0.814757**	0.055894	-0.081438
DLOGDEBT	-0.112519	-0.559264	0.255103	-0.124638
DLOGPSC	0.019046	-0.066998	0.642487	0.076321
REER	**0.842353**	-0.080137	-0.131739	0.076269
S_SPREAD1	-0.081862	-0.039533	**0.710497**	-0.043942

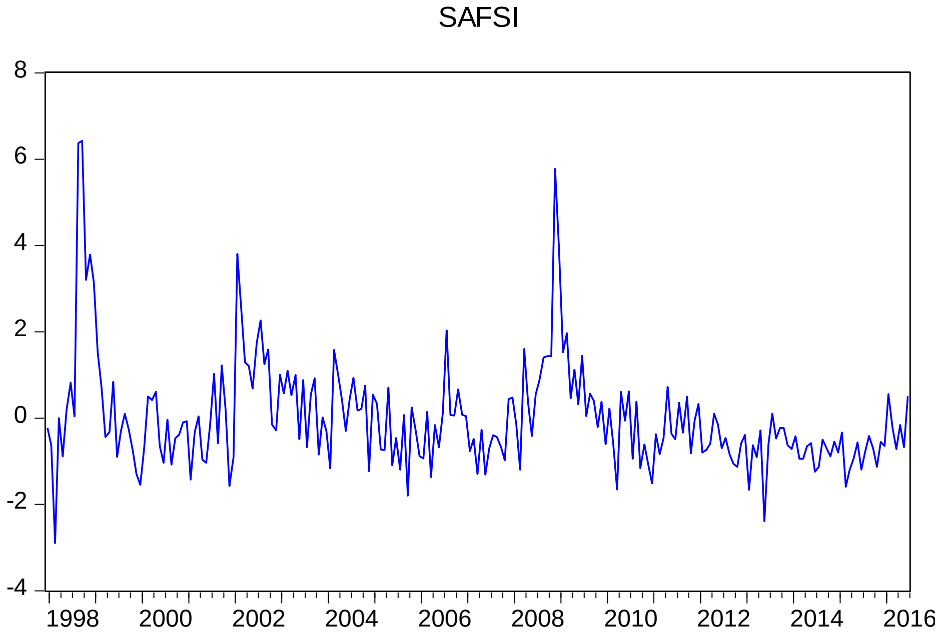
However the variables that affect SAFSI as a whole are those that are of interest as well as variables with loadings that represent how strongly they are associated with each factor are selected. Table 4.7 illustrates the factor score summary:

Table 4.7 Factor Score Summary

Factor Score Summary				
Factor Coefficients:				
	F1	F2	F3	F4
DLBSPRICE	0.040236	**0.380205**	**0.382191**	-0.006451
DLJALSH	**0.594152**	0.056973	**0.104565**	-0.089019
DLBOP	-0.018798	0.003895	0.020938	0.976794
DLMGDP	-0.059595	**0.630797**	-0.037801	-0.087715
DLOGDEBT	-0.059585	-0.459313	0.242298	-0.11885
DLOGPSC	0.057997	-0.111638	0.505378	0.068942
REER	**0.563443**	-0.045185	-0.034085	0.060537
S_SPREAD1	-0.003218	-0.095931	**0.549627**	-0.049629

While DLBOP has a very high loading for factor 4, overall the following variables have the most impact on all factors as whole (taking into account that factor 1 and 2 are more impactful that factor 3 and 4): DLBSPRICE, DLJALSH, DLMGDP, REER and S_SPREAD 1. The SAFSI is constructed using these variables as they correlate to the principal components identified using PCA. With regards to REER being a negative coefficient (identified by PCA) this is due to the nature that the data is presented. As descriptive stats in table 3.4 reveal, REER's mean has a negative coefficient similarly in figure 4.2 under the data and preliminary observations section, the REER trends downwards in times of turmoil, this means that depreciation is illustrated by a downturn in figure 4.2 It follows then that a depreciation of the rand (lower cash flows) correlates with heightened financial stress.

4.7 A financial stress index for South Africa



The SAFSI does well in identifying known episodes of financial stress, the peaks correspond to known financial turmoil events namely the East Asian crisis (1998), the 'dot.com' crisis (2000), the 9/11 events/rand (ZAR) crisis (2001) and global financial crisis (2008/2009) The graph suggests that the SAFSI and episodes of financial turmoil are highly correlated and that stress is well represented by the chosen variables. Sovereign spreads, exchange rate volatility, security market risk and trade finance had the most influence over the past two decades on the occurrence of crises in South Africa'.

As a measure of financial stress, the FSI does superbly; it very clearly singles out the 1998 East Asian crisis as the most stressful period over the last two decades. The contagion effects of the financial disorder that hit Asia from mid 1997 spread rapidly and had a profound effect on many emerging market economies including South Africa as massive cash outflows led to exchange rate depreciations. A decline in world demand and adversely affected commodity prices affected South Africa as it had just re-entered the world trade post-apartheid. The second most prominent peak is in 2008/2009 which represents the global financial crisis that triggered mayhem in advanced and emerging markets alike. The South African Reserve Bank's announcement in October 2001 that it would enforce the existing exchange control regulations regarding foreign-currency trading more strictly and its commitment to closing out the oversold forward book (which gave rise to a speculative attack against the rand), spurred a currency crisis in 2001 illustrated by the third most prominent peak. Interestingly, the SARB's opting against a policy response of intervention as they did in 1998 is received as one of the reasons why the consequences of this crisis were limited in comparison to 1998's crisis. (Bhundia & Ricci, 2005)

In contrast, the SARBFSI was formulated as an aggregated index that involves two-level construction processes that use variance-equal weight techniques across indicators. Variables are standardised before they are aggregated so that only deviations from the mean explain the movements in the SARBFSI. It is constructed for the period January 2006 – January 2015 on a monthly frequency and selects proxies of five dominants markets – credit, funding, equity, foreign exchange and real estate. Each market has an average of three proxies that serve as explanatory sub-indices for the main index.

SARB FSI correlates well with periods of stress particularly 2006 – 2009, it remained stable thereafter then increased again from 2014. The increase was mainly driven by the domestic equity market and rand volatility and, to a lesser extent, by real-estate prices It does not do well in signalling upcoming stress events as is common with financial stress indices that are constructed with aggregation models that are not robust. One could say that the FSI has an advantage over the SARB's FSI because it has a longer proven track record. The construction of the SARBFSI is first reported in the South African Bank Financial Stability Review report of March 2016.

4.7.1 Analysis of SAFSI against composite business cycle leading indicators

In South Africa, the Composite Leading Business Cycle Indicator examines the direction in which real economic activity is moving, in real time. It is calculated on the basis of the following components: building plans approved, new passenger vehicles sold, commodity price index for main export commodities, index of prices of all classes of shares traded on the JSE, job advertisements, volume of orders in manufacturing, real M1, average hours worked per factory worker in manufacturing, interest rate spread, composite leading business cycle indicator of the major trading-partner countries, business confidence index, gross operating surplus as a percentage of GDP.

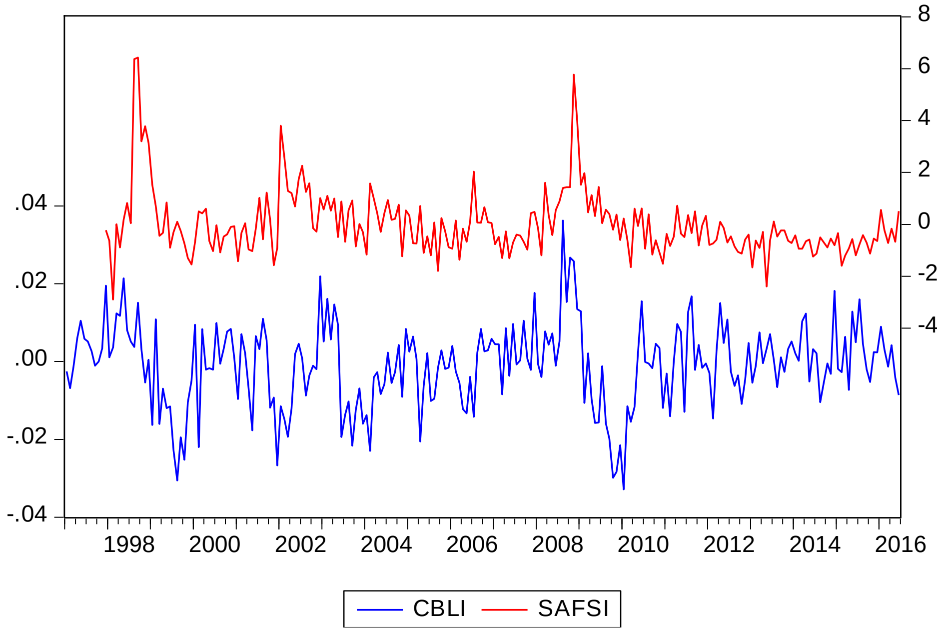


Figure 4.3 SAFSI and composite business cycle leading indicator

The SAFSI moves closely with the composite business cycle leading indicator, trends are mirrored between the index and the CBLI. They both increase during the beginning of a stress cycle and both decrease as the stress cycle ends and moves towards a recovery.

4.8 The relationship between financial stress and economic activity

4.8.1 VAR Estimation

The link between macroeconomic variables and episodes of financial stress is covered to a large degree in literature. Data that corresponds with the focal index period of 1997 – 2016 is analysed and VAR estimated using three variables which are key indicators of economic activity in South Africa– GDP, CPI inflation and interest rates. The SAFSI is transformed to quarterly frequency using the quadratic average method to match its frequency to the quarterly frequency of GDP and CPI. For interest rates averages of the 3-month interbank rate generated from monthly data obtained from Bloomberg are used.

After log-normalising the data, the Augmented Dickey Fuller (ADF) and the Phillips Perron (PP) tests as presented in table 4.8 below are used to confirm that returns are not stationary. All the transformed series (CPI_1, INT_1 and R_GDP) have a unit root process at levels and are integrated of the order I (1).

Table 4.8 ADF and PP results

	PP	ADF
SAFSI	I[0] $^{\times}$	I[0] $^{\times}$
R_CPI	I[0] $^{\times}$	I[0] $^{\times}$
R_INT	I[0] $^{\times}$	I[0] $^{\times}$
R_GDP	I[0] $^{\times}$	I[0] $^{\times}$
Notes: $^{\times}$ ***indicates statistical significance at 5% and 10%.***		

The lag length for the VAR (p) model is determination results using model selection criteria are recorded in table 4.9. The Akaike (AIC) suggests three lags while the Schwarz-Bayesian (BIC) and Hannan-Quinn (HQ) criterion suggest one lag therefore one lag is utilised to study the relationship between the SAFSI and indicators of economic activity.

Table 4.9 Lag order selection VAR(q) model

Lag	AIC	SC	HQ
0	5.998092	6.128651	6.049824
1	5.222116	**5.874912***	**5.480774***
2	5.267298	6.442331	5.732882
3	**5.145479***	6.84275	5.81799
4	5.224826	7.444334	6.104263
5	5.515863	8.257608	6.602226

Notes: * indicates lag order selected by the criterion

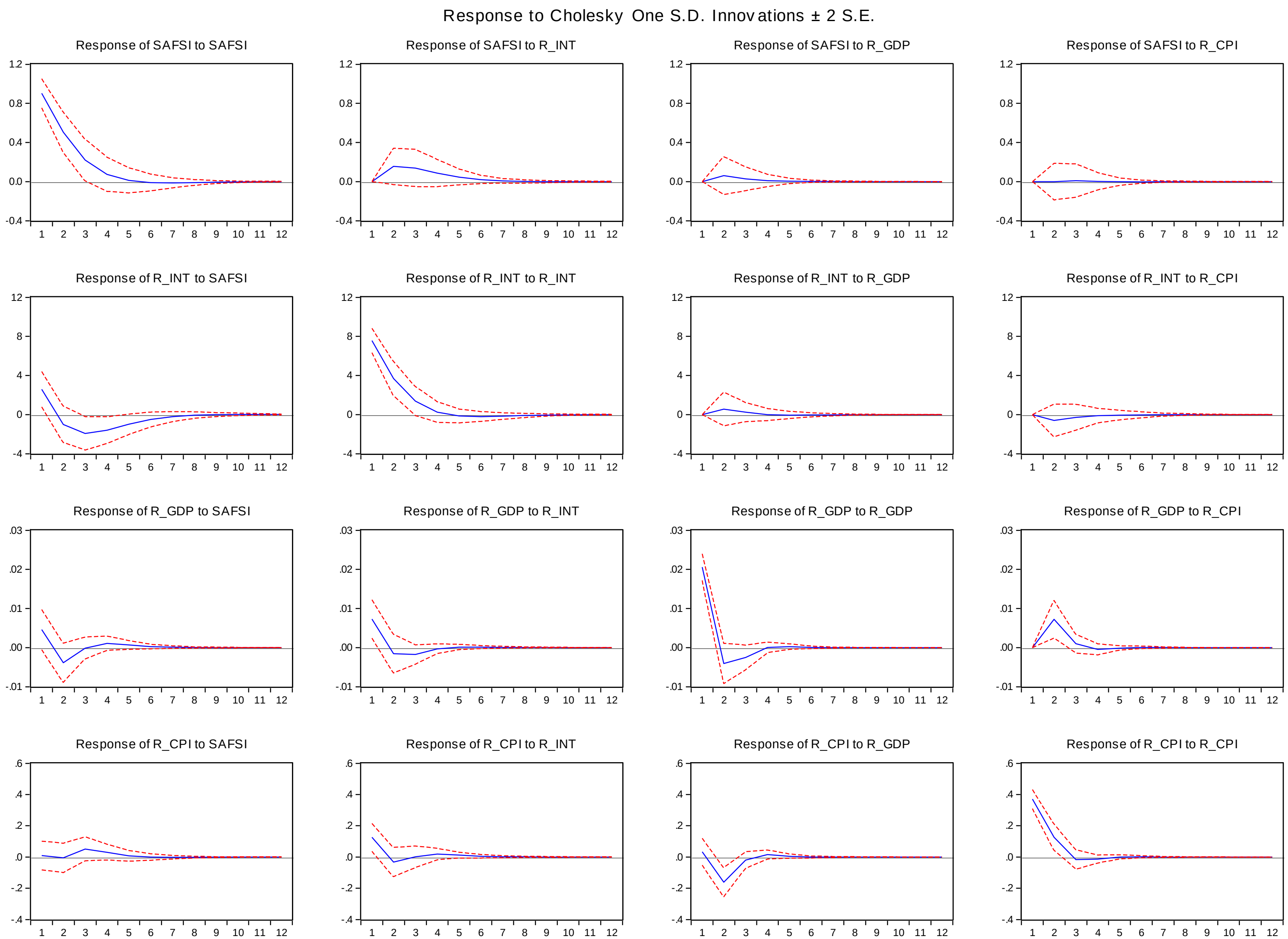
Please see Appendix C for VectorAutoregressive results. A t-statistic of above 2 suggests significance in the ability of past lags of one variable is helpful explaining another variable, in other words VAR suggest that the following variables in the model have statistical significance on the future values of other variables:

- SAFSI is positively related to its own lag
- R_CPI is positively related to its own lag and negatively related to one lag of R_GDP
- R_GDP is positively related to one lag of R_CPI
- R_INT is negatively related to one lag of SAFSI and positively related to its own lag.

4.8.2 Impulse responses

If there is a shock in the market, how long the system will revert to equilibrium? That is the main question impulse response functions seek to answer. Since the SAFSI measures risk in the overall economy, how long a shock takes to dissipate gives an indication for how long there will be a disturbance for. The response of the SAFSI to unexpected shocks to other variables is given in the first row. The response of the R_INT to unexpected shocks to other variables is given in the second row. The response of the R_GDP to unexpected shocks to other variables is given in the third row. R_GDP responds positively to unexpected decreases in R_CPI for a short period, while it responds negatively to all other variables initially. The response of the R_CPI to unexpected shocks to other variables is given in the fourth row. Overall, shocks take a little while to decay.

Please refer to Appendix D for Impulse response tables where it is clear that R_CPI has the least influence on responses to other variables and that the SAFSI has the most impact on R_INT.


Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of SAFSI to SAFSI
Response of SAFSI to R_INT
Response of SAFSI to R_GDP
Response of SAFSI to R_CPI
Response of R_INT to SAFSI
Response of R_INT to R_INT
Response of R_INT to R_GDP
Response of R_INT to R_CPI
Response of R_GDP to SAFSI
Response of R_GDP to R_INT
Response of R_GDP to R_GDP
Response of R_GDP to R_CPI
Response of R_CPI to SAFSI
Response of R_CPI to R_INT
Response of R_CPI to R_GDP
Response of R_CPI to R_CPI

4.8.3 Granger Causality Test

The causal relations reveal the direction of return, volatility and conditional asymmetry spillover between the FSI and its variables of macroeconomic activity, thus, helping to examine how they affect each other. A VAR Granger causality is utilised to capture the causal relations (Hylleberg, Engle, Granger, & Yoo, 1990). Explicitly, X is said to "Granger-cause" Y if previous values of X contain information that helps predict Y above and beyond the information contained in past values of Y alone.

Table 4.10. Pairwise Granger Causality

Pairwise Granger Causality Tests			
Lags: 3			
Null Hypothesis:	Obs	F-Statistic	Prob.
R_INT does not Granger Cause SAFSI	72	1.17228	0.3272
SAFSI does not Granger Cause R_INT		4.96265	0.0037
R_GDP does not Granger Cause SAFSI	72	0.53611	0.6592
SAFSI does not Granger Cause R_GDP		0.36011	0.782
R_CPI does not Granger Cause SAFSI	72	0.11504	0.951
SAFSI does not Granger Cause R_CPI		0.11711	0.9498
R_GDP does not Granger Cause R_INT	84	0.47536	0.7004
R_INT does not Granger Cause R_GDP		0.56777	0.6379
R_CPI does not Granger Cause R_INT	84	0.49094	0.6896
R_INT does not Granger Cause R_CPI		1.22251	0.3073
R_CPI does not Granger Cause R_GDP	84	4.24049	0.0079
R_GDP does not Granger Cause R_CPI		7.0508	0.0003

p values in table 4.8 results show that SAFSI does granger cause R_INT and R_GDP does granger cause R_CPI, that is changes in the SAFSI do cause changes in R_INT and changes in R_GDP do cause change in R_CPI. Indeed, it can be concluded that the SAFSI has predictive power over interest rates, in other words the SAFSI contains information that is relevant in explaining R_INT. The relationship between R_GDP and R_CPI is expected.

5. CONCLUSION AND RECOMMENDATION

Financial distress can lead to financial crises, which have significant and persistent adverse effects on the real economy, as the 2008/2009 financial crisis confirmed. Sustainable growth, acceptable employment levels and social welfare (factors are that important to the development of an emerging market) are encouraged by the maintenance of financial stability. The SAFSI is derived from five leading indicators of stress that was built using PCA and factor analysis by means of an amass of security market risk, banking sector fragility, currency risk, sovereign risk and liquidity risk, that is to say increasing uncertainty in financial markets and banking systems, currency pressure, a negative outlook on government's funding ability and underdeveloped financial markets lead to increased financial stress in South Africa.

This study quested to answer the following questions:

- Is it optimal considering the ongoing episodes in the financial industry to create an index that captures known episodes of financial stress in South Africa by using a variation of variables that have been proven to capture stress in other emerging markets?
- If so, can this FSI's performance be compared to the South African Reserve Bank's FSI in capturing historic crisis events?
- How well does the SAFSI track South Africa's composite leading business cycle indicator (CLBI)
- If the above questions are optimally answered, can the proposed FSI predict key indicators of economic activity within the South African domain?

To answer the first question, empirical results suggest that it is worthwhile to consider the variables that were identified as drivers of financial stress. The index performed well in capturing historic events of stress and it did so by using a substantially scaled down number of variables in comparison of the South African Reserve Bank's eleven indicators.

Proxies for the SAFSI's indicators are readily available in high frequency dating back as far two decades ago and there is room for considering different proxies for the variables that have been identified which may yield an even more meaningful result.

In contrast to the South African Reserve Bank's FSI, the SAFSI captured a longer history of stress events. This means it arguably has a longer proven track record. Although, the South African Reserve Bank's FSI did better in capturing recessionary conditions in South Africa in 2014/2015 while the SAFSI index does not signal to any strain at all during this period.

The SAFSI also tracks South Africa's composite leading business cycle indicator since leading indicators tend to include variables that have explanatory power over movements in the economy, it can be said that the SAFSI does indeed give a sense of the future state of the economy.

Empirical result shows that there is merit in using the variables that have pre-selected to detect more information about the state of the developing nation's economies because they also seem to offer information about the current and future state of the South African economy. Granger causality tests confirm a relationship between changes in the SAFSI and R_INT which indicates that the SAFSI is significant in influencing a variable of economic activity. Impulse response functions also point to a definite relationship between the two – that is, there is a negative response in R_INT to unexpected shocks in SAFSI

At the moment, the SAFSI is more useful in assessing whether stress is rising or falling, it could be more informative if it had predictive power across more variables. This element is not fully explored in this study. Future studies could explore the drawback of PCA – that it is not robust and is sensitive to outliers since it minuses squared distances from the multidimensional mean. To mitigate this risk, outliers and strong pairings could be scrutinised in the beginning to look for indication of whether data should be "smoothed". Additionally, a second methodology (CISS) could be employed to cater for the lack of robustness in the PCA methodology; CISS captures robustness and thus allows for robust historical comparisons to be made. It integrates a composite indicator of systemic stress into a VAR can have the advantage that it builds on what systemic crises have in common, namely instability that spreads widely across markets and institutions. Further, it is useful as a measure of the impact of policy intervention initiatives directed towards alleviating financial stress.

Appendix A

Variable	Proxy	Definition and construction	Data source(s)
Banking sector fragility	DLBSPRICE	TED Spread - spread between the 3-month interbank lending rate and the 91-day TB rate	JIBAR, IMF 91day TB rate for South Africa; Bloomberg
	T_SPREAD	Banking sector equity index variability modelled using GARCH (1,1)	JSE 40, FTSE/JSE Africa Bank Index - South Africa; Bloomberg
Securities market risk	DLJALSH	Time varying volatility stock market volatility modelled using the GARCH (1, 1) on FTSE/JSE ASI index	JALSH; Bloomberg
		Downside beta computed using excess MCSI Barra index and JSE all share index	MCSI Bara Index; Bloomberg
Currency risk	DZAR_USD	The exchange rate relative to the most traded currency in the world (US $)	ZAR/USD; Bloomberg
	REER	Real effective exchange rate volatility estimated using GARCH 1,1 model	BIS Indices
	EMPI	EMPI (Exchange Market Pressure Index) which incorporates exchange rate change, international reserves change and the overnight local interest rate change relative to the US interest rate computed to measure currency risk.	ZAR/USD, FDFD, SARPRT ; Bloomberg. RSA Reserves minus gold; IMF
External debt	DLOGDEBT	12-month growth rate of external debt (long and short term debt) computed using South Africa debt to GDP multiplied by GDP	SABTGDIQ Index and SACGDP Index; Bloomberg
Sovereign risk	S_SPREAD1	Sovereign bond spreads - difference between current South Africa 10YR government bond index and US 10-year treasury rate yield	CTZAR10YR, USGG10YR; Bloomberg
Trade finance	DLBOP	South Africa Balance of Payments Financial Account balance	SABPFABL; Bloomberg
Credit crisis	DLOGPSC	Growth rate of the claims of private sector (i.e private sector credit)r as a percentage of broad money	RSA IMF Claims on private sector
Liquidity risk	DLMGDP	Stock market capitalisation scaled by GDP	JALSH and SACGDP Indices; Bloomberg

Appendix B

Correlation

t-Statistic	DLBSPRICE	T_SPREAD	DLJALSH	REER	EMPI	DLOGDEBT	DDLBOP	S_SPREAD1	DLOGPSC	DLMGDP
DLBSPRICE	1									

T_SPREAD	0.007838	1								
	0.122431	-----								
DLJALSH	0.663561	-0.075406	1							
	13.85489	-1.181243	-----							
REER	0.242164	-0.042555	0.075016	1						
	3.89876	-0.665339	1.175103	-----						
EMPI	0.149274	-0.080903	0.08691	-0.025896	1					
	2.358158	-1.267894	1.362732	-0.404639	-----					
DLOGDEBT	-0.059883	-0.032068	-0.022025	-0.012477	-0.0411	1				
	-0.93709	-0.501176	-0.344118	-0.194919	-0.642	-----				
DDLBOP	-0.02983	-0.086473	0.082532	0.10861	-0.006	-0.153889	1			
	-0.466161	-1.355827	1.293611	1.706636	-0.0931	-2.432807	-----			
S_SPREAD1	0.010309	-0.027741	0.166255	0.040344	-0.0257	0.065893	0.00768	1		
	0.161043	-0.433495	2.633631	0.630713	-0.402	1.031517	0.11997	-----		
DLOGPSC	0.092902	-0.067749	0.141916	-0.205939	-0.0206	-0.016518	-0.0029	0.145088	1	
	1.457475	-1.060714	2.239466	-3.287338	-0.3224	-0.258048	-0.0447	2.290592	-----	
DLMGDP	0.218281	-0.074009	0.333675	-0.089186	0.1697	-0.138115	0.00577	0.020192	-0.02628	1
	3.493911	-1.159238	5.529054	-1.398706	2.68976	-2.178299	0.09019	0.315467	-0.41059	-----

Appendix C

	SAFSI	R_CPI	R_GDP	R_INT
SAFSI(-1)	0.493966	0.038192	-0.002404	-2.639175
	(0.10213)	(0.04446)	(0.00252)	(0.90507)
	[4.83668]	[0.85894]	[-0.95249]	[-2.91598]
R_CPI(-1)	-0.000975	0.341547	0.019527	-1.622029
	(0.25318)	(0.11023)	(0.00626)	(2.24371)
	[-0.00385]	[3.09851]	[3.12029]	[-0.72292]
R_GDP(-1)	2.934018	-8.368956	-0.230079	29.96316
	(4.81316)	(2.09553)	(0.11897)	(42.6544)
	[0.60958]	[-3.99371]	[-1.93390]	[0.70246]
R_INT(-1)	0.017661	-0.001830	-0.000310	0.484437
	(0.01225)	(0.00533)	(0.00030)	(0.10855)
	[1.44178]	[-0.34309]	[-1.02379]	[4.46265]
C	-0.045694	0.496338	0.020085	-0.491887
	(0.17442)	(0.07594)	(0.00431)	(1.54569)
	[-0.26198]	[6.53617]	[4.65866]	[-0.31823]
R-squared	0.311130	0.236019	0.166212	0.278657
Adj. R-squared	0.271196	0.191730	0.117876	0.236840

Appendix D

Response of SAFSI:				
Period	SAFSI	R_INT	R_GDP	R_CPI
1	0.903413	0.000000	0.000000	0.000000
	(0.07426)	(0.00000)	(0.00000)	(0.00000)
2	0.505655	0.155129	0.060359	-0.000362
	(0.10286)	(0.09324)	(0.09703)	(0.09392)
3	0.220750	0.137099	0.027939	0.010325
	(0.10683)	(0.09510)	(0.06030)	(0.08474)
4	0.074599	0.086869	0.010868	0.003107
	(0.08718)	(0.06915)	(0.03122)	(0.04450)
5	0.011741	0.046387	0.005586	-0.001751
	(0.06411)	(0.04035)	(0.01311)	(0.01892)
6	-0.009751	0.020726	0.002626	-0.002145
	(0.04280)	(0.02116)	(0.00547)	(0.00814)
7	-0.012912	0.006939	0.000729	-0.001357
	(0.02585)	(0.01207)	(0.00287)	(0.00390)
8	-0.009756	0.000842	-9.02E-05	-0.000721
	(0.01435)	(0.00821)	(0.00182)	(0.00229)
9	-0.005788	-0.001139	-0.000277	-0.000338
	(0.00762)	(0.00572)	(0.00117)	(0.00151)
10	-0.002849	-0.001335	-0.000235	-0.000125
	(0.00419)	(0.00367)	(0.00069)	(0.00095)

Response of R_INT:				
Period	SAFSI	R_INT	R_GDP	R_CPI
1	2.599104	7.572445	0.000000	0.000000
	(0.90583)	(0.62245)	(0.00000)	(0.00000)
2	-1.001234	3.683738	0.561852	-0.601702
	(0.93012)	(0.87579)	(0.86281)	(0.83379)
3	-1.926005	1.380180	0.251450	-0.278997
	(0.85090)	(0.74556)	(0.48713)	(0.65912)
4	-1.603079	0.251196	0.004216	-0.106220
	(0.67859)	(0.52686)	(0.30926)	(0.37126)
5	-0.990138	-0.146527	-0.049413	-0.053137
	(0.52321)	(0.35549)	(0.18347)	(0.24489)
6	-0.502196	-0.208217	-0.039335	-0.024509
	(0.37770)	(0.24918)	(0.10420)	(0.15225)
7	-0.208222	-0.159556	-0.024568	-0.006422
	(0.25625)	(0.16863)	(0.05448)	(0.08258)
8	-0.060581	-0.096046	-0.013643	0.001253
	(0.16624)	(0.10519)	(0.02665)	(0.04128)
9	6.29E-05	-0.048085	-0.006358	0.002873
	(0.10348)	(0.06149)	(0.01280)	(0.01958)
10	0.017172	-0.019456	-0.002230	0.002356
	(0.06168)	(0.03541)	(0.00653)	(0.00920)

Response of R_GDP:

Period	SAFSI	R_INT	R_GDP	R_CPI
1	0.004603	0.007333	0.020583	0.000000
	(0.00257)	(0.00247)	(0.00169)	(0.00000)
2	-0.003868	-0.001574	-0.004075	0.007244
	(0.00250)	(0.00248)	(0.00256)	(0.00240)
3	-0.000129	-0.001781	-0.002520	0.000995
	(0.00139)	(0.00122)	(0.00156)	(0.00120)
4	0.001102	-0.000321	5.37E-05	-0.000485
	(0.00092)	(0.00063)	(0.00066)	(0.00071)
5	0.000662	0.000140	0.000254	-0.000116
	(0.00055)	(0.00035)	(0.00036)	(0.00029)
6	0.000263	0.000130	4.29E-05	4.63E-05
	(0.00029)	(0.00019)	(0.00015)	(0.00015)
7	0.000101	7.98E-05	-5.58E-06	2.13E-05
	(0.00016)	(0.00011)	(6.2E-05)	(6.9E-05)
8	3.40E-05	4.85E-05	2.96E-06	-1.37E-06
	(8.7E-05)	(6.1E-05)	(2.1E-05)	(2.3E-05)
9	2.60E-06	2.61E-05	4.67E-06	-3.19E-06
	(5.2E-05)	(3.3E-05)	(6.6E-06)	(9.0E-06)
10	-8.24E-06	1.10E-05	1.81E-06	-1.36E-06
	(3.1E-05)	(1.8E-05)	(3.5E-06)	(4.5E-06)

Response of R_CPI:

Period	SAFSI	R_INT	R_GDP	R_CPI
1	0.008633	0.125997	0.033843	0.370957
	(0.04572)	(0.04452)	(0.04321)	(0.03049)
2	-0.005828	-0.032195	-0.160703	0.126699
	(0.04677)	(0.04670)	(0.04660)	(0.04220)
3	0.051528	0.001363	-0.019507	-0.016262
	(0.03841)	(0.03447)	(0.02676)	(0.03154)
4	0.030636	0.018085	0.015033	-0.012975
	(0.02550)	(0.01841)	(0.01449)	(0.01280)
5	0.007022	0.011721	0.005092	-6.15E-05
	(0.01727)	(0.00943)	(0.00701)	(0.00696)
6	-0.000884	0.004869	-8.07E-05	0.000983
	(0.01049)	(0.00566)	(0.00319)	(0.00344)
7	-0.001960	0.001744	-0.000215	-8.83E-05
	(0.00555)	(0.00329)	(0.00141)	(0.00121)
8	-0.001629	0.000485	4.61E-05	-0.000249
	(0.00287)	(0.00184)	(0.00050)	(0.00054)
9	-0.001103	-3.21E-05	1.25E-05	-0.000103
	(0.00150)	(0.00109)	(0.00024)	(0.00027)
10	-0.000620	-0.000185	-3.37E-05	-2.67E-05
	(0.00082)	(0.00066)	(0.00013)	(0.00017)

Appendix E

DLBSPRICE

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.481	-0.481	60.102	0.000
		2	-0.063	-0.382	61.124	0.000
		3	0.056	-0.258	61.946	0.000
		4	0.028	-0.144	62.148	0.000
		5	-0.076	-0.184	63.666	0.000
		6	0.053	-0.120	64.410	0.000
		7	-0.085	-0.237	66.349	0.000
		8	0.059	-0.215	67.274	0.000
		9	0.111	-0.004	70.610	0.000
		10	-0.165	-0.122	77.920	0.000
		11	0.029	-0.151	78.149	0.000
		12	0.050	-0.150	78.838	0.000

DLJALSH

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.521	-0.521	70.474	0.000
		2	-0.021	-0.401	70.590	0.000
		3	0.124	-0.164	74.594	0.000
		4	-0.060	-0.098	75.555	0.000
		5	-0.100	-0.229	78.222	0.000
		6	0.132	-0.123	82.838	0.000
		7	-0.072	-0.140	84.226	0.000
		8	-0.045	-0.209	84.763	0.000
		9	0.138	-0.065	89.882	0.000
		10	-0.100	-0.105	92.602	0.000
		11	0.032	-0.056	92.887	0.000
		12	-0.006	-0.101	92.896	0.000

REER

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.234	0.234	14.406	0.000
		2	-0.085	-0.148	16.305	0.000
		3	0.033	0.099	16.601	0.001
		4	0.042	-0.006	17.063	0.002
		5	-0.056	-0.057	17.903	0.003
		6	-0.145	-0.122	23.536	0.001
		7	-0.009	0.050	23.557	0.001
		8	0.150	0.124	29.591	0.000
		9	0.017	-0.039	29.670	0.000
		10	-0.056	-0.018	30.522	0.001
		11	-0.062	-0.082	31.570	0.001
		12	0.001	0.011	31.570	0.002

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