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Abstract

This paper develops a new index of financial market stress for South Africa (SAFSI) over the period 1995-2017, that has the advantage of capturing the interconnectedness of financial markets as well as enabling each indicator to be assessed in terms of its systemic importance. The index represents a technical improvement over past measures as it is comprised of financial indicators that have been selected based on their ability to capture key periods of financial stress in the economy. These indicators are aggregated using information weights and time-varying cross-correlations between markets to form a comprehensive index, that accounts for the systemic dimension of financial indicators. In addition to capturing the benchmark episodes of financial stress in South Africa, the SAFSI successfully captures other global and idiosyncratic risks that affect the financial markets in the country. Furthermore, the SAFSI outperforms alternative measures that tend to overstate the intensity of financial stress, particularly during normal times. The disaggregation of the SAFSI into contributions emanating from each market sub-index (with information weights) and the overall contribution from the cross-correlations is quite useful for regulatory purposes, especially in terms of the financial stability surveillance functions carried out by macroprudential authorities.

Keywords: Financial stress, South Africa, AUROC, GARCH

JEL Classification: B26, C58, F31, G01

1 Introduction

The role of financial market stress and its measurement has gained increasing popularity in the research domain, especially in the aftermath of the 2007-09 global financial crisis. Recent empirical research have stressed that considerable co-movement of financial sector variables usually characterise financial market stress (see for example Hollo et al. (2012), Louzis & Vouldis (2012), Vermeulen et al. (2015), and Chatterjee et al. (2017)). It is against this backdrop that we construct a new comprehensive index of financial stress for the South African economy (SAFSI), that captures the interconnectedness of financial markets (assessing the systemic importance of indicators) and exploits the information content inherent in market-based indicators. As such, the paper argues that there is a need for improved parsimony-promoting tools to measure financial stress in the context of growing complexities and instabilities in international and domestic financial markets.

The paper follows closely the methodology of Chatterjee et al. (2017) and as such offer two main contributions to the South African literature and emerging market literature in general.[1] Firstly, we identify key

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[1] Chatterjee et al. (2017) construct a financial stress index for the United Kingdom by incorporating some of the principles proposed by Duprey et al. (2017)

periods of financial stress in South African history, such as the 2008-2009 global financial crisis, and then use the partial 'Area Under the Receiver Operating Characteristic Curve' (pAUROC) metric to filter the candidate raw market-based indicators based on their ability to signal the contemporaneous materialisation of the identified stressful periods. It is worth mentioning that the AUROC methodology is fairly new in economic studies with examples including Schularick & Taylor (2012) and Drehmann & Juselius (2014). In the case of the South African economy that has not experienced any significant crisis of a local nature, the key episodes identified are mainly instabilities and imbalances in the international financial realm that have been particularly problematic for the local economy in terms of sparking episodes of drastic capital outflows alongside severe currency depreciations. The pAUROC allows for the usefulness of each candidate indicator to be ranked according to its information content, accounting for the assumed balanced preferences of policymakers between missing financially stressful/ crisis events and receiving false alarms. Secondly, we employ the portfolio theory-based aggregation scheme following Hollo et al. (2012), Louzis & Vouldis (2012), Vermeulen et al. (2015), and Chatterjee et al. (2017) to consider the interconnectedness of financial markets by means of time-varying cross correlations (estimated by means of a multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model) to quantify the level of systemic stress. The use of time-varying cross correlations across market segments and information weights in the aggregation of market sub-indices enhances the accuracy of the financial stress index. Such aggregation methods for constructing financial stress indexes (FSIs) have not previously been applied within the South African context. The literature on the construction of FSIs for South Africa is quite limited (see Gumata et al. (2012), Thompson et al. (2015), Kasaï & Naraidoo (2013), and Kabundi & Mbelu (2017)) with aggregation methods including mainly principle component analysis (PCA), Kalman filtering, and equal weights.

In general, financial stress is associated with an interruption to the normal functioning of financial markets. Hakkio & Keeton (2009) postulate that financial stress is normally characterised by growing uncertainty about the fundamental value of assets and investor behaviour; increased asymmetry of information; and flights to quality and liquidity. Similarly, Balakrishnan et al. (2011) mention that episodes of financial stress are normally associated with a sudden increase in uncertainty and/or risk, large shifts in asset prices, liquidity droughts, and concerns about the health of the banking system. To account for the different aspects of financial stress, the SAFSI comprises 17 financial indicators that stem from six major markets including the equity, credit, foreign exchange, housing, commodity, and money market. In contrast to Chatterjee et al. (2017), the SAFSI also captures vulnerabilities in the commodity market, given that South Africa is a resource-based and small open economy that depends on developments in international markets.

The monthly frequency stress indicators in each market segment are measured in terms of volatilities, valuation losses, and risk spreads and cover the post-apartheid period of 1995 to 2017, due to data availability. Since not all stress indicators are normally distributed, the individual indicators are transformed based on their empirical cumulative distribution function (ECDF) to achieve standardisation. Through this method of standardisation the value of each financial indicator is replaced by its ranking number which is scaled by the sample size. The six market sub-indices are computed by taking the average of the individual stress indicators weighed by their information content which is captured by the pAUROC. Thus, in a particular market sub-index, more weight is given to those financial indicators that possess better information content. The equity market (EM), foreign exchange market (FX), money market (MM), and commodity market (CM) are seen to be the main contributors to the increase of the overall stress in the financial system in all three of the stress episodes identified.

The six market sub-indices are aggregated using time-varying cross-correlations among them and information weights. Cross-correlations are based on standard portfolio theory and is analogous to the aggregation of individual asset risks into overall portfolio risk as similar elements of risk (i.e. large losses, volatility, or spreads) is captured by the individual stress indicators for each market segment. Furthermore, time-variation is allowed for in the cross-correlation structure between market sub-indices. In this case, the SAFSI puts more weight on situations in which high stress prevails in several market segments at the same time, thereby focusing on the systemic dimension of financial stress.

We evaluate the performance of the constructed SAFSI in terms of its ability to capture the benchmark periods of financial stress as well as other periods of stress impacting the South African financial system. In this regard, the SAFSI is also compared to alternative measures of financial stress constructed using different aggregation techniques. The SAFSI spikes sharply during the benchmark periods of financial stress, and also reassuringly picks up instances of global and idiosyncratic risks that affect financial markets in South Africa. The SAFSI and its perfect correlation counterpart are relatively close to each other when correlations are high, but the simple weighted average measure tends to demonstrate a relatively high level of financial stress even during normal times. The breakdown of the SAFSI into contributions emanating from each market sub-index (with information weights) and the overall contribution from the cross-correlations is quite useful for regulatory purposes, especially in terms of the financial stability surveillance functions carried out by macroprudential authorities. Compared to financial stress measures computed with either PCA or equal weights, the SAFSI does better in capturing most of the episodes of financial stress compared to the other stress measures. Furthermore, the financial stress measures computed with PCA and equal weights seem to overstate the intensity of financial stress, particularly during normal times. Further evidence in support of the SAFSI construction methodology is provided by the AUROC and partial AUROC values, which captures the ability of the stress indices to match the identified episodes of financial stress in SA.

The remainder of the paper is organised as follows. Section 2 reviews the literature on the construction of financial stress indexes (FSIs) and the assessment of its impact on economic activity. Section 3 covers the construction of the SAFSI, which includes the selection of market-based indicators, and the weights used to aggregate these indicators into a comprehensive FSI. Section 4 evaluates the performance of the SAFSI and Section 5 concludes.

2 Literature

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

During the pre-global financial crisis period, Illing & Liu (2006) used daily data from the equity and debt markets, banking sector and foreign exchange market to construct an FSI for Canada for the period 1981-2006. The authors use various construction methods including PCA, equal weights, credit weights, transformations using sample cumulative distribution functions (CDFs), and variance-equal weights. In addition, the various indicators were compared in terms of their ability to signal a crisis. Oet et al. (2015) also compares various methods to aggregate stress indicators into a composite FSI for the United States, including credit weights, equal market weights, portfolio theoretic weights and principle component weights. The exploration of each index by means of its information quality validates the adoption of the credit weights methodology. The authors demonstrate that their constructed index is useful in decomposing stress, monitoring development and historical analysis.

The Kansas City FSI introduced by Hakkio & Keeton (2009), is constructed via a PCA of 11 standardised financial indicators over the period February 1990 to March 2009. Their FSI includes seven spreads between different bond classes, expected stock price volatility, bank stock price volatility, cross-section dispersion

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

of bank stock returns, and correlations between returns on stocks and treasury bonds. They find that the index captures known periods of financial stress, leads changes in credit standards, and provides valuable information about future economic growth. Hatzius et al. (2010) uses PCA to construct a FCI for the United States, but allow for unbalanced panels, and incorporates observed macroeconomic variables so as to purge the FCI of macro influences. The authors find that the constructed FCI can help predict economic activity.

Cevik, Dibooglu & Kutan (2013) construct a FSI using PCA for Bulgaria, the Czech Republic, Hungary, Poland, and Russian, and then examines its relationship with economic activity (measured by industrial production, investment, and foreign trade). The FSI incorporates indicators spanning the stock market, sovereign debt spreads, banking sector, exchange market pressure index, and trade credit. Employing bivariate VAR analysis, the authors find significant linkages between financial stress and most measures of economic activity, concluding that the stress index provides valuable information on economic activity. Similarly, Cevik, Dibooglu & Kenc (2013) uses PCA to construct a monthly FSI for the Turkish economy for the period 1997-2010, incorporating a spectrum of financial market indicators (related to stress in the banking sector and stock market, bond spreads, external debt, foreign exchange, trade finance, and liquidity). They find that the stress index captures all recessions in the Turkish economy and acts as a good leading indicator of aggregate economic activity. In addition, they reveal that financial stress has important and significant implications on the real sector. Stolbov & Shchepeleva (2016) construct a FSI for 14 emerging economies, using PCA. Their index incorporates developments in the banking sector, real estate market and sovereign debt risks over the period February 2008 to September 2015. The authors find that financial stress adversely affects industrial production (proxy for economic activity) in 9 of the countries analysed.

Cardarelli et al. (2011) estimate FSIs for 17 advanced economies by equal-variance weighted average of 7 financial sub-indexes for each country, to examine the impact of financial stress on the real economy. Their FSI incorporates indicators related to the banking sector, securities market, and foreign exchange volatility. They find that episodes of financial vulnerability characterised by banking stress, rather than securities or foreign exchange market stress, are more likely to be associated with severe and protracted economic downturns. Balakrishnan et al. (2011) builds on the methodology used by Cardarelli et al. (2011) to construct FSIs for emerging economies. They aggregate five financial variables for each emerging economy that captures stress in the securities, banking, and exchange markets. The authors find that previous episodes of financial crisis in advanced economies have passed through strongly and rapidly to emerging economies, and the extent of the transmission depends on the depth of financial linkages between emerging and advanced economies. Park & Mercado Jr (2014) draws on the construction methodology used by Cardarelli et al. (2011) and Balakrishnan et al. (2011). In particular, the authors use variance-equal weights and PCA to construct quarterly FSIs for a set of advanced and emerging economies; and using panel regression analysis finds that financial stress emanating from advanced and emerging market economies exert significant influence on financial stress conditions of other emerging market economies.

Using a simpler technique of equal weighting of financial indicators, Duca & Peltonen (2013) constructs FSIs for 28 countries including emerging market and advanced economies. The authors use discrete choice models to predict systemic events and find that the combination of both global and domestic indicators of macro-financial vulnerabilities significantly improves the ability to predict systemic events. In a similar manner, the FSI constructed by Hubrich & Tetlow (2015) for the United States over the period December 1988-2011 is a simple demeaned sum of 9 financial indicators, weighted by the inverse of their sample standard deviations. The authors use a Markov-switching vector autoregression model and finds that output reacts differently to financial shocks in stressful versus tranquil periods, particularly shifts to stressful events are highly detrimental for an economy and conventional monetary policy is weak during such periods.

Hollo et al. (2012) was the first to employ the principles of portfolio theory to construct a FSI for the euro area. Particularly, the authors aggregate five financial market segments by considering the time-varying cross correlation (estimated using exponentially weighted moving average (EWMA) method) between them, assigning more weight to situations in which stress prevails in several market segments at the same time. Threshold VAR analysis reveals that shocks to the FSI are more detrimental to real economic activity during high-stress regimes than during low-stress regimes. Furthermore, a negative output shock leads to a subsequent increase in financial stress during high-stress regimes. Vermeulen et al. (2015) develops quarterly FSIs for 28 OECD countries for the period 1980-2010, following the methodology of Hollo et al. (2012). Their measures of stress include indicators related to the money market, stock market, banking sector, bond market and foreign exchange. The authors results suggest that policy makers should be wary of the limited usefulness of FSIs as an early warning signal, as their analysis reveals there to be a weak relationship between the stress index and the onset of a crisis (particularly, a banking crisis). Vašíček et al. (2017) uses the FSI constructed by Vermeulen et al. (2015) for 25 of the OECD countries. They employ Bayesian model averaging to identify leading indicators of stress, and using panel analysis, they find that the model has good in-sample performance, but poor out-of-sample performance.

Louzis & Vouldis (2012) extend the portfolio-theoretic approach by Hollo et al. (2012) by using a multivariate GARCH model to estimate time-varying cross-correlations between market segments. The authors construct a FSI for Greece by weighting the market segments by their time-varying cross-correlations and find that the index has the ability to identify crisis events and the level of systemic stress in the Greek financial system. In a similar manner, Chatterjee et al. (2017) extend on this method by constructing a comprehensive FSI for the United Kingdom (UK) over 45 years, using portfolio theory in conjunction with information weights to aggregate 6 market segments. They use identified episodes of financial stress in UK history to inform their analysis of potential future stress on financing conditions. The authors use the 'Area under the Receiver Operating Characteristic Curve' (AUROC) metric to rank the individual raw indicators in terms of their usefulness in signalling a binary crisis event. Employing threshold VAR analysis, the authors find that the transmission of shocks to the real sector in financially stressful periods significantly differs from tranquil periods.

van Roye (2014) derives a FSI for Germany using a dynamic approximate factor model to summarise various financial stress variables. Employing threshold VAR analysis, the author finds that an increase in financial stress is detrimental to economic activity when the FSI exceeds a certain threshold, whereas the impact on economic activity is almost negligible when the index is below this threshold. Similarly, Aboura & van Roye (2017) constructs a FSI for France using a dynamic factor model. Employing a Markov-Switching Bayesian vector autoregression (MS-BVAR) model, the authors find evidence in line with van Roye (2014), but for the French economy. Cevik et al. (2016) employ a dynamic factor model to construct FSI for five South Asian economies for the period 1995-2013. The index covers riskiness in the securities market, banking sector, currency market, external debt, and sovereign risk. The authors find that the index picks up episodes of financial turmoil in the sample and seems to be a leading economic indicator.

The literature on FSIs for South Africa is quite limited. Gumata et al. (2012) construct a quarterly FCI for South Africa over the period 1999 to 2011, from 11 nominal indicators, employing the alternative approaches of principle component analysis (PCA) and Kalman filtering with constant loadings. The authors find that their estimated indicators have strong predictive information for the near-term GDP growth, and tends to outperform the leading indicator of the South African Reserve Bank and individual financial variables. Thompson et al. (2015) improve on the FCI derived by Gumata et al. (2012) by applying a recursive PCA to 16 monthly financial variables (incorporating domestic and global measures) and 3 macroeconomic variables (output, inflation, and interest rates), purging the index from endogeneity. Their FCI covers a much longer period from 1966 to 2011, and causality tests indicate that the index is a good in-sample predictor of industrial production growth and interest rate but performs poorly in terms of predicting inflation. Employing the FCI constructed by Thompson et al. (2015), Balcilar et al. (2016) makes use of a nonlinear logistic smooth transition vector autoregressive model (LSTVAR) and finds that inflation in the South African economy responds more to financial shocks during recessions, while output growth and interest rates responds more significantly during expansions. Kasaï & Naraidoo (2013) estimate a monthly FCI for the period 2000 to 2008 by means of equal weighted averaging of 5 variables. Their FCI is constructed for inclusion in the monetary policy reaction function of the South African central bank, reflecting the central bank's concern to maintain financial stability. In a recent study, Kabundi & Mbelu (2017) follow very closely the technique of Koop & Korobilis (2014) (they construct an FCI for the United States) by using time-varying factor modelling (based on PCA and Kalman filtering) to construct an FCI from 39 monthly financial market variables spanning the period January 2000 - April 2017. The constructed index captures financial conditions in the markets for credit, equity, funding, real estate, and foreign exchange, as well as foreign data. They then include 2 macroeconomic variables with the FCI to estimate a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model, finding that the responses of the macroeconomic variables change over time following a shock to financial conditions. These authors do not consider the potential interconnectedness of financial markets.

3 Construction of SAFSI

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

3.1 Selection of stress indicators

3.1.1 Candidate indicators of financial stress

In general, financial stress is associated with an interruption to the normal functioning of financial markets. However, agreeing on a more precise definition of financial stress is difficult, since financial stress episodes differ. Hakkio & Keeton (2009) postulate that financial stress is normally characterised by growing uncertainty about the fundamental value of assets and investor behaviour; increased asymmetry of information; and flights to quality and liquidity. Similarly, Balakrishnan et al. (2011) mention that episodes of financial stress are normally associated with a sudden increase in uncertainty and/or risk, large shifts in asset prices, liquidity droughts, and concerns about the health of the banking system. To account for the different aspects of financial stress in an emerging economy, in this case South Africa, the SAFSI will cover indicators from 6 market segments (see Table 1) that are thought to be most significant for the SA economy. The SAFSI also captures vulnerabilities in the commodity market, given that SA is a resource-based and open economy that depends on developments in international markets, in contrast to Chatterjee et al. (2017).

The stress indicators in each market segment are measured in terms of volatilities, valuation losses, and risk spreads. The full list of raw candidate indicators considered are summarised in Table 1, according to the corresponding market segments.[3] The indicators are all on a monthly basis, and cover the post-apartheid period of 1995 to 2017. The sample was chosen so to have the largest possible dataset for calibration and satisfy the objective of the paper which focuses on the backward performance of the index rather than capturing the latest observations. Furthermore, changing the sample will not change the calibration and the results. The monthly SAFSI includes 17 financial indicators spanning the equity market (EM), credit market (CM), foreign exchange market (FX), money market (MM), housing market (HM), and commodities market (ComM). The inputs to the SAFSI are identified using the approach by Chatterjee et al. (2017), which is based on the statistical selection of the most informative or relevant indicators for the identification of financial stress in SA.

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

Table 1: Full list of indicators of financial stress

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

Notes: The table briefly outlines all the candidate indicators being considered. Indicators highlighted in bold are those that have been selected for the construction of the SAFSI, based on the selection methodology outlined in Section 3.1.4.

3.1.2 Benchmark episodes of financial stress in South Africa

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

- 1998-1999: The South African economy experienced a currency crisis in 1998, which originated from nominal shocks induced by a combination of relaxed monetary policy stance and shifts in financial market expectations following the East Asian financial crisis of 1997 and the Russian financial crisis of 1998 (Nowak & Ricci (2006)). The rand depreciated by 28 per cent in nominal terms against the U.S. dollar over the period April-August 1998. This was accompanied by interventionist policy responses by the central bank of SA, increasing the short-term interest rates and long-term bond yields by about 700 basis points (to 21.86 per cent). This exacerbated the crisis and deepened its macroeconomic impact, as output contracted during the third quarter of 1998 and the stock market declined heavily and remained below initial level for more than one year (Nowak & Ricci (2006)). South African banks experienced a continuous decline in the growth of total loans and advances since August 1998 (following the rapid increase in the cost of borrowing), impacting negatively on the interest income of banks and the efficiency of the sector. Small banks in SA were faced with liquidity pressures in 1999 and there was a subsequent gradual loss in depositor confidence in some smaller to mid-sized banks (South African Reserve Bank (2002)).
- 2001-2002: The economy experienced a currency crisis in 2001 as the rand depreciated by 28 per cent, due mainly to the slowdown in global economic activity that began in 2000 (particularly due to the stock market crash/ internet bubble bursting) and that reduced world demand for South African goods and services (Nowak & Ricci (2006)). As a result, net capital outflows and a decline in the country's net international reserves were recorded during the last quarter of 2001. In addition to this, the efficiency of the SA banking sector deteriorated (return on assets and return on equity deteriorated) over the period 2001-2002 and participation of foreign banks in the local banking industry declined for the first time in 6 years (South African Reserve Bank (2002)). Over the period 2002 up to the first few months of 2003, 22 banks exited the South African banking system. This was due to the contagion that set in following the imposition of curatorship over Saambou Bank Limited (7th largest bank in SA) in February 2002 and the subsequent takeover of BOE Bank Limited (6th largest bank in SA) by Nedbank Limited which arose from the bank's liquidity strain (Havemann (2018),Schoombee (2004)). Saambou Bank Limited was seen by regulators as being systemically significant (as was BOE Bank Limted), given that the bank had both a large retail deposit base and a well-established branch network. These banks as well as smaller banks experienced large withdrawals of deposits as confidence in banking system dampened and consequently share prices of these banks deteriorated.
- 2008-2009: The global financial crisis of 2007-2009 dampened confidence among participants in financial markets. Despite a relatively rigid regulatory environment, the South African economy faced the pressure of the crisis in 2008 when a sudden stop in international capital flows eroded share prices and the exchange rate of the rand (Viegi (2008)). Deteriorating investor sentiment and international commodity prices resulted in the JSE All Share Index losing more than 20 per cent of its value and rand devaluation of more than 40 per cent against the US dollar in 2008. The effects of the crisis rapidly spread to the real economy plunging the South African economy into a recession in 2009 (Saayman (2010)). The mining and manufacturing sector were the main contributors to the contraction in economic growth amid subdued global and domestic demand conditions and electricity supply constraints. Share prices gained momentum towards the latter part of 2009, supported by an improvement in international equity markets and good performance in the local resources sector as commodity prices increased significantly and there were signs of recovery in the global economy. Similarly, the exchange value of the rand improved significantly towards the second half of 2009, while still maintaining its

volatility. The South African banking system remained relatively stable during the financial crisis, however commercial banks' profitability suffered somewhat in 2009 amid rising bad debts, curtailment of credit extension and progressive decline in domestic demand (South African Reserve Bank (2009)).

3.1.3 Methodology used to capture benchmark episodes of financial stress

Given the episodes of financial stress identified above, this section will outline the technique employed to signal the materialisation of these stressful/crisis periods. The 'partial AUROC' metric will be used to rank the market-based indicators in terms of their information content. This section briefly outlines the signalling approach and then introduces the concepts of AUROC and partial AUROC.

3.1.3.1 Signalling approach

This approach is a type of early warning system that identifies indicators based on their ability to signal economic vulnerabilities early enough to enable policy makers to implement mitigative action.[4] Based on a predetermined threshold, an indicator issues a signal if it breaches this threshold, or else no signal is issued (i.e. when the indicator is below the predetermined threshold). The four possible outcomes can be classified by a so called "Confusion Matrix" as follows:

Table 2: Confusion Matrix

	Crisis	No crisis
Signal issued (above threshold)	A	B
Signal is not issued (below threshold)	C	D

When a signal is issued and a crisis occurs, this is classified as outcome (A) (i.e. this is a good signal as the crisis is well predicted) but when no crisis occurs outcome (B) results (i.e. this is a false alarm or Type II error). On the other hand, when no signal is issued and a crisis occurs, the observation is characterised as outcome (C) (i.e. a missed signal or Type I error), but when no crisis occurs outcome (D) results (i.e. this is a good silence as a tranquil period is well predicted). However, in the South African context 'crisis' versus 'no crisis' would amount to ' stressful period' versus 'tranquil period', as the economy did not experience actual crisis but were confronted with significant financial stress over certain periods of the sample.

On the basis of the Confusion Matrix, a number of key ratios can be calculated. The true positive rate (TPR) or signal ratio ($\frac{A}{(A+C)}$) is the fraction of correctly predicted crisis. From this, the fraction of missed crisis (Type I error rate) is 1-TPR or the ratio ($\frac{C}{A+C}$). The false positive rate (FPR) or noise ratio ($\frac{B}{B+D}$), which is also referred to as the Type II error rate, represents the fraction of false alarms (i.e. falsely signalled crisis). The optimal threshold is identified by assessing the trade-off between Type I error (missed crisis) and Type II error (issuing false alarms). A higher (lower) threshold increases (decreases) the probability of missing a crisis but at the same time decreases (increases) the probability of issuing a false alarm.

The predictive performance of indicators can be assessed through the noise-to-signal ratio (which is the ratio of falsely signalled crisis to correctly signalled crisis) since the number of crisis and non-crisis observations are fixed. Based on any given threshold, policymakers would reasonably prefer an indicator which possesses a high signal ratio and low noise ratio. However, at low thresholds the indicator will emit signals most of the time, resulting in both high noise and signal ratios. While at high thresholds, both the noise and signal ratios will be low. Thus, there will be a trade-off between these two desirable features. A noise-to-signal ratio of less than 1 implies that the indicator is useful or relevant, while a value of 1 implies that the indicator emits purely random signals. A shortcoming of the noise-to-signal ratio is that it

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

relies on a specific threshold that minimises this ratio (while failing to consider the preferences of the policy maker), which is often reached at very low noise and signal ratios (Chatterjee et al. (2017)). As mentioned above, this configuration is achieved at unjustifiably high threshold values. This high threshold implies that policymakers disregard Type I errors (missing a crisis), while being extremely averse to Type II errors (receiving false alarms). In practice, this is unlikely to reflect the true preferences of policymakers, especially if the cost of macroprudential interventions are low and benefits high. This is especially reflective of the perception of most policymakers when viewed in the context of the recent global financial crisis. In this case, policymakers may prefer a low threshold to avoid Type I errors rather than Type II errors (Chatterjee et al. (2017)).

3.1.3.2 Area under the receiver operating characteristic curve (AUROC)

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

Figure 1 displays the ROC and associated AUROC for a financial indicator in the money market, the interbank spread, which is the spread between the 3-month interbank rate and the 3-month treasury bill rate. The AUROC ranges from 0 to 1, since it is a portion of the area of a unit square. However, the diagonal line between $(0,0)$ and $(1,1)$ has an area of 0.5, which indicates that an indicator issues random signals. Therefore, an AUROC value of 0.5 or less suggest that the indicator is uninformative, while an AUROC value larger than 0.5 means that the indicator is relevant and informative. Furthermore, an AUROC value of 1 implies that the indicator is fully informative. The AUROC value for the interbank spread in Figure 1 is 0.78, which suggests that this indicator is relevant (the ROC is well above the diagonal line) as it detects a high percentage of crisis/ stressful episodes with few false alarms. The ROC curve slopes upwards since as the threshold value falls (i.e. moves away from the origin towards the opposite end of the chart), both the noise and signal ratio rise. This means that progressive lowering of the threshold from its maximum value to its minimum value, results in a continuous increase in the number of emitted signals - The percentage of well predicted crisis and false alarms goes from 0 to 100 per cent.

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

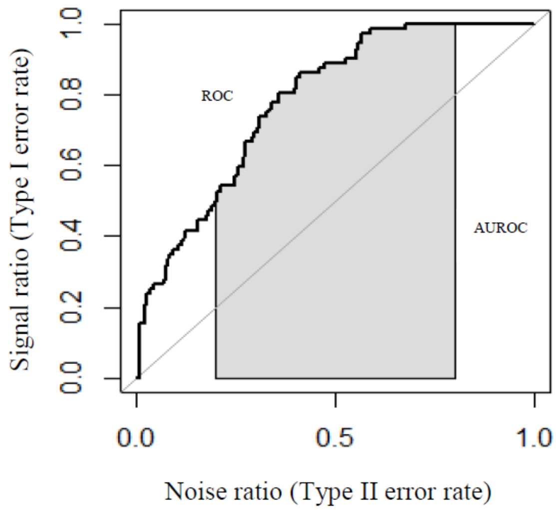
3.1.3.3 Partial AUROC

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

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

where T_1 depicts the Type I error rate corresponding to the fraction of missed crisis (i.e. $(\frac{C}{(A+C})$), and T_2 reflects the Type II error rate which represents the percentage of false alarms (i.e. $(\frac{B}{B+D}))$. The policy maker's relative risk aversion between the two types of errors is captured by the parameter θ. Hence, the policy maker's loss function L is a weighted average of these two errors generated by the indicator crossing a given threshold. The weighting parameter θ ranges between 0 and 1, where $\theta > 0.5$ implies that the policy maker has a larger aversion towards missing a crisis than towards receiving a false alarm. Alessi &

Figure 1: AUROC for the interbank spread



Notes: The solid line represents the ROC curve. The diagonal line corresponds to an uninformative indicator. The AUROC evaluates the ability of the financial indicator to capture the benchmark episodes of financial stress in SA outlined in Section 3.1.2. The partial AUROC (pAUROC) is shown as the shaded region incorporating policy-maker preferences (i.e. when the relative preferences between Type I and Type II errors are 0.2 or 0.8.

Detken (2014) argue that before the global financial crisis policymakers responsible for financial stability were more averse towards receiving a false alarm than missing a crisis. However, after the experience of the global financial crisis, the preferences of policymakers' have become more balanced. This balanced perspective of policymakers' preferences has highlighted the need to focus on the pAUROC rather than the full AUROC metric. In this case, the pAUROC cuts off areas associated with implausibly low and high values of a policy maker's aversion between the two types of errors discussed above. The pAUROC is estimated by specifying the restricted range of false positives and the computation of the partial area under the ROC curve.

In this paper, we follow Chatterjee et al. (2017) by estimating the pAUROC of indicators where the parameter θ ranges from 0.2 to 0.8, hence assuming that policymakers in South Africa have balanced preferences. The pAUROC for the interbank spread is depicted by the shaded area in Figure 1, which restricts combinations of noise and signal ratios that are outside of the range $0.2 - 0.8$. This measure (i.e. pAUROC) will be used to rank indicators in terms of their information content.

The use of the pAUROC as information weights in the aggregation of stress indicators across the different market segments into a composite index is one of the main methodological contributions of the SAFSI compared to other FSIs that have been constructed for SA. Only stress indicators that have a pAUROC above 0.5 are considered for the construction of the SAFSI, as such indicators meaningfully coincide with the episodes of financial stress outlined in Section 3.1.2.

3.1.4 Selection procedure of indicators and standardisation

The list of candidate financial indicators in Table 1 are further narrowed down by selecting only those indicators which keep adding more information to the overall ability of the market segment to match the episodes of financial stress in SA. In this way, parsimony is preserved in the construction of the SAFSI. When looked at individually, indicators may appear to be less powerful in identifying stressful periods than when their information content is incremented with that of other indicators in the market segment.
All the candidate indicators for each of the 6 market segments are first ranked by their pAUROC (Table 3). Then the following steps are implemented in selecting the set of relevant financial indicators to be used in the construction of the SAFSI.

1. For each of the market segments, candidate stress indicators that have a pAUROC less than 0.5 are discarded, as these indicators are uninformative i.e. these indicators are doing worse than a coin flip in terms of matching the episodes of financial stress in SA.

2. The indicator with the largest pAUROC for a given market segment is always selected i.e. CMax_rBPI for the equity market.

3. For a given market segment, we consider the inclusion of the candidate indicator that has the next largest pAUROC i.e. for the equity market this means CMax_rALSI. The weighted average of the previously selected stress measure with this additional one is then computed, which in this case is the temporary equity market segment S'_{EM}:

$$S'_{EM} = \frac{CMax\_rBPI \times (pAUROC_{CMax\_rBPI} - 0.5)}{(pAUROC_{CMax\_rALSI} - 0.5) + (pAUROC_{CMax\_rBPI} - 0.5)} + \frac{CMax\_rALSI \times (pAUROC_{CMax\_rALSI} - 0.5)}{(pAUROC_{CMax\_rALSI} - 0.5) + (pAUROC_{CMax\_rBPI} - 0.5)} \quad (2)$$

   The partial AUROC of the temporary market segment (i.e. $pAUROC_{S'_{EM}}$ for the above example) is then calculated. This is shown in the column 'partial AUROC of market segment' in Table 3. The incremental partial AUROC which can be positive or negative is calculated as $pAUROC_{S'_{EM}} - pAUROC_{CMax\_rBPI}$ for the example above. The indicator will be selected only if the incremental pAUROC is positive i.e. $pAUROC_{S'_{EM}} > pAUROC_{CMax\_rBPI}$, otherwise it will not be selected. This is because a positive incremental partial AUROC implies that adding the additional candidate stress indicator improves the informational content of the overall market segment.

   Step 3 is repeated with the candidate stress indicator with the next largest partial AUROC, and so on, until all candidate indicators in the market segment are considered. The idea is that an individual stress indicator with lower informational content (i.e. lower pAUROC values) can nevertheless add relevant information to the overall market stress measure when considered jointly, if it captures a different aspect of financial stress, hence resulting in a higher pAUROC.

Table 3 displays the AUROC and pAUROC values for the full list of the raw candidate stress indicators, however the 17 indicators highlighted in bold are those that were finally selected based on their information content as outlined in the steps above.

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

$$F_n(x_t) = \begin{cases} \frac{r}{n} \; for \; x_{[r]} \leq x_t < x_{r+1}, & \text{r=1,2,...,n-1} \\ 1, & \text{for } x_t \geq x_{[n]} \end{cases} \quad (3)$$

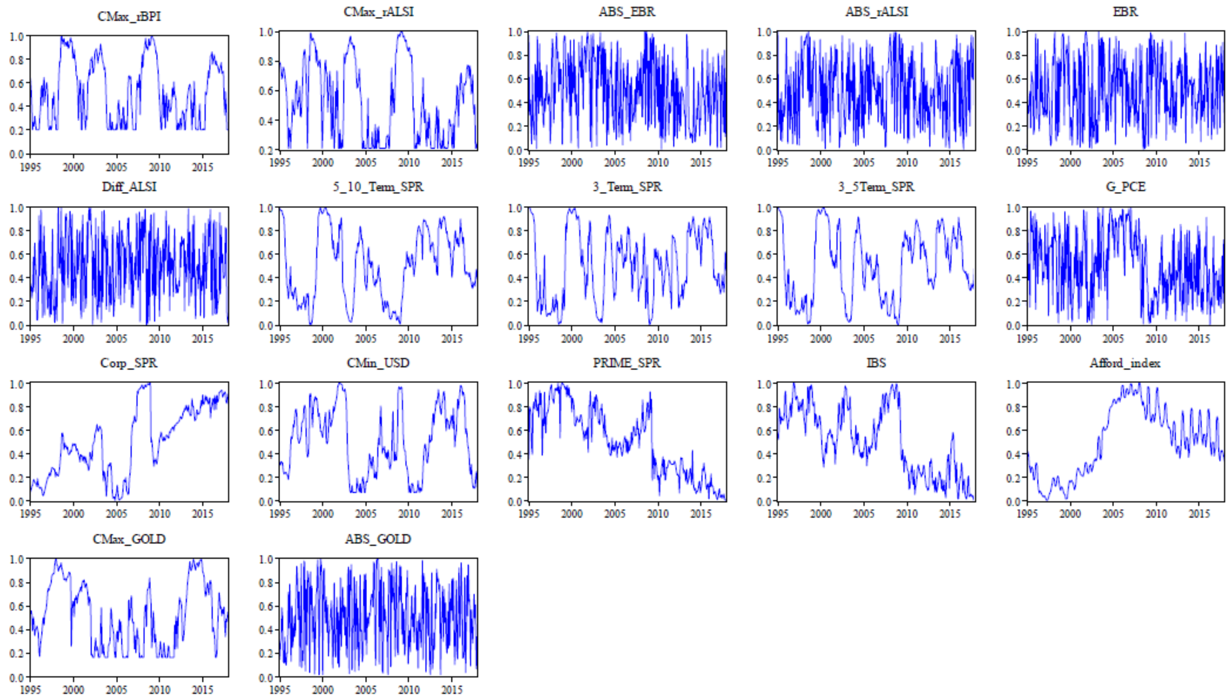
for t=1,2,...,n. It measures the fraction of observations of x_t not exceeding a specified value x^* (which equals the corresponding ranking number r^*). In this way, the ECDF transforms each raw stress indicator

Table 3: AUROC and partial AUROC of raw stress indicators

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

Notes: This table lists 17 of the most useful stress indicators (highlighted in bold) selected based on the selection procedure outlined above. Descriptions of the indicators are provided in Table 1. The stress indicators in each market segment are ranked in ascending order based on their pAUROC value. pAUROC of market segment is computed by adding one extra indicator each time on top of the ones with the higher individual pAUROC. The incremental pAUROC in the last column computes the incremental change in the pAUROC of the market segment when an extra indicator is added. The indicators SSPR, CDiff_SSPR, and CMin_rRGOV10 are discarded in the selection procedure as they have pAUROC values less than 0.5.

Figure 2: Standardised stress indicators, January 1995 - December 2017



Notes: The figure shows the empirical cumulative distribution function (ECDF) for each of the 17 indicators selected based on the selection procedure outlined above. Descriptions of the indicators are provided in Table 1.

to lie in the range $[0, 1]$, hence being unit-free. The ECDF is a non-decreasing function that jumps up by $1/n$ at each observed point. However, for purposes of construction of the SAFSI and to evaluate it efficacy in capturing stressful periods, we match the ECDF value of each observation to its original value in the dataset. The standardised stress indicators for the 17 selected indicators are shown in Figure 2.

3.2 Aggregation of indicators

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

3.2.1 Construction of market sub-indices

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

For instance, if one considers the equity market (EM) segment as shown in Table 3, where six indicators

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

are chosen to capture stress in this market, then the equity market sub-index is computed as

$$S_{EM} = \frac{\sum_{j=1}^{6} EM_{j,t} \times (pAUROC_j - 0.5)}{\sum_{j=1}^{6} (pAUROC_j - 0.5)} \tag{4}$$

where $j = 1, 2, ..., 6$ denotes the six stress indicators, and $\mathrm{EM}_{j,t}$ is the ECDF of the stress indicator j in the equity market segment. Applying this method of aggregation to each market segment yields the market sub-indices as shown in Figure 3. The shaded areas correspond to the stress periods as identified in Section 3.1.2. The equity market (EM), foreign exchange market (FX), money market (MM), and commodity market (ComM) are seen to be the main contributors to the increase of the overall stress in the financial system in all of three of the stress episodes identified.

3.2.2 Construction of the SAFSI by aggregating market sub-indices

The six market sub-indices are aggregated based on the application of standard portfolio theory that weights each sub-index by its cross-correlation with the others, since indicators capture similar element of risk.[6] Positive (negative) correlation across market sub-indices imply that overall financial stress index is larger (smaller) than the sum of its sub-components. Furthermore, time-variation is allowed for in the cross-correlation structure between market sub-indices. In this case, the SAFSI puts more weight on situations in which high stress prevails in several market segments at the same time, thereby focusing on the systemic dimension of financial stress. The stronger the co-movement across financial market segments, the more widespread is the state of financial instability Hollo et al. (2012). Therefore, the ability of the SAFSI to capture the co-movement across financial market segments will determine its effectiveness in detecting systemic stress episodes.

The SAFSI is computed according to (5), inheriting all properties from its individual stress factors i.e. the SAFSI is a unit-free index bounded by the half-open interval (0,1]:

$$SAFSI_t = (w \times S_t)' \times C_t \times (w \times S_t) \tag{5}$$

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

$$w_{EM} = \frac{pAUROC_{EM} - 0.5}{\sum_m pAUROC_m - 0.5}, \quad \text{m=EM, CM, FX, MM, HM, ComM} \tag{6}$$

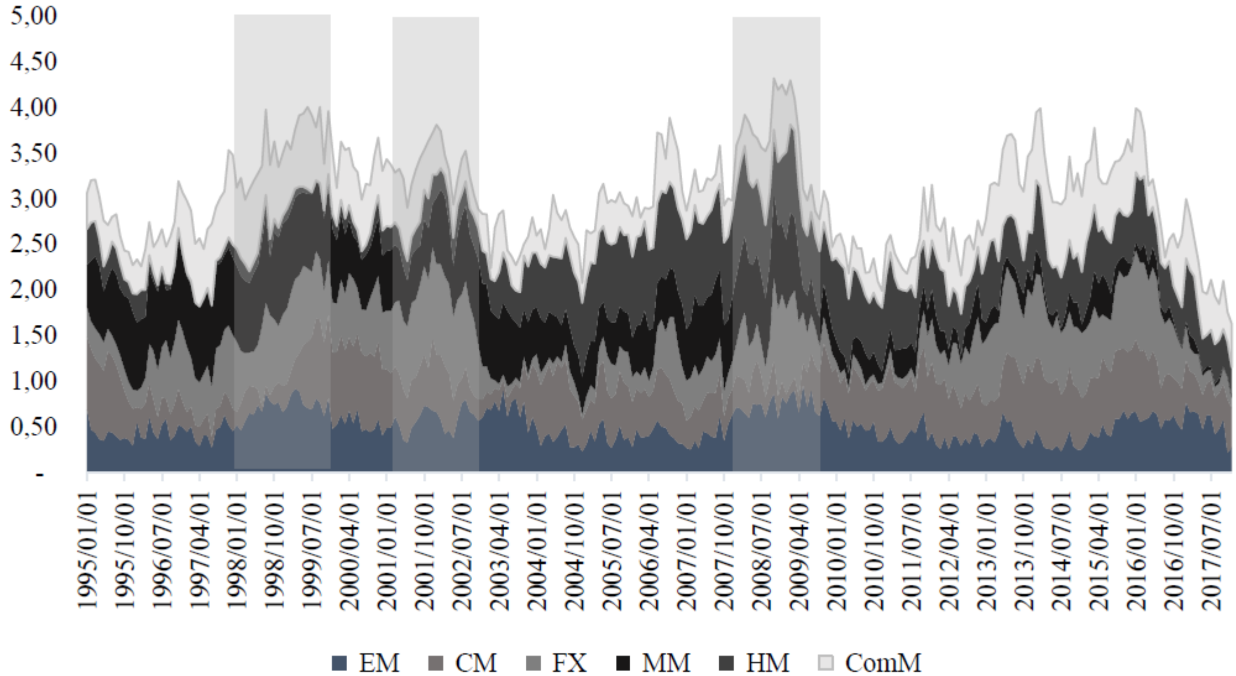
Note that the weights are computed using pAUROC - 0.5, since the measure is informative only if it is above 0.5. Lastly and most importantly, C_t in formula (5) is the 6x6 matrix of time-varying cross-correlations $\rho_{m,m',t}$ (where $m \neq m'$), that emphasizes the extent of co-movement across different market segments at each point in time.

$$C_t = \begin{bmatrix} 1 & \rho_{EM,CM,t} & \rho_{EM,FX,t} & \rho_{EM,MM,t} & \rho_{EM,HM,t} & \rho_{EM,ComM,t} \\ \rho_{EM,CM,t} & 1 & \rho_{CM,FX,t} & \rho_{CM,MM,t} & \rho_{CM,HM,t} & \rho_{CM,ComM,t} \\ \rho_{EM,FX,t} & \rho_{CM,FX,t} & 1 & \rho_{FX,MM,t} & \rho_{FX,HM,t} & \rho_{FX,ComM,t} \\ \rho_{EM,MM,t} & \rho_{CM,MM,t} & \rho_{FX,MM,t} & 1 & \rho_{MM,HM,t} & \rho_{MM,ComM,t} \\ \rho_{EM,HM,t} & \rho_{CM,HM,t} & \rho_{FX,HM,t} & \rho_{MM,HM,t} & 1 & \rho_{HM,ComM,t} \\ \rho_{EM,ComM,t} & \rho_{CM,ComM,t} & \rho_{FX,ComM,t} & \rho_{MM,ComM,t} & \rho_{HM,ComM,t} & 1 \end{bmatrix} \tag{7}$$

The time-varying cross-correlations $\rho_{m,m',t}$ are estimated by means of a multivariate GARCH. This method is preferred as it data-driven (i.e. it uses the information provided by the data to estimate the parameters of the model), is able to capture abrupt changes in the correlation structure, and limits the risk

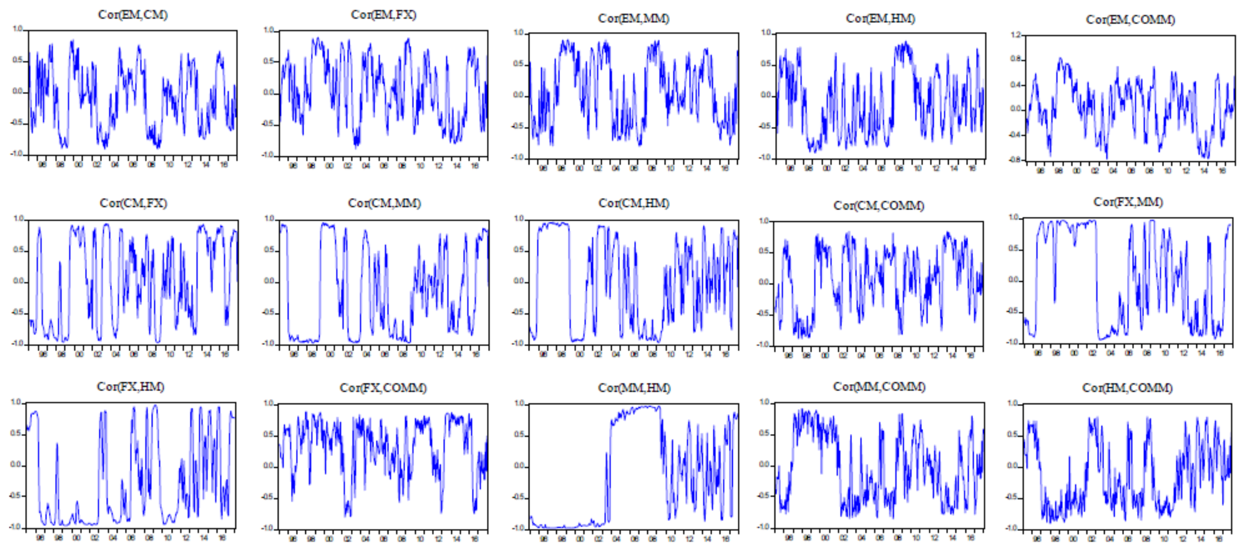
[6] The application of portfolio theory to the aggregation of market sub-indices into a composite indicator was used by Hollo et al. (2012), Vermeulen et al. (2015), Louzis & Vouldis (2012), and Chatterjee et al. (2017) (see Section 2).

Figure 3: Market sub-indices, January 1995 - December 2017



Notes: The six market sub-indices used for the construction of the SAFSI as depicted in the figure are constructed using formula (4). Shaded regions are the identified periods of financial stress (see Section 3.1.2).

Figure 4: Time-varying cross-correlations between market sub-indices, January 1995 - December 2017



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

of omitted variable bias given its multivariate nature Louzis & Vouldis (2012). The commonly used diagonal Baba, Engle, Kraft, and Kroner (BEKK) multivariate GARCH model introduced by Engle & Kroner (1995) is used in this paper. The diagonal representation of the model assists in coping with the dimensionality problem (i.e. given the large number of parameters that have to be estimated). We use the diagonal BEKK multivariate GARCH (1,1) specification as in all cases this specification turns out to be the best model, in terms of the Schwarz criterion and Akaike information criterion, over models with more lags. This model is defined as

$$H_t = V_0 V_0' + A' \bar{S}_{t-1} \bar{S}_{t-1}' A + B' H_{t-1} B \tag{8}$$

where V_0 is a 6x6 lower triangular matrix, A and B are 6x6 diagonal matrices; $\bar{S}_{t-1}$ is the vector of lagged demeaned normalised market sub-indices where $\bar{S}_t = S_t - 0.5$ because of the properties of the cumulative density function; and H_t is the 6x6 variance-covariance matrix of the demeaned normalised sub-indices. The constant term $V_0 V_0'$, which is the product of the two lower triangular matrices constant term, ensures the positive definiteness of the covariance matrices. Maximising the Gaussian likelihood function of the multivariate process determines the parameters of the model. The resulting time-varying cross correlations between the market sub-indices are depicted by Figure 4.

Most of the pair-wise cross correlations are shown to increase during the periods of financial stress, however to different extents. It should be emphasized that, following Hollo et al. (2012), the cross-correlations simply indicate whether the historical ranking of the level of stress in two market segments is relatively similar or dissimilar at any point in time, rather than being an economic prediction of correlation risk.

4 The SAFSI and evaluation of its strength

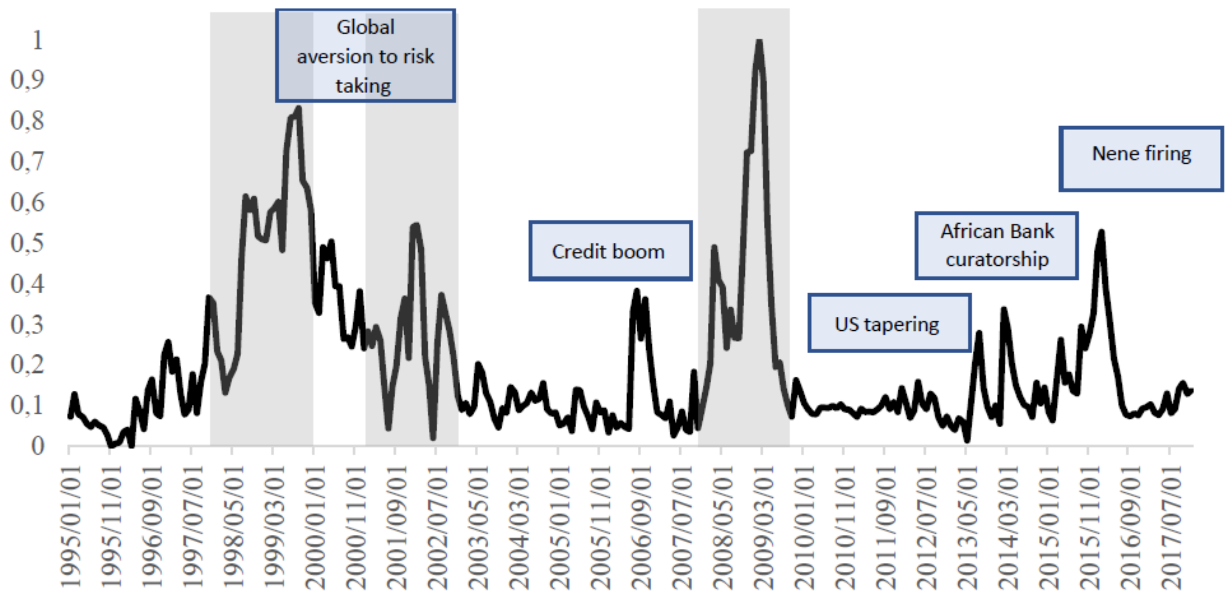
4.1 The South African Financial Stress Index (SAFSI)

Figure 5 displays the SAFSI over the period 1995 - 2017, with the shaded regions corresponding to the benchmark periods of financial stress as detailed in Section 3.1.2. The index identifies instabilities in the financial system of the country with values of 0.5 and greater indicative of stressful times. As can be seen from the figure, the constructed index spikes sharply during the key periods of financial stress. In addition to capturing the benchmark periods of financial stress, it is quite reassuring that the SAFSI captures other global and idiosyncratic risks that affect the financial markets in the country. The index picks up the stress in financial markets during the end of 2015 and beginning of 2016 which was mainly caused by the depreciation of the rand amid declining investor confidence, following the political turmoil that lead to the axing of former Finance Minister Nhlanhla Nene. In 2014, African Bank experienced liquidity stress and a sharp decline in the share price of its holding company, African Bank Investment Limited (ABIL), which generated risk in financial markets. The bank was put under curatorship by the South African Reserve Bank due to its inability to make sufficient provisions for bad debts and engaging in unsustainable lending. However, in the wake of central bank-led bailout of ABIL, at least 10 SA money market funds "broke the buck" significantly widening money market spreads. Financial contagion was however limited following the imposition of complementary interventions by authorities Havemann (2018). The SAFSI captures the vulnerability of the South African economy in 2013 following the announcement by the US Federal Reserve Bank of the possible tapering of its quantitative easing (QE) program. Following the announcement in May 2013 and in anticipation of the possible normalisation of monetary policy in the U.S., the South African economy experienced significant capital outflows together with a weakening currency. Financial stress captured by the SAFSI in 2006 coincided with the higher rates of credit extension and consequently increased household indebtedness during that period, increasing the probability of higher default on loan repayment. Higher credit extension growth during this period was supported by lower interest rates (the tighter interest rate environment in the second half of 2006 had a lagged effect on credit extension growth) and the buoyancy of the housing market, as house prices continued to rise firmly throughout the first ten months of 2006, however, at a slowing pace. The National Credit Act, No. 34 of 2005 which became effective on 1 June 2006, and was implemented in three phases until 1 June 2007, aided in containing the growth in credit extension by regulating consumer credit. In addition, the constructed SAFSI captures the dampened investor confidence in the economy in the first half of 2000, as reflected by capital outflows and the depreciation of the rand. It is worth mentioning that during this period there was heightened global aversion to risk taking in emerging market economies in general.

The constructed SAFSI using formula (5) as well as its counterpart without using correlation weights (i.e. implicitly assuming all sub-indices are perfectly correlated) are displayed in Figure 6. The SAFSI counterpart is a simple weighted average of the six sub-indices, such that only the vector $(w \times S_t)$ in formula (5) is applicable. Visual inspection reveals that SAFSI and its perfect correlation counterpart are relatively close to each other when correlations are high, especially during the stressful periods 1998-1999 and 2008-2009. Both the indicators peak at the same time (there is a 74% correlation between the two indicators), but the simple weighted average measure tends to demonstrate a relatively high level of financial stress even during normal times. The SAFSI that is constructed using both information weights and correlation weights, reduces the risk of combining informationally redundant data that would over-emphasize a given market segment, thus avoiding overstating the intensity of financial stress during normal times.

The comparison of these two indicators forms the basis for a decomposition of the SAFSI into contributions coming from each of the six market sub-indices (with information weights) and the overall contribution from the cross-correlations. Such a decomposition is useful for regulatory purposes, especially in terms of the financial stability surveillance functions carried out by macroprudential authorities. The decomposition is depicted in Figure 7 such that the SAFSI is a weighted average of the contributions from each sub-index and the cross-correlations between them. All the weights sum up to 1, and therefore at a given point in time, the contribution of a particular market to the SAFSI is simply the fraction of the SAFSI accounted for by that particular market sub-index. The residual component of the SAFSI unaccounted for by the six

Figure 5: The SAFSI



Notes: The construction methodology of the SAFSI is detailed in Section 3. Shaded areas depict the benchmark episodes of financial stress in SA as identified in Section 3.1.2.

markets, reflects the contributions from the cross-market correlations described by the matrix C_t in formula (5). The choice of aggregation method using time-varying cross-correlations is affirmed by the strength of the correlation components during periods of financial stress.

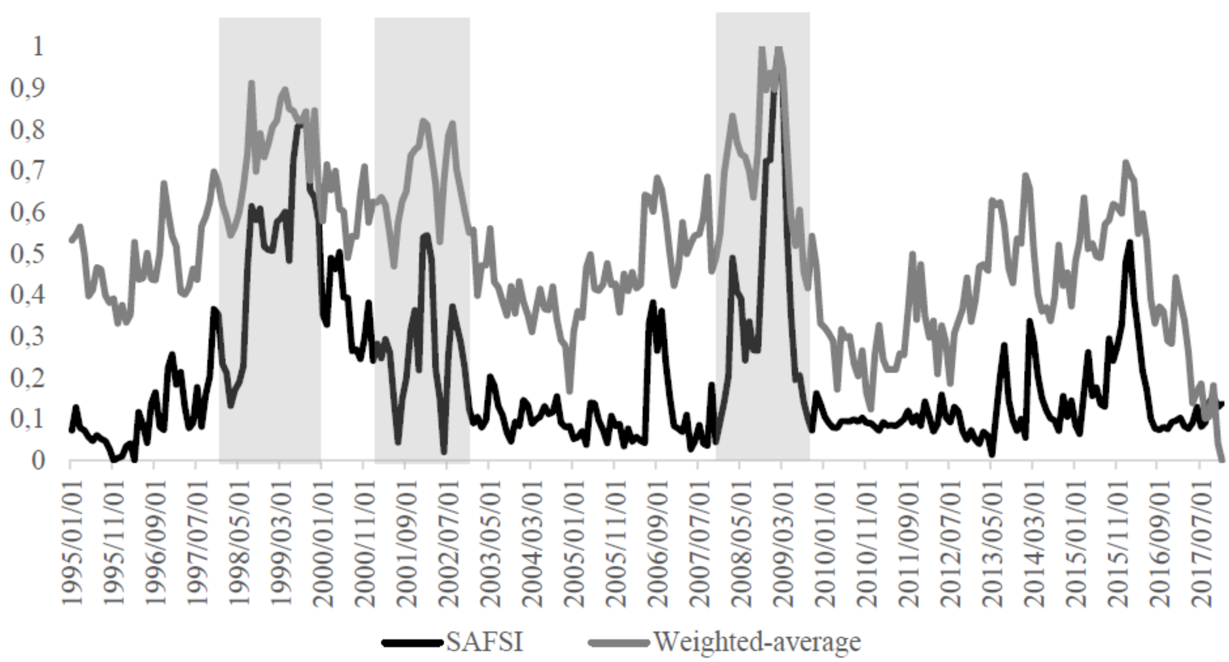
4.2 Comparison of SAFSI with alternative measures of financial stress

Figure 8 compares the SAFSI constructed via formula (5), with a financial stress index computed using principal component analysis (PCA) on the individual stress indices, and an alternative measure constructed by simply averaging the selected stress indicators (i.e. indicators are equally weighted).[7] Compared to the other stress measures, the figure shows that the SAFSI does better in capturing the benchmark episodes of financial stress as well as other global and idiosyncratic risks that affect the financial markets in SA. Furthermore, the financial stress measures computed with PCA and equal weights seem to overstate the intensity of financial stress, particularly during normal times. Further evidence in support of the SAFSI construction methodology is provided by the AUROC and partial AUROC values in Table 4, which captures the ability of the stress indices to match the benchmark episodes of financial stress in SA.

The SAFSI has the largest AUROC and partial AUROC compared to the alternative financial stress indices which yields lower information content. Table 4 also shows that aggregating market sub-indices that have partial AUROC ranging from 0.625 to 0.917 yields overall financial stress indices with better information content (partial AUROC ranging from 0.856 to 0.933, depending on the method of aggregation). This suggests that a combination of the sub-indices yields an improvement over individual markets, even if the equity market or money market on their own already provide good results.

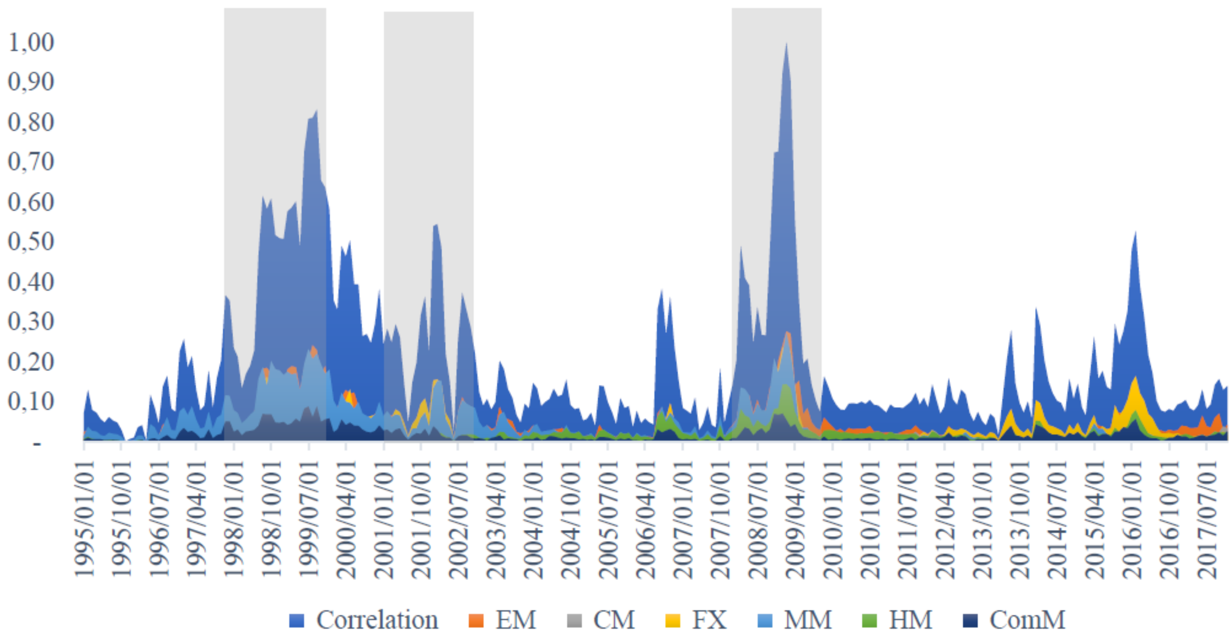
[7]PCA combines many variables into a few linear combinations or principal components. Various studies highlighted in the literature review (Section 2) use PCA analysis and can be referred to for the econometric methodology. The first principal component of the 17 selected stress indicators, which accounts for about 23 percent of the total variance, is chosen as the financial stress index employing PCA analysis. The equal-weights financial stress measure is simply the average of the 17 stress indicators that were selected using the procedure in Section 3.1.4.

Figure 6: SAFSI versus the simple weighted average of sub-indices ("perfect correlation")



Notes: The figure shows the comparison of the SAFSI (i.e. with information weights and correlation weights using formula (5)) with its perfect correlation counterpart using simple weighted average of market sub-indices (i.e. with information weights only) over the sample period (January 1995 - December 2017). The shaded regions correspond to the identified periods of financial stress (see Section 3.1.2).

Figure 7: Decomposition of the SAFSI



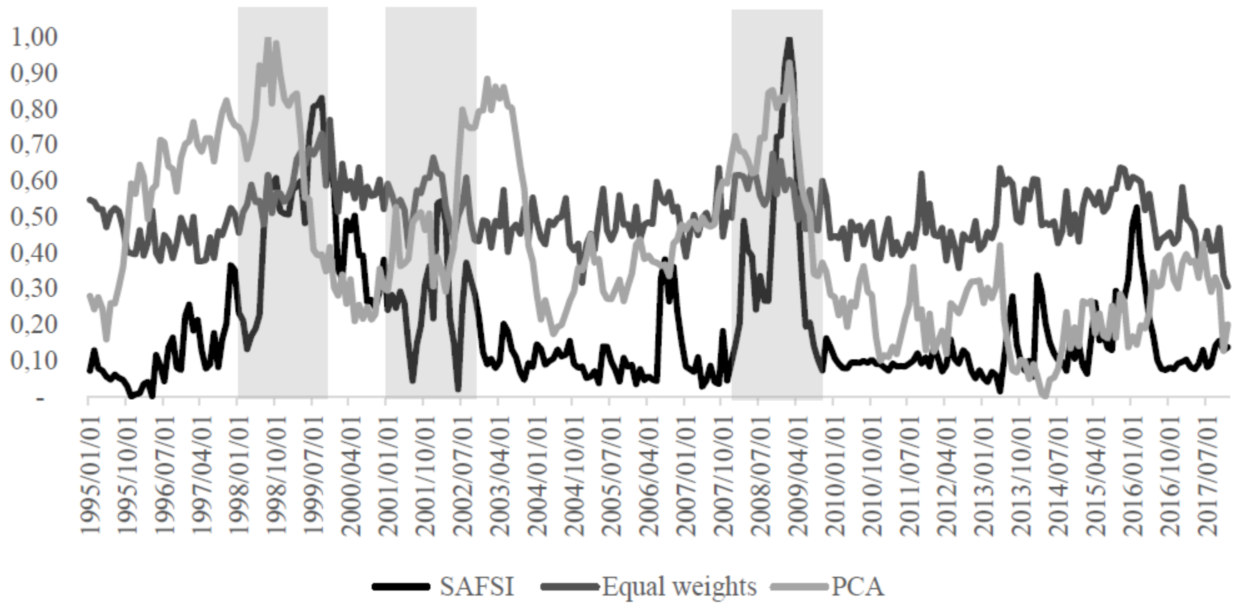
Notes: The figure shows the decomposition of the SAFSI into contributions from each market sub-index (with information weights - pAUROC) and the overall contribution from the cross-correlations. 'EM', 'CM', 'FX', 'MM', 'HM', 'ComM' respectively denotes the equity market, credit market, foreign exchange market, housing market, and commodity market. Overall contribution from the cross-correlations is denoted by 'Correlation'. The shaded regions correspond to the benchmark periods of financial stress (see Section 3.1.2).

Table 4: AUROC and partial AUROC of alternative stress measures and individual markets

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

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

Figure 8: SAFSI and alternative measures



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

5 Concluding remarks

The paper develops a monthly comprehensive financial stress index for the South African economy (SAFSI), covering the period January 1995 - December 2017. The sample chosen was large enough for calibration purposes and adequate given that the objective of the paper was to evaluate the backward performance of the index. The SAFSI has the advantage of capturing the interconnectedness of six financial markets that are thought to be most significant for the South African economy, enabling an indicator to be assessed in terms of its systemic importance. Only those individual stress indicators that are most useful in terms of signalling the contemporaneous materialisation of the identified benchmark stressful periods are included in the index. We evaluate the performance of the SAFSI relative to alternative measures of financial stress and show that the index successfully captures the major financial events in the South African economy.

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

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Appendix

A Derivation of the candidate indicators of financial stress

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

A.1 Equity market (EM)

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

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

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

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

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

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

Cumulative maximum loss in the real bank price index over a two-year moving window (CMax_rBPI) Analogous to the computation of CMax_rALSI,

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

Difference in stock returns over bank returns (Diff_ALSI)

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

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

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

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

$$ABS\_EBR_t = |\epsilon_t|$$

A.2 Credit market (CM)

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

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

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

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

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

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

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

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

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

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

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

$$Term\_SPR_t = RGOV10_t - Tbill_t$$

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

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

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

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

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

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

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

$$Corp\_SPR_t = Corp_t - RGOV10_t$$

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

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

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

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

A.3 Foreign exchange market (FX)

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

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

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

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

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

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

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

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

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

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

A.4 Money market (MM)

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

$$IBS_t = JIBAR_t - Tbill_t$$

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

$$PRIME\_SPR_t = PRIME_t - Tbill_t$$

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

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

Cumulative difference corresponding to the maximum increase of the prime rate spread (CDiff_PRIME)

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

A.5 Housing market (HM)

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

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

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

Monthly growth of the real house price index (G_HPI)

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

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

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

A.6 Commodity market (ComM)

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

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

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

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

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

Realised volatility of real oil price (ABS_OIL)

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

Realised volatility of real gold price (ABS_GOLD)

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

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

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

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

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