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Financial stability surveillance tools: Evaluating the performance of stress indices

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Financial stability surveillance tools: Evaluating the performance of stress indices

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Abstract

In this study, we aim to address the emerging debate about whether financial stress indices (FSIs) constructed using advanced methods such as the dynamic factor model and the principal component analysis method, perform better than those aggregated using simple averages, for the case of South Africa. To do so, we construct three FSIs using: the equal-variance weighting method (EVM), the principal component analysis method (PCA) and the dynamic factor model (FAM). We compare the performance of the indices for the period 2009-2020, using four criteria: quantile regressions, ordered probit model, local projections and the autoregressive integrated moving average (ARIMA) forecasting model. The results suggest that FSIs aggregated using the dynamic factor model and the principal component analysis method have a significant comparative advantage in predicting a financial crisis and capturing the vulnerability of the South African financial system to external monetary policy shocks. This suggests that the aggregation method and weighting system involved in constructing a financial stress index affects its performance in monitoring financial stability.

JEL Classification: B26, C22, C43, C53, E44, E47

Keywords: Financial stress index; forecasts; local projections; ordered probit model; quantile regression

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1 Introduction

Illing and Liu (2006) define financial stress as “the force exerted on economic agents by uncertainty and changing expectations of loss in financial markets and institutions” (p. 343). Financial stress is an outcome of weak financial systems and exogenous shocks. It is typically preceded by prolonged periods of economic stability and loose financial conditions, characterised by low borrowing rates and rising asset prices, which result in the build-up of financial imbalances. The increased intensity and frequency of financial crises over the years has stimulated efforts by policymakers to develop comprehensive indices and policies that can minimise the probability of financial crises (Morris, 2010). This has led to the adoption of financial stress indices as measures of instability in the financial system. In this paper, we measure instabilities in the financial system using the financial stress index (FSI), with extreme values representing financial crises. The FSI can help regulators to monitor the phase of imbalances build-up and to calibrate effective macroprudential policies to address instabilities in the financial sector (Adrian et al., 2019). Policymakers can therefore use the indices to achieve the financial stability objective by monitoring the behaviour of financial indicators, identifying shocks in the financial system and gauging the effects of their policy actions on the macroeconomy.

Historical narratives mostly considered financial stress as a currency and/or banking phenomena rather than an economic system-wide event (Illing and Liu, 2006). However, empirical work has highlighted the significance of macro-financial linkages and emphasises that large co-movements in variables linked to the financial sector typically depict financial stress (Chatterjee et al., 2017; Kremer et al., 2012). Consequently, financial stress indices have become standard methods to describe and measure system-wide stress emanating from the financial sector. Compared with earlier indices which did not allocate financial indicators to a specific market and hence made it difficult to know the exact market from which the stress emanated, the composite indicator of systemic stress (CISS) by Kremer et al. (2012) is the first to aggregate financial indicators according to specific markets when measuring financial stress. Similarly, aggregating market-specific sub-indices is the basis of the empirical work in this paper, as it effectively captures systemic stress. We aggregate the sub-indices according to six markets: banking sector, bond market, equity market, foreign exchange market, money market and the property market, to capture financial stress in all the areas of the financial sector.

This paper therefore addresses an emerging debate about whether financial stress indices based on sophisticated methods such as the dynamic factor model and the principal component analysis method, outperform those based on the simple averaging method, in detecting stress in the financial system. To the best of our knowledge, this is the first study to include evidence about the vulnerability of the indices to external monetary policy shocks in the performance evaluation of financial stress indices, specifically from South Africa’s major trading partners. This is in contrast to the previous literature on South Africa, which mainly focus on assessing the forecasting ability of the financial stress indices. As an emerging economy, South Africa is extensively integrated into the global markets. In this regard, policymakers need to monitor the potential cross-border effects of financial stress. This is particularly critical because there is evidence that economies with strong macroeconomic linkages are more affected by peer country crises (Chadwick and Ozturk, 2019a). In addition, the existing literature on South Africa mainly covers financial stress in the bond, equity, foreign exchange and money markets. We, therefore, contribute to the existing literature by incorporating stress prevailing in the property market[1] and the banking sector[2]. The US house price bubble burst that occurred prior to the 2007-2008 global financial crisis demonstrated a significant interaction between the financial sector and the property market. Including this sector in the financial stress index can therefore improve the monitoring of stress in the financial system. We also include the banking sector in our financial stress index since it plays a crucial role in transmitting monetary and macroprudential policy changes. Including the banking sector, therefore, enables the financial stress index to reflect the presence of shocks that can interfere with policy transmissions and the sector's capacity to respond to severe deposit withdrawals (Peltonen et al., 2019).

Assessing the performance of stress indices constructed using different aggregation methods is particularly important to enable policymakers to effectively contain imbalances in the financial system. This follows the assumption that the performance of the financial stress indices is closely linked to the weights allocated to the different sectors in the financial system. To assess the performance of the financial stress indices, we identify 18 indicators from six different markets: banking sector, bond, equity, foreign exchange, property and money markets. We then use the equal-variance weighting method (EVM), the principal component analysis method (PCA) and the dynamic factor model (FAM) to construct the indices. We evaluate the performance of these indices using four criteria. First, we utilise the quantile regression to examine the leading indicator properties of 12 macroeconomic variables[3] suggested in the literature, as determinants of financial stress in South Africa. Several studies suggest that excessive credit growth increases often precede a financial crisis. Lowe and Borio (2002) argue that variables such as household credit and GDP growth, can serve as early warning indicators of financial stress. For instance, a low rate of GDP growth per capita is associated with a high probability of a debt crisis (Lanoie and Lemarbre, 1996). The results indicate that the lower quantiles of all the three indices display similar results and are more sensitive to financial stress, compared with the middle and upper quantiles.

Since the financial stress indices display similar findings in the quantile regressions and do not give conclusive results, we also use the ordered probit model to estimate the probability that the indices correlate with financial crisis incidents. We find that the index constructed using the dynamic factor model is more accurate in predicting a financial crisis because it gives a predominant role to the money market, which is crucial for the transmission of policy changes. Third, we use local projections to examine the response of the financial stress indices to a contractionary monetary policy shock from South Africa's two major trading partners (the United States and China). The results suggest that the index aggregated using the PCA method is more efficient in responding to external monetary policy shocks and this is possibly because the index loads heavily on variables that are closely linked to monetary policy. Lastly, we use the autoregressive integrated moving average (ARIMA) model to assess which index provides efficient out-of-sample forecasts of financial stress. This is important because a credible estimate of the financial stress index is necessary for preventing financial system vulnerabilities since it informs policy and banking supervision decisions. We find that the EVM-based index outperforms the other indices and provides out-of-sample forecasts that

[1]We follow Kisten (2019) by incorporating the property market in the aggregation of the financial stress index. It is the only study that we are aware of that incorporates the volatility of the property market in the construction of the South African financial stress index.

[2]We construct a financial soundness indicator to capture stress in the banking sector. The indicator is a weighted average of the liquidity ratio, the z-score, the bank capital to assets ratio and the non-performing loans to total loans ratio. Using the financial soundness indicator as a measure of banking stress allows us to go deeper into the volatility of the different segments in the banking sector compared to using the banking beta, which only gives a compressed evaluation of the banking sector.

[3]The variables are not specific to the financial sector. They also cover other parts of the economy: real and public sector, current account and the foreign sector (see Appendix Table A1). Unlike the indicators used to construct the financial stress index, these variables measure the overall economic performance.

accurately sync with the historical data. In addition, the EVM index can pick the increase in financial stress associated with COVID-19. Our results suggest that the weighting method used to aggregate the index affects its performance and in our case, sophisticated methods (PCA method and dynamic factor model) outperform simple averaging (EVM). We therefore conclude that the choice of which index to use depends on the economic objective of the policymakers.

However, some scholars such as Arrigoni et al. (2020) argue that indices aggregated using sophisticated techniques (e.g., PCA and FAM indices) are prone to some flaws because the aggregation of the composite index, in most cases, is limited to financial indicators that have high collinearity. Therefore, financial stress indices that use sophisticated methods primarily reflect the changes in a limited number of indicators in the dataset. The authors who support this argument, highlight that most financial indicators have heterogeneous behaviour and are usually characterised by a lack of collinearity. They, therefore, emphasise that financial stress indices constructed using these methods are not representative of the changes in the entire financial sector. This is corroborated by the correlation structure of the market sub-indices across different financial industry segments in our study (see Appendix Tables A2 and A3). Moreover, the proponents of this line of thought also emphasise that financial stress indices constructed using the simple method of averaging (e.g., EVM index) perform better in identifying imbalances across the whole financial sector because all the indicators from different segments of the financial sector are allocated weights. Hence, the heterogeneity of each component is mirrored in the composite index. However, the trade-off when using the simple averaging method is that the data aggregation does not follow any objective statistical function, which can increase the margin of error.

The paper is structured as follows. Section 2 reviews the literature; Sections 3 and 4 present the methodologies used to construct the financial stress index and the empirical analysis, respectively; Section 5 details the robustness tests and section 6 concludes.

2 Related Literature

This section reviews the existing literature on financial stress. Our discussion is in three parts. First, we analyse the literature relating to the concept of financial stress. We then review the literature examining the link between the real economy and financial stress. Finally, we review the previous literature on financial stress indices.

2.1 The concept of financial stress

Over the years, most policymakers have been using financial stress indices as a monitoring tool for financial stability, however, the main challenge in identifying crises periods is the lack of a precise definition of financial stress. Like Illing and Liu (2006), earlier studies have defined financial stress in several ways. This section, therefore, highlights some of the definitions in the literature. For example, Hakkio and Keeton (2009) described financial stress as the disruption of the normal functioning of the financial system. However, the authors explained that it is difficult to precisely define financial stress because each episode is unique. Hence, the definitions may also vary. Cardarelli et al. (2011) provided an alternative definition of the concept. They argued that financial stress which usually leads to an economic crisis, is characterised by an abrupt increase in risk or uncertainty, large changes in asset prices and failure of the financial sector to meet its financial obligations.

Another contribution was provided by Huotari (2015). The author highlighted that the dynamics of financial stress can consist of the horizontal or vertical perspectives. The horizontal perspective is when instability spreads within the sectors in the financial system, whereas the vertical perspective refers to when the risk is transferred from the financial sector to the real economy. This is similar to Illing and Liu (2003), who stated that financial stress results in large shifts in economic behaviour which adversely impacts the real economy. On the other hand, the contribution by Kremer et al. (2012) focused on systemic risk and stress. They relied on De Bandt and Hartmann (2000)'s definition of systemic risk. They defined it as the increased probability that instability in certain areas of the financial sector becomes widespread and interferes with the functions of the financial system. They further define systemic stress as collective instability in the financial sector. This study relies on the definitions of De Bandt and Hartmann (2000) and Kremer et al. (2012) and defines financial stress as instability that interferes with the normal functioning of the financial system with the potential to adversely affect the real economy.

2.2 The link between the real economy and financial stress

Subsequent to the definition of financial stress, the main characteristic associated with financial stress is that households and businesses withdraw from purchases and new investments due to tighter credit conditions and economic uncertainty. However, Davig and Hakkio (2010) highlight that in most cases, the relationship between the real economy and financial stress is complex and not well understood. They argued that even though financial stress and economic activity are closely related, the connection and the effects vary over time. Nonetheless, Hakkio and Keeton (2009) highlighted three channels through which an increase in financial stress can negatively affect economic activity. These are tight credit conditions by banks, increased uncertainty about the economic outlook and the precipitous decline of asset prices. For instance, financial stress can lead to tight credit conditions by banks and therefore result in decreased economic activity. More specifically, increased liquidity flight and information asymmetry can make banks less willing to lend. This can result in banks raising the interest rates charged on new loans and the minimum credit standards. Moreover, the uncertainty surrounding the economic outlook may lead to increased volatility in asset prices. As a result, firms and households may cut back on spending. Overall, this results in a reduction in spending and consequently, decreased economic activity. Some studies such as, Malega and Horváth (2017), further associate financial stress with an increase in the unemployment rate, mainly due to a decline in activity across the economy.

The studies reviewed here emphasise that financial stress can adversely affect the real sector, irrespective of whether it occurs in advanced or emerging economies. Kabundi and Mbelu (2021) recently documented the variation in the macroeconomic effects of financial shocks in South Africa, using a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model. In a related study, Kremer et al. (2012) examined the potential non-linearity in the transmission of financial shocks by estimating a threshold vector autoregressive model. They both confirm that the transmission of shocks from the financial system to the real sector during a financial crisis significantly differs from periods when there is no crisis. Other notable studies, such as Balcilar et al. (2015), Chatterjee et al. (2017) and Hubrich and Tetlow (2015) analysed the impact of financial shocks on the real economy by considering the underlying state of the economy. Balcilar et al. (2015) were the first to examine whether non-linearities existed in the transmission of financial shocks in South Africa, employing the financial conditions index (FCI) constructed by Thompson et al. (2015). They used a non-linear logistic smooth transition vector autoregressive model (LSTVAR). They found that inflation in South Africa responds more to financial shocks during an economic recession, while the response of interest rates and output growth is significant during economic booms. Although examining different economies and using different estimation methodologies, the studies found similar evidence that economic activity reacts differently to financial shocks in stressful compared to tranquil periods. This implies that periods of financial stress are detrimental, and the implementation of conventional monetary policy alone is inadequate. It is therefore essential to carry out an evaluation analysis to identify efficient aggregation methods that can accurately highlight stressful periods in the financial system. This is to enable policymakers to establish which policy tools to use to alleviate disruptions in the financial sector.

2.3 Financial stress indices in previous literature

Table 1 provides a summary of selected studies that have constructed financial stress indices over the years. The table shows the authors, indicators used, and sample size for each study. The studies are arranged in the order they are discussed in the text below. Although there have been several attempts to develop a composite index for measuring financial stress (e.g. Balakrishnan et al., 2011; Chadwick and Ozturk, 2019b; Illing and Liu, 2003; Kim et al., 2020; Kim and Shi, 2021; Kremer et al., 2012; Slingenberg and de Haan, 2011; Yurteri and Önder, 2021), the literature is very extensive for advanced economies but very limited for emerging economies. This is mainly on account of data unavailability. For instance, researchers have developed financial stress indices (FSIs) for the financial systems in Canada, the Euro area and Kansas City (Hakkio and Keeton, 2009; Illing and Liu, 2003). These studies confirm that FSIs can predict developments in the real economy. Thus, the authors select variables that are correlated with economic activities.

The FSI developed by Illing and Liu (2003) for the financial system in Canada, accurately captured the previous stress events such as the 1998 Long-Term Capital Management (LTCM) and the 1992 credit loss. The FSI covers the banking, foreign exchange, equity and bond markets. The variables included in the index were weighted according to their market size. Illing and Liu (2003) employed various methods to construct an FSI for Canada, which include the principal component analysis, equal-variance weighting and sample cumulative distribution functions. They found that the indices were useful in decomposing financial stress, monitoring development and historical analysis. They argued that even though the FSIs captured the contemporaneous level of stress, they did not have strong predictive power for future episodes of financial stress.

Focusing on the Euro area, Kremer et al. (2012) developed the Composite Indicator of Systemic Stress (CISS). They use the portfolio theory to aggregate market specific sub-indices. Compared to other aggregation methods, the portfolio theory allocates more weight to crisis events in which financial stress prevails in several markets concurrently. This is mainly because the method accounts for the time-varying cross correlations between the sub-indices. Unlike the earlier FSIs, the CISS accurately captures the concept of systemic stress more clearly.

TABLE 1: Summary of selected related studies on the financial stress indices

	Illing and Liu (2003)	Kremer et al. (2012)	Kim and Shi (2021)	Kim et al. (2020)	Yurteri and Önder (2021)	Chadwick and Ozturk (2019b)	Cardarelli et al. (2011)
Foreign exchange market	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Debt market	Yes						
Risk spreads	Yes						
Liquidity measures	Yes						
Dev. in ST/LT int. rates	Yes						
Equity Market	Yes	Yes				Yes	
Money Market		Yes				Yes	
Bond Market		Yes		Yes		Yes	
Financial intermediaries		Yes					
Banking sector	Yes	Yes			Yes	Yes	Yes
Insurance sector		Yes					
Other		Yes					
Infrastructure		Yes					
Payment systems		Yes					
Settlement systems		Yes					
Clearing systems		Yes					
Stock market			Yes	Yes	Yes		
Financial industry				Yes			
Output and income			Yes				
Consumption & inventories			Yes				
Labour market			Yes				
Property			Yes				
Money & credit			Yes				
Interest rate			Yes				
Prices			Yes				
Sovereign risk					Yes		
Securities market							Yes
Sample size	1 country	Emerging countries	1 country	1 country	13 emerging countries	1 country	17 advanced economies

* The table presents a comparison of different studies on the construction of financial stress indices. It specifically shows the financial indicators included in the aggregation of a financial stress index, for the selected studies.

In a related study, Bianco et al. (2011) also developed an FSI for the United States termed the Cleveland Financial Stress Index (CFSI). The index is based on 11 financial indicators and focuses on the foreign exchange, equity, credit, and interbank markets. The CFSI mainly consists of spreads (such as the liquidity spread and the interbank liquidity spread), while the remaining components are ratios. The latest study by Kim and Shi (2021) also estimated the forecasting ability of the CFSI using a factor-based forecasting model. They forecast the CFSI out-of-sample from 170 monthly frequency macroeconomic data. They conclude that the factor model predicts the out-of-sample index better than the autoregressive benchmark models and the random walk for the short-term forecast horizons. Since financial crises are often a surprising realisation, they argue that this is a desirable feature.

Using a panel of 198 monthly frequency macroeconomic data for Korea, Kim et al. (2020) developed the financial stress index using factor-based forecasting models. The index is estimated using four sub-indices developed by the Bank of Korea. They employed the principal component analysis method to extract latent common factors after differencing them. They then formulated the out-of-sample forecasts of the financial stress index by using the estimated common factors augmented with an autoregressive-type model. Their models outperform the non-stationary benchmark and stationary models in predicting the financial stress indices for up to 12-month forecast horizons. Their results suggest that both the financial market and real activity variables have a dominant explanatory role in predicting the vulnerability of the financial markets in Korea.

Similarly, Yurteri and Önder (2021) analysed the determinants of financial stress and showed the impact of the spatial linkages, using data from 13 emerging economies. The novelty of their study was to consider the effects of neighbour countries' macroeconomic factors on domestic financial stress and consider the financial stress interaction between emerging economies using spatial econometric approaches. They found that the most important determinants of financial stress are economic growth, current account balance/GDP, global risk and geopolitical risk. They also found a strong interaction of financial stress among emerging market economies. In addition to the geographical linkage, financial and trade linkages also play an essential role in the transmission of financial stress among economies.

Also, Chadwick and Ozturk (2019b) constructed a financial stress indicator (FSI) for Turkey, using 14 variables representing five markets, namely: the banking sector, money, bond, foreign exchange and equity markets, by employing a variety of econometric approaches, including basic portfolio theory, principal component analysis method, variance equal weights and the Bayesian dynamic factor model. They compared 15 different FSIs, and their results suggested that no simple best indicator can measure Turkey's financial systemic stress. This is because various indicators offer different forecasting power, with some giving stronger predictive power for systemic risk while others have stronger power for economic growth.

In addition, Cardarelli et al. (2011) use a uniform set of data and construct an FSI for 17 advanced economies, using the equal-variance weighting method. They contribute to the debate about the effect of financial stress on the real economy and conclude that financial stress emanating from the banking sector is more likely to cause severe economic recessions than stress in the foreign exchange market. For the United States, Hakkio and Keeton (2009) constructed the Kansas City Financial Stress Index (KCFSI). The index is comprehensive, and it includes 11 financial indicators that reflect yields or prices in the financial markets. The authors use the principal component analysis method and define financial stress as the underlying factor for the co-movement in the 11 variables. Alongside the equal-variance weighting method, the principal component analysis method is the commonly used aggregation method in the literature. Cardarelli et al. (2011), and Hakkio and Keeton (2009) depart from the work of Illing and Liu (2003) and include financial indicators from the money market in their FSIs.

For the case of South Africa, Ncube et al. (2016) used the equal-variance weighting and principal component analysis methods to construct an FSI. They conclude that the real economy is extensively distorted during episodes of financial stress. Despite the simplicity of the equal-variance weighting method, it has some shortcomings. For instance, the disadvantage of assigning equal weights to all the markets is that it overlooks the varying importance of the indicators in the financial system. Hence, in most cases, the weights used in this method do not correspond to the variances and correlations among the financial variables. In addition, the method assumes that all variables are normally distributed, which is not always the case. More recently, aggregation methods of dynamic factor modelling have been gaining momentum. The advantage of dynamic factor modelling is that it accounts for time variation in the parameters, which is essential for accurately forecasting macroeconomic conditions.

There has been extensive literature about financial stress in emerging economies, after the 2007-2008 global financial crisis. For example, Balakrishnan et al. (2011) suggested five indicators (banking sector beta, exchange market pressure index, stock market returns, sovereign debt spreads and time-varying stock market return volatility) to measure financial stress in emerging economies. Although different aggregation methods have been used to develop financial stress indices in the literature, there is a limited number of studies that incorporate stress prevailing in the property market and the banking sector, especially in the case of South Africa. Therefore, the financial stress index in this empirical work is broader and includes indicators for the property market and banking sector. Compared to the existing studies that use the banking sector beta to capture stress in the banking sector, our paper is the first attempt in the literature to construct a financial soundness indicator to measure stress in the banking sector for the South African financial system.

While we know that there is somewhat extensive work on constructing financial stress measures for South Africa (e.g., Ilesanmi and Tewari, 2020; Kisten, 2019), we believe there is room for some technical improvements. We depart from the previous studies on South Africa and other emerging markets by using econometric evaluation tools to assess the performance of three indices of financial stress. More specifically, this study aims to confirm whether financial stress indices constructed using sophisticated methods have any comparative advantage in signalling and predicting a financial crisis. To the best of our knowledge, this is the first study to document the effect of the monetary policy shocks from South Africa's major trading partners (the United States and China) on the financial stress indices, as part of the performance evaluation. The study that comes closest to ours is Arrigoni et al. (2020), which assessed the performance of the financial conditions indices for 18 advanced and emerging economies. Our proposed analysis has, however, not been done for an emerging economy in Africa.

3 Statistical design of the financial stress index

3.1 Selection of markets and financial indicators

A crucial step when constructing the financial stress index is the selection of the markets. In addition to the four market categories covered by Ilesanmi and Tewari (2020), we include the property market and the banking sector. We use the property index and the financial soundness indicator to capture facets of stress related to the property market and the banking sector in South Africa, respectively. To measure financial stress in the South African financial system, we consider six segments of the financial sector: the banking sector, bond market, equity market, foreign exchange market, money market and property market. Each sector is represented as a sub-index of the financial stress index and provides information for specific aspects of the financial system. Thereafter, we select the financial indicators that correspond to each chosen market. We therefore identify 18 financial indicators that we group into the six market categories. This study is more akin to financial stress indices constructed using spreads and volatilities (e.g., interbank rate volatility). We consider these to be more effective measures of financial stress compared to variables that predominantly measure credit conditions (e.g. household credit) and therefore place more emphasis on the cost of credit and not financial stress (Arrigoni et al., 2020).

We expect a high correlation between the financial stress index and the market segments from which the financial stress emanates during a financial crisis episode (Kremer et al., 2012). For example, suppose financial stress was caused by instability in the banking sector during the study period. In that case, we expect the financial stress index to be highly correlated with the banking sector.

3.1.1 *Money market sub-index*

The money market mainly trades in short-term financial instruments. Therefore, this market offers investors a safe haven during a financial crisis because it is perceived as a low-risk investment. Thus, the variables in this sub-index measure the level of risk and liquidity in the inter-bank market. The indicators also reflect specific characteristics of the financial sector, such as the flight-to-liquidity effects and the effects of adverse selection on the banking sector when financial stress is heightened. The money market is closely connected to policies concerned with money supply, such as monetary policy. Money markets, therefore, serve as the primary transmission mechanism for changes in monetary policy (Cerqueira and Murcia, 2015).

Volatility of the interbank rate (VIR): The interbank rate is the interest rate charged on loans borrowed between banks. In this case, we consider the volatility of the interbank rate. Considering that the variable reflects increasing asymmetric information, we expect it to have a positive relationship with financial stress. The formula for calculating the indicator is specified as:

$$VIR = \sqrt{\Sigma_{t=1}^{n} R_t^2} \,, \tag{1}$$

where n is the frequency of trading, t is the month of trading and R is the log returns of the interbank rate (Ilesanmi and Tewari, 2020; Kremer et al., 2012).

Liquidity spread: This variable measures the level of liquidity in the financial sector. It is specified as the difference between the three-month interbank rate and the three-month treasury bill.

$$Liquidity\ spread = 3\ month\ Johannesburg\ interbank\ rate - 3\ month\ treasury\ bill \,, \tag{2}$$

where the 3 month Johannesburg interbank rate is the rate at which banks sell and buy money, while the 3 month treasury bill is the US government security with a fixed maturity period of 3 months.

Cost of interbank borrowing: The variable captures the risk premium imposed by banks when lending to one another. An increase in the cost of interbank borrowing signals increased vulnerability in the financial sector.

$$Cost\ of\ interbank\ borrowing = 3\ month\ Johannesburg\ interbank\ rate - policy\ rate \,, \tag{3}$$

3.1.2 *Equity market sub-index*

The variables in this sub-index reflect changes in the financial asset prices, most common during financial crisis episodes.

Equity market volatility (EMV): The variable captures stress in the equity market and is calculated as the monthly log-returns of the all-share index. The all-share index measures the average change in the share prices of all the companies in the stock exchange. It is a good indicator of the performance of the stock market.

$$EMV = \sqrt{\Sigma_{t=1}^{n} R_t^2} \,, \tag{4}$$

where n is the frequency of trading, t is the month of trading and R is the monthly log-returns of the all-share index.

Maximum cumulative loss (CMAX): This indicator measures the cumulative loss in the financial sector over the sample period.

$$CMAX_i = \frac{X_t}{max[x \in (x_{t-j}) j = 0, 1, 2 \ldots, T]}\ , \tag{5}$$

x denotes the stock market index which compares the current and past stock prices (market performance) and T is the time period, defined over 24 months.

3.1.3 *Bond market sub-index*

The variables in this sub-index capture the state of liquidity and solvency in the bond market. The movements in this market may also reveal the level of risk aversion by investors. That is, the preference of certainty over uncertainty by the investor (Cerqueira and Murcia, 2015).

Government bond index volatility (GBIV): This variable reflects the risk spread required to invest in the South African 10-year government bond. It measures the yield spread between the 10-year government bond for South Africa, the US, the UK and the Euro.

$$GBIV = SA\ government\ bond\ yield - (US\ bond\ yield, UK\ bond\ yield, Euro\ bond\ yield)\ , \tag{6}$$

Sovereign bond spread: This indicator captures the difference between the US bond yield and the South African bond yield.

$$Sovereign\ bond\ spread = South\ African\ bond\ yield - US\ bond\ yield\ , \tag{7}$$

3.1.4 *Foreign exchange market sub-index*

This sub-index reflects the fluctuations in the exchange rate. Therefore, the variables included in this market capture the movements in the foreign exchange market.

Foreign exchange market volatility: This indicator captures the volatility between the South African rand and the major currencies: the British pound, the euro and the US dollar. An increase in the volatility indicates uncertainty in the foreign exchange markets. To obtain the volatility of the exchange rate, we divide the differences between the lowest and highest exchange rate values by the total number of differences (Kočišová and Stavárek, 2015).

Maximum cumulative loss (MCL): This is the cumulative loss for the US dollar, British pound and euro to the South African rand. It measures the cumulated loss in the exchange rate over the sample period and its advantage is that it makes any sharp declines in prices more visible.

$$MCL = \frac{X_t}{max[x \in (x_{t-j}) j = 0, 1, 2 \ldots, T]}\ , \tag{8}$$

As previously defined, x denotes the stock market index and T is the time period defined over 24 months.

3.1.5 *Property market sub-index*

The property market sub-index is essential because, in most economies, mortgage defaults cause a surge in non-performing loans, which reduces the profitability of banks and may result in financial stress (Hanschel and Monnin, 2005). In most emerging economies such as South Africa, households hold most of their wealth in real estate. A sudden decline in property prices may therefore cause systemic stress and imbalances in the financial system. Consequently, we expect a large part of the stress in the financial system to be reflected in the property market.

Property price index: The index measures the changes in property prices in South Africa and also serves as an indicator of mortgage defaults. It plays a vital role in measuring financial stress because investors use it to monitor potential shifts in the stock market and developments in the economy (Ilesanmi and Tewari, 2020).

3.1.6 *Banking sector sub-index*

The indicators in this sub-index reflect the level of solvency in the financial sector. The banking sector plays a significant role in the efficiency of the financial system. For instance, increased stress conditions in the banking sector can spread to other parts of the financial system and negatively affect the real economy. For this study, we use the financial soundness indicator as a proxy to capture any volatilities in the banking sector. The financial soundness indicator is a weighted average of the variables outlined below.

Non-performing loans to total loans ratio: In this case, non-performing loans refer to loans for which the interest payments and the monthly principal have not been paid for more than 90 days. Therefore, the ratio measures the banks' quality of outstanding loans and credit risk. A high ratio implies an increased probability that the bank may not recover the outstanding loans, which may translate into increased financial stress in the economy. On the other hand, a small ratio indicates that the financial system is at low risk of financial stress (Huotari, 2015).

Bank capital to assets ratio: The ratio captures the level of capitalisation in the banking sector. It measures the banks' available capital as a percentage of the risk-weighted credit exposures. It is, therefore, a good indicator of the efficiency and stability of the financial system. The ratio indicates whether banks can absorb losses without ceasing operations. The risk-weighted assets in this ratio show the minimum amount of capital banks should hold to minimise the risk of insolvency (Chatterjee et al., 2017).

Z-score: This ratio measures the probability of the risk of insolvency in the banking sector (Morris, 2010). It precisely captures the likelihood of defaults in the South African banking system. A low z-score reflects instability in the banking sector. It compares the banking system's returns and capitalisation with their volatility level. It is specified as:

$$Z-score = \frac{Returns\ on\ Assets + Capital\ to\ Assets\ Ratio}{Standard\ Deviation(Returns\ on\ Assets)}, \tag{9}$$

Liquidity ratio: Measures the resilience of banks to cash flow shocks. It identifies if the banks in the South African financial system can accommodate sudden withdrawals of deposits held with them. It assesses whether financial institutions have enough liquid assets to meet their short-term financial obligations[4]. The financial system is considered at low risk of financial stress when the liquidity ratio is above 1.

3.2 Standardisation of the dataset

Before aggregating the sub-indices into the composite indicator of financial stress, we standardise the data by converting it into a conventional unit of measure. This helps to normalise fluctuations that may be present across variables and ensures that the values have the same scale, for ease of interpretation. Following Cardarelli et al. (2011); Hakkio and Keeton (2009); Huotari (2015), we transform the stress indicators using the standardisation approach. Each financial indicator is therefore computed as:

$$z_t = \frac{(x_t - \bar{x})}{\sigma}, \tag{10}$$

where z_t is the standardised series, σ denotes the standard deviation and $\bar{x}$ is the series mean. Each indicator in the dataset is therefore standardised by subtracting the series mean, $\bar{x}$, and dividing by the standard deviation, σ.

3.3 Aggregation of sub-indices into composite index

The literature highlights various aggregation methods for constructing an FSI, but the most used are the equal-variance weighting method (EVM) and the principal component analysis method (PCA). The EVM averages the six market sub-indices to develop a financial stress index. The PCA method extracts principal components that reflect most of the common variation in the group of sub-indices. The extracted components are therefore aggregated to construct the financial stress index. Even though the EVM is the commonly used aggregation method, it does not account for the degree of correlation between the sub-indices in the construction of the index. Unlike the EVM, the requisite for using the PCA method is that there should be sufficient correlation among the financial indicators[5]. However, the main drawback of using the PCA method is that it is constructed as a stationary variable with a zero mean, which implies that the estimated financial stress index may not accurately reflect the gradual shifts in the financial sector.

[4] The Basel III conditions require banks to maintain an adequate amount of liquid assets that can fund unexpected cash outflows for about 30 days (Georgiev, 2012).

[5] We use the Kaiser-Meyer-Olkin (KMO) test statistic to assess the correlation among the indicators. The rule of thumb is that, the KMO value should be above 0.5 in order to apply the PCA method. Our dataset satisfies this condition (see Appendix Table A4).

This paper acknowledges the limitations of the two approaches. It, therefore, employs an alternative aggregation method to estimate the financial stress index. We therefore propose using the Kalman filter in a dynamic factor model, to construct an additional index. This approach estimates an FSI that captures the gradual shifts in the financial sector as it allows for autocorrelation (Klein et al., 2012). In this paper, we, therefore, use three methods to construct an FSI: the EVM, the PCA and the Kalman filter in a dynamic factor model (FAM). More importantly, the three aggregation methods use different weighting systems. The intuition is that the weights have an important impact on the performance of the indices.

Overall, a positive financial stress index indicates favourable economic conditions, while a negative index is associated with a deterioration in economic conditions. For example, in the case of the foreign exchange market, an appreciation of the rand suggests high capital inflows, which is correlated with a positive financial stress index and favourable economic conditions. It is however important to note that favourable macroeconomic conditions accompanied by uncontrolled credit expansion and a rapid increase in asset prices, can result in an overheated economy and eventually, an economic bubble. In most instances, when the economic bubble bursts, it leads to stress in the financial sector (Hodula et al., 2019). This line of thought informs our classification of financial stress in Figure 1, whereby a financial system is identified as stable when the stress index is within a range of +1 and -1. This is because an index above +1 could be a signal of an overheating economy, while values below -1 coincide with turmoil in the financial system. The aggregating methods are discussed in detail below.

3.3.1 Equal-variance weighting method (EVM)

This is the most used aggregation method in the literature because it is the most intuitive and straightforward (Balakrishnan et al., 2011; Cardarelli et al., 2011; Huotari, 2015). In this case, the financial stress index is the arithmetic average of the six financial sector segments. This implies that the six market sub-indices are allocated equal weights when constructing the index.

$$FSI\_EVM = \frac{\Sigma_{i=1}^{6} S_i}{n} , \tag{11}$$

where S_i denotes the market sub-indices, and n is the number of market sub-indices in the FSI. The allocation of the weights in the EVM-based FSI is shown in Table 2, where each market sub-index is given equal weights. However, it is evident from the correlation structure between the FSI_EVM and its sub-components (see Table 3) that allocating equal weights to the sub-indices does not guarantee that the different segments of the financial sector will have equal importance and contribution. For example, the correlation structure in Table 3 (row 7) shows that despite the allocation of equal weights, the FSI_EVM predominantly reflects the behaviour of the bond market (0.80), which gives the sector more importance compared to the other segments of the financial system.

TABLE 2: Weights for FSI_EVM (in percentage)

	Weights
Banking sector	16.67
Bond market	16.67
Equity market	16.67
Foreign exchange market	16.67
Money market	16.67
Property market	16.67

Notes.- The table shows the weights for the sub-components of the FSI_EVM index, in percentage.
Source: Authors' computation

TABLE 3: The correlation structure of the equal-variance weighted financial stress index (FSI_EVM)

	Banking sector	Bond market	Equity market	FX market	Money market	Property market	FSI EVM
Banking sector	1.00						
Bond market	0.63	1.00					
Equity market	0.15	0.20	1.00				
Foreign exchange market	0.34	0.50	0.21	1.00			
Money market	0.00	0.12	0.61	0.05	1.00		
Property market	0.05	0.53	0.41	0.31	0.39	1.00	
FSI EVM	**0.60**	**0.80**	**0.67**	**0.63**	**0.50**	**0.66**	**1.00**

Notes.- The table shows the correlation structure across the FSI_EVM and the six market specific sub-indices.
Source: Authors' computation

It is also worth noting that some researchers that use this method do not aggregate the financial indicators into specific markets (Islami and Kurz-Kim, 2013). They compute the FSI_EVM as the arithmetic average of the indicators. However, the main benefit of using market specific sub-indices is that it becomes easy to identify the stress conditions in different parts of the financial sector. Notwithstanding that the EVM approach is simple and easy to interpret, its shortcoming is that it does not incorporate the correlation that may exist between the financial indicators. It assumes perfect correlation across all the six sub-indices, which may not always be accurate. It is for this reason that most studies use the PCA method.

3.3.2 Principal component analysis method (PCA)

The PCA method pioneered by Hotelling (1933) extracts a principal component, P_t that captures the co-movement among the observable financial indicators, X_t. The model is presented as follows:

$$X_t = \beta P_t + U_t \ , \tag{12}$$

where β is an nxm matrix of loadings for the principal components and measures the strength of the relationship between X_t and P_t. Where P_t is a vector of mx1 unobserved variables (principal components) and U_t is an nx1 vector of errors. The model assumes that the principal components have a mean of zero, $[E(P) = 0]$, and the errors are orthogonal to the principal components, $[E(PU') = 0]$.

For the FSI_PCA, the principal component is a new variable that explains most of the variation in the observed variables (i.e., the six markets). In this study, the first principal component (Component 1) in Table 4 captures most of the variation in the observed variables (80 percent). We, therefore, use the coefficients of the first principal component (PC 1 in Table 5) to estimate the weights for the PCA-based financial stress index[6]. Considering the allocation of the weights for the FSI_PCA, it is evident in Table 6 that this method gives a predominant role to the bond market (23 percent), banking sector (21 percent) and equity market (20 percent).

TABLE 4: Total variation in the PCA method

	Eigen value	Variance	Proportion
Principal Component 1	**2.01**	**0.80**	**0.33**
Principal Component 2	1.21	0.20	0.20
Principal Component 3	1.00	0.24	0.17
Principal Component 4	0.76	0.15	0.13
Principal Component 5	0.62	0.20	0.10
Principal Component 6	0.41	...	0.10

Notes.- The table shows the eigen values and the total variation for the corresponding components in the PCA method.
Source: Authors' computation

TABLE 5: Principal components coefficients

	PC 1	PC 2	PC 3
Banking sector	**0.49**	0.39	-0.03
Money market	**0.21**	0.55	0.56
Bond market	**0.53**	-0.24	0.13
Foreign exchange market	**0.24**	-0.51	0.63
Equity market	**0.47**	0.25	-0.37
Property market	**0.41**	-0.41	-0.37

Notes.- The table shows the coefficients of the first three principal components, for each segment of the financial sector.
Source: Authors' computation

3.3.3 FSI by Kalman filter in a dynamic factor model (FSI_FAM)

Following the influential work of Bai and Ng (2002), and Stock and Watson (2016), we use the Kalman filter in a dynamic factor model to estimate the financial stress index for the differenced series[7]. We model the financial indicators, X_t, as linear functions of the unobserved factor, F_t. The model's premise is that some elements, F_t, influence the movements of the time series variables, X_t. This method differs from the PCA method in two ways. First, the

[6] Ilesanmi and Tewari (2020) suggest that using the coefficients of a principal component that explains a small variation in the financial indicators may add noise to the index and make it challenging to detect crisis periods.

[7] The data is differenced to remove trends and unit roots. The observable variables are therefore stationary at first difference.

TABLE 6: Weights for the sub-components of the FSI_PCA (in percentage)

	Weight
Banking sector	21
Money market	9
Bond market	23
Foreign exchange market	10
Equity market	20
Property market	17

Notes.- The table shows the weights for the sub-components of the FSI_PCA, in percentage.
Source: Authors' computation

parameters in the model are estimated by maximum likelihood, which increases the probability of obtaining the correlations that exist among the financial indicators. Second, we use the Kalman filter to estimate the unobserved factors, F_t, that drive the correlations among the financial indicators, X_t.

The main advantage of extracting the unobserved factors using the Kalman filter is that the factors are unbiased and more robust to measurement errors compared to the unobserved principal components in the PCA method. This is because the PCA method estimates averages across the series at the same date (contemporaneous smoothing) to extract the unobserved principal components, while the Kalman filter averages across both the series and time (intertemporal smoothing) to estimate the unobserved factors (Stock and Watson, 2016). We, therefore, find it imperative to contrast the FSI_EVM and the FSI_PCA with an alternative financial stress index based on the dynamic factor model. Assuming linearity between the factors, F_t and observed variables, X_t, the dynamic factor model is specified as:

$$X_t = \alpha F_t + \varepsilon_t \ , \tag{13}$$

$$F_t = \beta(L)F_{t-1} + u_t \ , \tag{14}$$

Where X_t is the vector of nx1 observed variables. α is the matrix of nxp factor loadings, which measure the sensitivity of the observed variables to the unobserved dynamic factors. F_t is the vector of px1 unobserved dynamic factors, and ε_t is the vector of nx1 idiosyncratic shocks. L is the lag operator, and β is a parameter matrix. The main assumption in the model is that ε_t is uncorrelated with both F_t and u_t.

The first stage of the dynamic factor estimation is represented by equation 13, which allows extracting the unobserved dynamic factors, F_t, from the financial indicators, X_t. The second equation (equation 14) measures the dynamic factors, F_t, that drive the fluctuations of the data over time. Given that X_t is a zero-mean process, equation 13 and equation 14 do not contain intercepts. The dynamic factors follow a vector autoregression (VAR) process, represented in equation 15:

$$F_t = \beta_1 F_{t-1} + \ldots + \beta_p F_{t-p} + u_t \ , \tag{15}$$

where $E(u_t) = 0$ and $E(u_t u_t') = U$.

We also allow α_t and β_t in the dynamic factor model to evolve as driftless random walks:

$$\alpha_t = \alpha_{t-1} + \gamma_t \; , \tag{16}$$

$$\beta_t = \beta_{t-1} + v_t \; , \tag{17}$$

Where γ_t and v_t are the independent and identically distributed errors. They are uncorrelated with ε_t and u_t. The Kalman filter is therefore based on a state-space format which consists of two equations, the measurement equation and the state equation. For this time series, equations 13 and 16 are the measurement equations while equations 14 and 17 are the state equations[8].

Table 7 summarises the results of the dynamic factor model. Column (I) indicates that the persistence and significance of the dynamic factors are restricted to the banking sector and the equity market. The allocation of the weights for the sub-components of the FSI_FAM in Table 8 further support this, where the equity market and the banking sector are apportioned with the highest weights, 24 percent and 22 percent, respectively. However, it is worth noting that the results in Table 7, (Column II), suggest that all the segments of the financial sector play a significant role in financial stability. We, therefore, include all the six markets and their corresponding weights (Table 8) to construct the financial stress index. We consider the coefficients of Factor 1 in Appendix Table A5, to calculate the corresponding weights for the sub-components of the FSI_FAM. This is informed by the results in Appendix Table A6, which suggests that Factor 1 explains most of the variation (88 percent) in the time series data and is, therefore, more instrumental in constructing the dynamic factor-based index.

Some scholars, such as Arrigoni et al. (2020), argue that using sophisticated methods (e.g., principal component analysis method and dynamic factor model) to construct financial stress indices may reduce information dimensionality (data reduction), as most of them only focus on the time series that have high collinearity, to summarise large datasets and extract an economic indicator. They recommend that researchers should exercise caution when using these methods to construct financial stress indices because the resulting composite index may represent only a few indicators that exhibit high collinearity. The argument is that the financial indicators typically used to construct a financial stress index are heterogeneous in nature and may therefore not always behave similarly. For example, the foreign exchange rate market is mainly characterised by pronounced cyclicality, while the equity market usually displays a stationary process with occasional jumps.

Appendix Tables A2 and A3 support this claim, where the correlation between the market sub-indices and the financial stress indices (FSI_PCA and FSI_FAM) indicate that the indices load heavily on a few markets that characterise the financial sector. For example, in

[8] The measurement equations relate the observed variables, X_t, to the unobservable dynamic factors, F_t. The state equations exploit the intertemporal smoothing technique, which averages across both series and time, to estimate the dynamic factors (Stock and Watson, 2016).

TABLE 7: Results of the dynamic factor model

	(I)	(II)	(III)
Banking_sector	0.027***	0.016***	
	(0.008)	(0.002)	
Bond_market	0.000	0.007***	
	(0.001)	(0.001)	
Equity_market	0.091***	0.000***	
	(0.005)	(0.000)	
FX_market	0.002	0.014***	
	(0.007)	(0.002)	
Money_market	0.003	0.004***	
	(0.004)	(0.000)	
Property_market	0.000	0.003***	
	(0.003)	(0.000)	
L.F			-0.795***
			(0.079)
L2.F			-0.331***
			(0.083)
Unobserved Factors	Yes	No	Yes
N	142	142	142

Notes.- The table shows the results of the dynamic factor model. ***, **, * indicate the statistical significance at 1 percent, 5 percent and 10 percent levels respectively.
Source: Authors' computation

TABLE 8: Weights for FSI_FAM (in percentage)

	Weights
Banking sector	22
Bond market	8
Equity market	24
Foreign exchange market	9
Money market	20
Property market	17

Notes.- The table shows the weights for the sub-components of the FSI_FAM, in percentage.
Source: Authors' computation

Appendix Table A2 the FSI_PCA primarily reflects the behaviour of the equity market and the money market, while the FSI_FAM is highly correlated with the bond market. The correlations indicate that other markets that make up the financial sector may have a negligible contribution to the composite index. This suggests that the weighting criteria in these methods undermine the heterogeneity of the different sectors of the financial system and implies that some markets may exit the radar of policymakers.

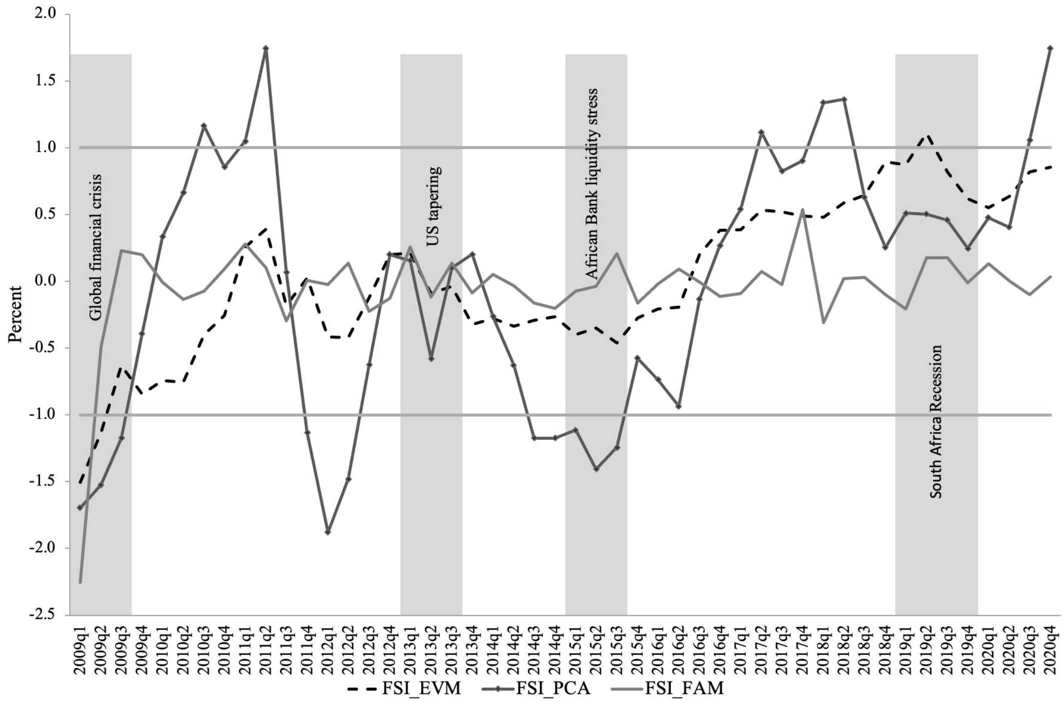
On the contrary, financial stress indices aggregated using the simple averaging method (e.g., FSI_EVM) largely reflect the behaviour of all the markets in the financial sector because none of the markets is allocated a weight of zero. This is mirrored by the high correlations between the FSI_EVM and the six sub-components in Table 3. In this case, the composite index largely reflects the heterogeneity of the six markets. In this aggregation method, the researcher has control over the markets that they want to include in the final index. However, it is essential to note that some trade-offs may exist when researchers do not follow any statistical objective to construct a financial stress index. It is, therefore, imperative to assess the trade-offs of using the simple average method compared to the use of sophisticated methods (PCA method and dynamic factor model). This motivates us to use several econometric techniques to assess the performance of the financial stress indices aggregated using different methods.

3.4 The evolution of the financial stress indices: A comparison

Figure 1 presents the financial stress indices over the period 2009 - 2020, estimated using three methodologies (equal-variance weighting method, principal component analysis method and dynamic factor model). Hatzius et al. (2010) emphasise that an economic index such as the financial stress index can serve as a good indicator about the effectiveness of the monetary policy stance. This is mainly because the financial stress index, can identify periods in which financial frictions may impair the transmission of monetary policy. In order to efficiently identify periods in which monetary policy may be impaired by large fluctuations in the financial stress index, we standardised the data. Standardising the data implies that values close to 0 suggest a fairly stable financial system, while values within the range of -1 and +1 coincide with low financial stress levels. The trajectory of the financial stress indices therefore indicates that fluctuations outside this range (below -1 and above +1) are associated with potentially high stress conditions in the financial system (financial instability), which can interfere with the transmission of monetary policy.

According to figure 1, the indices constructed using the EVM and the PCA method follow a similar trajectory, albeit at differing levels and magnitudes. Even though the two indices closely track the financial stress in the South African financial system over the sample period, the PCA-estimated index exhibits larger fluctuations compared to the FSI_EVM. The three indices deteriorated to below -1 during the global financial crisis period, while the FSI_PCA also deteriorated below -1 in 2012. This indicates that the economic conditions were not conducive for the efficient transmission of certain channels of monetary policy. More specifically, stock prices and house prices plummeted during the financial crisis period, which resulted in historic increases in non-performing loans and a significant decrease in credit. The devaluation in prices therefore weakened the credit channels and thus increased financial frictions and impaired the transmission of monetary policy changes. Post the financial crisis period, the EVM-based index mostly oscillates within the range of +1 and -1. Comparatively, the PCA-based index exceeds +1 in 2011 and 2018. The differences in the behaviour of the three indices is governed by the underlying techniques used to construct them. For instance, even though the FSI_EVM captures the global financial crisis in 2009, it does not appear to efficiently capture the financial instabilities that occur in the South African financial system post the crisis. The importance given to the weights of the market sub-indices is therefore highlighted by the abilities of the

FIGURE 1: Financial Stress Indices for South Africa: 2009 - 2020



Notes.- The financial stress indices for South Africa constructed using the equal-variance weighting method (FSI_EVM), principal component analysis method (FSI_PCA) and the dynamic factor model (FSI_FAM) over the 2009 - 2020 period.
Source: Authors' calculations.

PCA-based index and the FSI_FAM to identify the financial instabilities in the South African financial system throughout the sample period.

In addition to the global financial crisis, the FSI_FAM captures the incidence of financial stress in 2013, to a much larger extent. During this period, the South African economy experienced a weak currency and significant capital outflows when the US Federal Reserve Bank announced that it will start the tapering of its quantitative easing programme. From Figure 1, both the PCA-based index and the FSI_FAM are able to pick another deterioration in the financial stress index in 2014, which was due to the liquidity stress experienced by African Bank. The liquidity stress was caused by spiralling bad debt and unsustainable lending. The financial contagion was however limited following the imposition of interventions by the South African Reserve Bank. The two indices also exhibit sharper swings in 2015 when the South African rand depreciated due to dampened investor confidence caused by political instability. The FSI_FAM however reacts to the 2015 financial stress about two quarters later. Following South Africa's financial recession in 2019, the FSI_FAM deteriorated faster compared to the other two indices. The factors behind the 2019 financial stress included declining commodity prices and budgetary cuts. The South African financial system therefore experienced heightened stress during this period.

4 Empirical analysis

This section provides details about the econometric analysis that was performed to evaluate the performance of the financial stress indices[9]. We expect an index that allocates more weight to markets that play a large role in the transmission of financial stress, to perform better in financial stability monitoring.

4.1 Quantile regression: Explanatory power of macroeconomic variables

The first part of the analysis employs the quantile regression approach to examine the leading indicator properties of several macroeconomic variables[10]. Slingenberg and de Haan (2011) suggest that a financial crisis is often preceded by an expansion in variables such as household credit. In addition, Misina and Tkacz (2009) also report that in linear frameworks, credit growth accurately predicts financial stress, while asset prices accurately predict financial stress only in non-linear frameworks. More specifically, we examine if several macroeconomic variables highlighted in the literature, have explanatory power in identifying a financial crisis period. In this case, the financial stress indices are used as proxies for a financial crisis.

The quantile regression technique is preferred over the classical linear regression model because it provides a framework for estimating the correlation between the independent and dependent variables, on the entire conditional distribution. We achieve this by estimating coefficients for the lower, middle and upper quantiles. Comparatively, a classical linear regression model only stipulates the changes in the conditional mean of the dependent variable, while the quantile regression estimates the changes in the conditional quantiles. Adrian et al. (2018) support this claim and highlight that the lower quantiles of the macroeconomic variables are more reactive to economic recessions and downside risks, compared to the upper quantiles. We therefore follow conventional wisdom and practice in this aspect and use the quantile regression to identify the variables that can effectively serve as early warning indicators of a financial crisis. For the $\theta - th$ conditional quantile of y_i, we specify the quantile regression as:

$$Q_{y_i(\theta)|x_i} = X_i^T \beta_\theta \ , \tag{18}$$

where X_i^T represents $kx1$ vector of explanatory variables, y is the dependent variable, β and θ denote the coefficient vector and the conditional quantile, respectively. We therefore make the following assumption about θ:

$$Q_\theta(u_{i,\theta}|x_{i,\theta}) = 0 \ , \tag{19}$$

[9] The details of the explanatory variables used for the performance evaluation are in Appendix Table A1.

[10] In this paper, we choose to use high frequency data to construct the financial stress indices. This enhances financial stability monitoring. The macroeconomic variables in Appendix Table A1 are mostly low frequency data and therefore do not form part of the financial stress indices.

where $u_{i,\theta}$ represents the residual term at the $\theta - th$ quantile. Compared with a classical linear regression method, quantile regressions are based on minimising asymmetrically weighted residuals. By setting $\theta = 0.5$, the quantile regression provides the median solution while values of θ at 0.25 and 0.75 represent the lower and upper quantiles, respectively.

Furthermore, Hao and Naiman (2007) confirm that the coefficients for the different quantiles are not based on the portion of the sample, but on the weighted data of the whole sample. The interpretation of $\hat{\beta_\theta}$ in the quantile regression is therefore the same as in the classical linear model:

$$\hat{\beta_\theta} = \frac{dQ_\theta(y_i|x)}{dx} , \tag{20}$$

where the $\hat{\beta_\theta}$ coefficient is interpreted as the change in the $\theta - th$ quantile of the dependent variable per unit change in the corresponding regressor, holding all else constant.

TABLE 9: Results of the quantile regressions (FSI_EVM)

	Quantiles		
	q25	q50	q75
$REER_{t-1}$	**0.034****	0.026	**0.031****
	(0.011)	(0.017)	(0.015)
$CA\_balance_{t-1}$	-0.006	0.014	0.031
	(0.037)	(0.057)	(0.050)
$M1_{t-1}$	0.018	0.008	-0.006
	(0.011)	(0.018)	(0.016)
$M3_{t-1}$	**0.034*****	**0.031*****	**0.036*****
	(0.006)	(0.009)	(0.008)
$RGDP_{t-1}$	**0.032***	0.018	-0.005
	(0.019)	(0.029)	(0.025)
$Credit_{t-1}$	0.043	-0.050	-0.089
	(0.052)	(0.081)	(0.071)
CPI_{t-1}	**0.081***	0.074	**0.121***
	(0.044)	(0.068)	(0.060)
Oil_{t-1}	0.003	0.002	-0.003
	(0.002)	(0.003)	(0.003)
$MSCI_{t-1}$	**0.023****	0.017	0.013
	(0.010)	(0.015)	(0.014)
$Debt_{t-1}$	-0.107	-0.154	-0.214
	(0.112)	(0.173)	(0.151)
$Bankruptcy_{t-1}$	-0.002	0.000	0.002
	(0.002)	(0.003)	(0.003)
$Gold_{t-1}$	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)

Notes.- The table shows the variables that have explanatory power in explaining financial stress when the index is constructed using the equal-variance method. ***, **, * indicate the statistical significance at 1 percent, 5 percent and 10 percent levels respectively.
Source: Authors' calculations.

Table 9 shows the results for the financial stress index constructed using the equal-variance weighting method (FSI_EVM). It indicates that considering the lower quantile[11] of the FSI_EVM, five variables (REER, M3, real GDP, CPI and the Morgan Stanley Capital International index (MSCI)) have explanatory power as determinants of financial stress. The signs of the significant variables are as expected, except for real GDP. For instance, in the case of the REER, overvaluation of the currency can lead to external weaknesses and deteriorations in the current account. If the deterioration is big enough to raise the ratio of the current account to GDP, it can facilitate asset price booms and credit booms and subsequent stress in the financial sector when the economic bubbles burst. In the case of the M3 money multiplier, rapid growth in monetary expansion is correlated with the rapid growth in credit, which is associated with higher risk-taking by lenders. Hence, if borrowers find it difficult to service the debt, the stress in the banking sector will increase due to the expansion in the non-performing loans. Interestingly, other variables that have often been linked to financial stress in the literature, such as credit, are not significant. Slingenberg and de Haan (2011) highlight that in some instances, the weak performance may be linked to the fact that some variables such as credit may take longer to lead to financial stress, which underscores the importance of using lagged variables.

Table 10 shows the variables that are significantly correlated to the PCA-based financial stress index (FSI_PCA). Considering the lower quantile of FSI_PCA, only four variables (REER, credit, the household debt ratio and the bankruptcy index) are significant. The signs of the significant variables are as expected in the literature. For example, the coefficient for the debt ratio in the lower quantile, which is associated with economic recessions, displays a positive sign, indicating that an overall increase in the household debt signifies a high level of financial stress. This is most likely because of the positive relationship between household debt, the level of non-performing loans and banking crisis.

For the dynamic factor-based index (FSI_FAM), Table 11 indicates that six variables (REER, M3, RGDP, the household debt ratio, the bankruptcy index and Gold prices) can convey signals of financial stress in the South African economy. All the significant variables display the expected sign. The results suggest that the macroeconomic variables have a more widespread impact on the lower quantiles of the FSI_FAM. More specifically, since most of the macroeconomic variables are significant at the lower quantiles, we conclude that the lower quantiles of the three financial stress indices are more sensitive to developments in the macroeconomic variables compared to the median and upper quantiles. This asymmetry in the conditional distribution of the financial stress indices therefore indicates that the macroeconomic variables are more reactive to downside risks than upside risks in the financial sector. The results for the middle and upper quantiles however suggest that the financial stress indices do not convey potent early warning signals when there are economic booms. Given that we obtained similar results for the financial stress indices, the main policy takeaway in this case is that, irrespective of the aggregation method used to construct a financial stress index,

[11] For the quantile regression analysis, we focus on the results for the lower quantiles. This is because it is more representative of the periods when there is financial stress. By doing this, we are therefore able to accurately identify macroeconomic variables that are more responsive to the downside risks in the financial sector.

TABLE 10: Results of the quantile regressions (FSI_PCA)

	Quantiles		
	q25	q50	q75
$REER_{t-1}$	**0.114*****	**0.078****	**0.058***
	(0.035)	(0.034)	(0.031)
$CA\_balance_{t-1}$	-0.082	-0.033	0.039
	(0.114)	(0.112)	(0.102)
$M1_{t-1}$	0.028	0.013	-0.004
	(0.036)	(0.035)	(0.032)
$M3_{t-1}$	0.023	0.010	0.007
	(0.017)	(0.017)	(0.015)
$RGDP_{t-1}$	0.087	0.043	**0.093***
	(0.058)	(0.057)	(0.052)
$Credit_{t-1}$	**0.289***	-0.017	0.004
	(0.163)	(0.159)	(0.145)
CPI_{t-1}	-0.054	-0.062	-0.180
	(0.138)	(0.135)	(0.123)
Oil_{t-1}	0.004	0.002	0.005
	(0.006)	(0.006)	(0.006)
$MSCI_{t-1}$	0.030	0.024	0.029
	(0.031)	(0.030)	(0.028)
$Debt_{t-1}$	**0.602***	0.377	0.261
	(0.349)	(0.340)	(0.310)
$Bankruptcy_{t-1}$	**0.016****	0.011	**0.014****
	(0.007)	(0.006)	(0.006)
$Gold_{t-1}$	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)

Notes.- The table shows the variables that have explanatory power in explaining financial stress when the index is constructed using the principal component analysis method. ***, **, * indicate the statistical significance at 1 percent, 5 percent and 10 percent levels respectively.
Source: Authors' calculations

the macroeconomic variables convey similar signals regarding downside risks in the economy Arrigoni et al. (2020).

4.2 Ordered Probit model: Predicting a financial crisis

Considering that the results from the quantile regression do not give conclusive results on which of the three indices conveys precise information about the occurrence of a financial crisis, we use the ordered probit model as an additional assessment tool.

Based on the available data at quarterly frequency, we use an ordered probit model to identify which of the three financial stress indices can accurately predict a financial crisis. In our ordered probit model, we transform each financial stress index into a dependent variable (Y) that takes two values, 0 (low fragility in the financial system) and 1 (high fragility in the financial system)[12]. X on the other hand, is a vector of lagged explanatory variables[13]. We do

[12]The ordered probit model in this case, estimates the probability that a given value of the financial stress index falls into one of the two categories.
[13]Refer to Table A1 for the list of explanatory variables. Lagging the explanatory variables allows us to estimate the predictive power of the regressors.

TABLE 11: Results of the quantile regressions (FSI_FAM)

	Quantiles		
	q25	q50	q75
$REER_{t-1}$	**0.033****	-0.002	-0.005
	(0.016)	(0.020)	(0.017)
$CA\_balance_{t-1}$	0.006	0.045	0.008
	(0.053)	(0.067)	(0.057)
$M1_{t-1}$	0.026	-0.006	-0.003
	(0.016)	(0.021)	(0.018)
$M3_{t-1}$	**0.020****	0.005	0.003
	(0.008)	(0.010)	(0.009)
$RGDP_{t-1}$	**-0.062****	0.015	-0.005
	(0.027)	(0.034)	(0.029)
$Credit_{t-1}$	0.033	0.047	0.032
	(0.075)	(0.095)	(0.081)
CPI_{t-1}	-0.043	-0.034	-0.065
	(0.063)	(0.081)	(0.069)
Oil_{t-1}	-0.003	-0.001	-0.002
	(0.003)	(0.004)	(0.003)
$MSCI_{t-1}$	0.020	0.006	-0.004
	(0.014)	(0.018)	(0.015)
$Debt_{t-1}$	**0.642*****	-0.215	-0.156
	(0.160)	(0.204)	(0.173)
$Bankruptcy_{t-1}$	**0.006****	0.001	0.004
	(0.003)	(0.004)	(0.003)
$Gold_{t-1}$	**0.001*****	0.000	0.000
	(0.000)	(0.001)	(0.000)

Notes.- The table shows the variables that have explanatory power in explaining financial stress when the index is constructed using the dynamic factor method. ***, **, * indicate the statistical significance at 1 percent, 5 percent and 10 percent levels respectively.
Source: Authors' computation

not transform the explanatory variables into dummy variables, we instead include their lagged values in a linear way. The probability of a crisis is therefore a function of the vector of lagged explanatory variables. The probit model is specified as:

$$Pr(Y_t = 1|X_{t-1}) = \int_{-\infty}^{X'_{t-1}\beta} \psi(t)dt = \psi(X'_{t-1}\beta), \tag{21}$$

The crisis dummy series and the lagged explanatory variables are represented by Y and X, respectively. β is the vector of parameters and F denotes the normal cumulative distribution function. F ensures that the probability outcome lies between 0 and 1.

We assume that the probit model follows a latent variable model, $y^* = x'\beta + \varepsilon$, where ε is normally distributed and y^* is unobserved. However, the classified category Y is observed (Ziegler, 2002). The observed component Y, is determined using y^*. We therefore use Y as an indicator of whether the latent variable, $y*$, is positive:

$$Y = \begin{cases} 1 & y* > 0 \\ 0 & otherwise \end{cases}, \tag{22}$$

We design the analysis for the ordered probit model such that there are four specifications[14]. Table 12 shows that the coefficients of the financial stress indices at time t_{-1} are positive. This suggests that there are tight financial conditions at time $t-1$, which then translates to high fragility at time t, in the financial system[15]. The coefficients for FSI_EVM (column (I) and FSI_FAM (column III) are statistically significant. However, the model for the FSI_FAM (column III), has the largest coefficent and the lowest absolute value of the log likelihood (7.22). This indicates that the FSI_FAM outperforms the other indices as a predictor of a financial crisis. The results in column (IV) confirm this as the coefficient of the FSI_FAM is significant even when we simultaneously include all the indices in the model.

TABLE 12: Results of the probit model: Predicting a financial crisis

	(I)	(II)	(III)	(IV)
FSI_EVM_{t-1}	0.555*			0.730
	(0.313)			(0.443)
FSI_PCA_{t-1}		0.088		0.262
		(0.202)		(0.277)
FSI_FAM_{t-1}			2.494**	1.444**
			(0.984)	(0.629)
Observations	51	51	51	51
Log likelihood	-32.09	-23.67	-7.22	-28.37

Notes.- The table shows the ability of the financial stress indices to predict a financial crisis. ***, **, * indicate the statistical significance at 1 percent, 5 percent and 10 percent levels respectively.
Source: Authors' computation

Compared to the other financial stress indices, Table 8 shows that FSI_FAM gives a predominant role to the equity market, banking sector and the money market. While the FSI_EVM allocates equal weights to all the segments of the financial system (Table 2), the FSI_PCA on the other hand loads heavily on the bond market, banking sector and the equity market (Table 6). It is therefore important to note that the key difference between the FSI_FAM and FSI_PCA is that, the FSI_FAM is more representative of indicators in the money market. Over the years, policymakers and scholars have highlighted that liquidity in the money market is crucial for financial stability. This is mainly because money markets provide the key participants in the financial system, e.g., commercial banks, with the required funding and serves as the transmission of macroprudential and monetary policy changes. This also highlights the important link that exists between the money market and the banking sector. For example, Ari et al. (2021) specifically point out that there is a close relationship

[14] We start by estimating three separate models for each financial stress index. Afterwards, we estimate a fourth model, in which we include all the three indices simultaneously.

[15] Tight financial conditions are characterised by an increase in the interest rates which reduces the availability of funding in the economy. This is usually in response to such things as, high energy prices. The tight financial conditions are therefore associated with stress in the financial system (Brave and Butters, 2012). In this case, we therefore link the positive values of the financial stress index at time t_{-1} with tight financial conditions and financial stress at time t.

between increased non-performing loans[16] in the banking sector and the severity of economic recessions. Disruptions in the money market and the banking sector therefore have the potential to interfere with the flow of liquidity in the real economy and in the financial system. In addition, stress in the US dollar-denominated money markets can spill over to other sectors of the financial system such as, the foreign exchange market. Regarding the financial stability impact of the delisting of companies in the bond and equity markets, a study by Rigg and Schou-Zibell (2009a), highlights that the impact of stress from the equity and bond markets has a limited impact on the South African financial system. This validates the importance of the money market in the South African economy and therefore favours the FSI_FAM, which loads heavily on the money market compared to the FSI_PCA, which gives a minimal role to the money market.

4.3 Local Projections: Transmission of external monetary policy shocks

We also empirically examine the response of the financial stress indices to monetary policy shocks in the US and China. The focus on the US and China is motivated by the fact that the two countries are the major trading partners of South Africa. Hence, we expect the monetary policy shocks from the two countries to have significant spillover effects on the South African financial system, given the trade linkages that exist among the countries. A useful financial stress index should respond to external monetary policy shocks; which reflects the role of the external financial system in the global market. To analyse the vulnerability of the financial stress indices to the external monetary policy shocks, we rely on the local projection methodology by Jordà (2005). We specify the model as:

$$FSI_{t+h} - FSI_{t-1} = \alpha_h + \gamma_h(L)X_{t-1} + \beta_h Shock_t + u_{t+h} \;, \tag{23}$$

where X_{t-1} is a vector of lagged control variables, real GDP and inflation. $Shock_t$ represents the contractionary monetary policy shocks from the US and China. The slope, β_h, is the response of the financial stress index at horizon h, to the monetary policy shock at time t. Similar to Jordà (2005) and Merrino (2021), we use the Newey-West correction to estimate robust standard errors, in order to account for the serial correlation in the error term (u_{t+h}). The monetary policy shock is further specified as:

$$Shock_t = \theta + \delta W_t + \varepsilon_t \;, \tag{24}$$

we then substitute equation 24 into equation 23 to obtain:

$$FSI_{t+h} - FSI_{t-1} = \alpha_h + \beta_h\theta + \gamma_h X_t + \beta_h\delta W_t + \beta_h\varepsilon_t + u_{t+h} \;, \tag{25}$$

[16] Kozlow (2003); Joseph et al. (2012) define non-performing loans as loans which the debtor has not made repayments of the interest and/or the principal amount for at least 90 days and the prospect of repayment is very minimal. Even though the ratio of non-performing loans to total gross loans for South Africa was 6 percent in 2009, the ratio is expected to reach its highest level due to the economic effects of Covid-19.

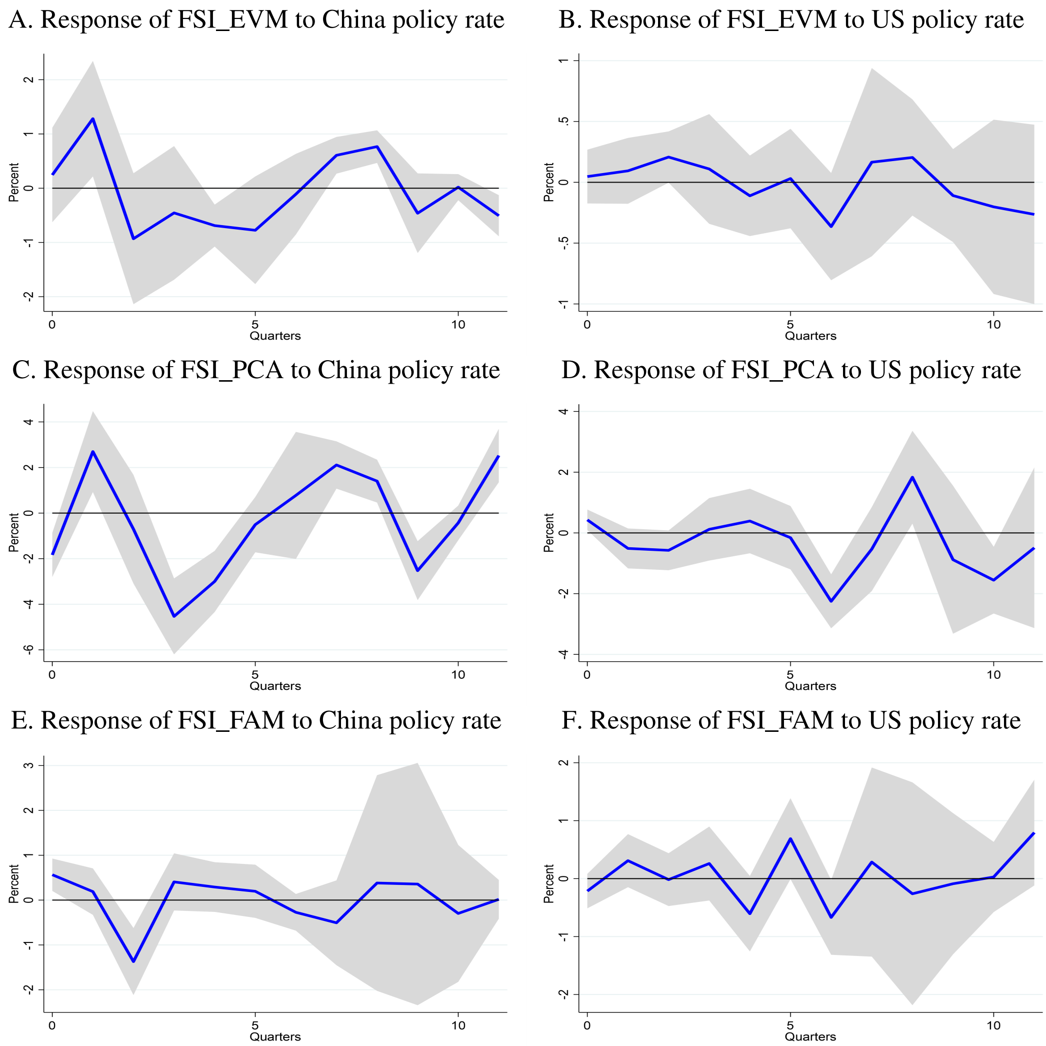
where h = 0,1,...,12 represents the projection horizon and the impulse response function is therefore $\{\beta_h\}_{h=0}^{12}$. Even though most researchers emphasise that there are negligible differences between the estimations from the local projection and the vector autoregression (VAR) methods, the decision to use local projections in this paper is informed by the findings from Li et al. (2022). The authors highlight that even though the two methods have similar levels of bias at short horizons ($h \leq 4$), the bias for the VAR estimators increases at longer horizons ($h > 4$), while the local projection bias is close to zero at longer horizons. We therefore prefer to use local projection estimators, considering that they are less prone to bias.

We utilise the literature on the global financial cycle to examine the spillover effects of the contractionary monetary policy shocks. Financial stress has a strong global component and in the case of South Africa, it is linked to the monetary policies in the US and China. This is particularly important because of the trade relations that exist among the countries. The spillovers operate via three channels: the domestic demand of imports, financial conditions and exchange rate adjustments. From a theoretical standpoint, contractionary monetary policy in China and the US may lead to an appreciation of their currencies. As a result, exports from South Africa to the US and China become cheaper, while imports to South Africa from the trading partner countries become expensive. In such a case, the global demand is reallocated toward South Africa. There is also empirical evidence in the literature that, there are significant spillover effects, irrespective of whether central banks implement conventional or unconventional monetary policy. However, the effects vary across countries and depend on the country-specific features, such as the degree of vulnerability to shocks and the exchange rate regime. Given this background, an efficient financial stress index should properly respond to external monetary policy shocks (Arrigoni et al., 2020).

The results are reported in Figure 2 and suggest that the response of the FSI_EVM to the monetary policy shocks is very minimal. This may indicate that the index is not very useful in measuring the degree of vulnerability to external shocks, in the South African financial system. On the other hand, the FSI_PCA records a significant decrease after a positive shock in China's monetary policy. This is economically meaningful as we expect a positive shock in China's monetary policy to result in: an appreciation of the Chinese currency and thus a decrease in credit and asset prices and ultimately, result in a decrease in financial stress. In this case, we therefore expect the financial stress transmitted to South Africa to be very low as evident in the FSI_PCA. However, the effect is short-lived as the FSI_PCA follows an upward trajectory in the long-run. Comparatively, the FSI_PCA initially reacts positively to a contractionary monetary policy shock in the US but thereafter, it decreases significantly compared to the other stress indices and displays a decreasing trend in the long-run. This implies that the shock in the US monetary policy initially results in an increase in the financial stress transmitted to South Africa but later on decreases over the horizon, which supports the economic intuition.

The results suggest that the FSI_PCA is more efficient and responsive to external monetary policy shocks compared to the other indices. The explanation behind this could be that the PCA method allocates more weights to variables that are closely linked to monetary policy, which

FIGURE 2: Local projections: Response of financial stress indices to China and US monetary policy, 2009Q1 - 2020Q4



Notes.- The graphs show the response of the financial stress indices to a positive shock in the policy interest rates of China and the US

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better captures the effects of external monetary policy shocks[17]. On this note, Table 6 shows that compared to the other indices, the FSI_PCA index reflects heavily on the bond market. Macroeconomic theory predicts sharp swings in the bond market following a contractionary monetary policy shock, which has financial stability consequences (Alessi and Kerssenfischer, 2016). In the related literature, Viceira et al. (2014) proceed in a similar spirit and emphasise that the changes in monetary policy are fundamental in understanding the changes in the bond market. They highlight that monetary policy persistence contributes heavily to a negative bond yield[18]. More specifically, they expect a contractionary monetary policy shock to result in

[17]Even though the stress in the bond and equity markets has limited effects in the context of the South African financial system, it however, has a significant impact in countries with more developed financial markets, such as China and the US, which is reflected in the FSI_PCA.

[18]A negative bond yield occurs when the money that an investor receives when the bond matures, is less than the purchase price (Viceira et al., 2014).

an increase in the cost of borrowing, which decreases the investment levels and consequently decreases the asset prices, including bond prices. They therefore associate this developments with an increase in financial stress.

4.4 ARIMA Model: Forecasting financial stress

Finally, we assess which measure of financial stress provides better forecasts using the ARIMA model. We provide forecasts of financial stress for eight quarters ahead (2021Q1 to 2022Q4), in an effort to assist policymakers to determine the future state of vulnerability in the South African financial system.

The ARIMA model merges the AR and MA polynomials into a complex polynomial. We apply the following ARIMA (p, d, q) model to the time series data:

$$y_t = \mu + \sum_{i=1}^{p}(\sigma y_{t-1}) + \sum_{i=1}^{q}(\theta \varepsilon_{t-1}) + \varepsilon_t \ , \tag{26}$$

μ denotes the mean of the time series, p represents the number of autoregressive lags, σ is the autoregressive coefficients (AR), q is the number of lags for the moving average process; θ is the moving average coefficients (MA) and ε is the white noise for the time series. In this case, d represents the differences that are calculated from the following equation:

$$\delta y_t = y_t - y_{t-1} \ , \tag{27}$$

The ARIMA model is employed stochastically, based on the values of the parameters; p, d and q for different scenarios. All the time series data are included for each scenario. After exploring different scenarios for ARIMA (p, d, q), we use the ARIMA parameters (2, 0, 2) because alternative scenarios do not provide reasonable forecasts.

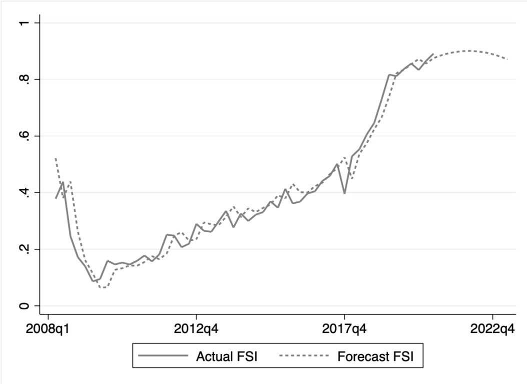
We use a polynomial trend curve in Figure 3 to illustrate the relationship between the historical data and the forecast data. Even though the forecast data seems to be in sync with the historical data in all the three models, it is clear that the FSI_EVM which allocates equal weights to the segments of the financial system, outperforms the FSI_PCA and the FSI_FAM over the eight quarters. This is because the forecasts are closely linked to the actual values. In addition, compared to the other indices, the FSI_EVM is able to pick the increase in the financial stress associated with Covid-19 in 2020.

We also show the forecasting ability of the financial stress indices using fan charts[19] in Figure 4. It is clear that the FSI_EVM, which allocates equal weights to the segments of the financial system performs better than the FSI_PCA and the FSI_FAM over the eight quarters. In comparison with the other fan charts, the width of the FSI_EVM fan chart is smaller which indicates that there is an increased probability that the forecasts are closer to the central

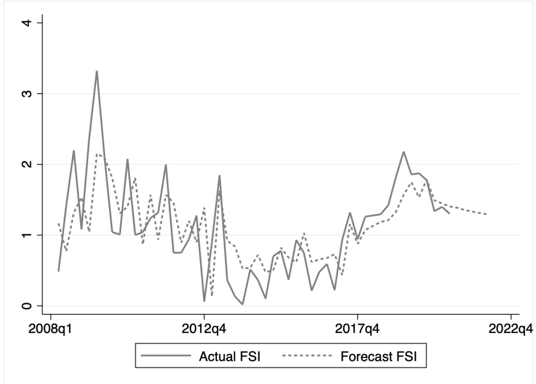
[19] A fan chart shows a range of possible forecast values. The width of the fan chart represents the probability of achieving accurate forecasts. That is, the fan chart widens as the uncertainty surrounding the forecasts increases. The uncertainty of the predictions also follows an increase in the forecast horizon (Sokol, 2021).

FIGURE 3: Forecasts for different methods of the FSI

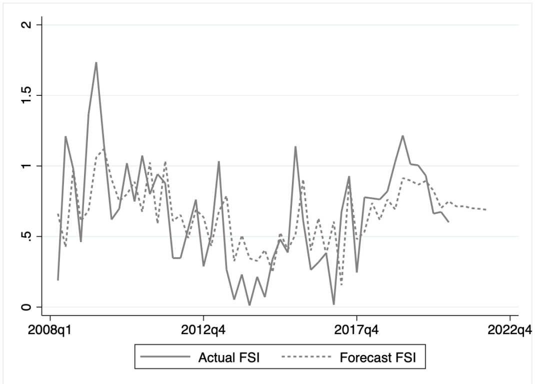
A. Equal-variance weighting method



B. Principal component analysis



C. Dynamic factor model



Notes.- The graphs show the trajectory of the policy tightening/easing alongside the inflation and credit series.

projection. More specifically, the forecast range for the FSI_PCA and the FSI_FAM is wider, which conveys increased uncertainty in their predictions, compared to those of the FSI_EVM. We further evaluate the forecasts of the three FSIs using the root mean square error (RMSE),

TABLE 13: Forecast Evaluation

	RMSE	MAE	MAPE	Theil Coefficient
FSI_EVM	0.090	0.088	11.58	0.062
FSI_PCA	0.115	0.100	27.21	0.071
FSI_FAM	0.032	0.028	108.81	0.971

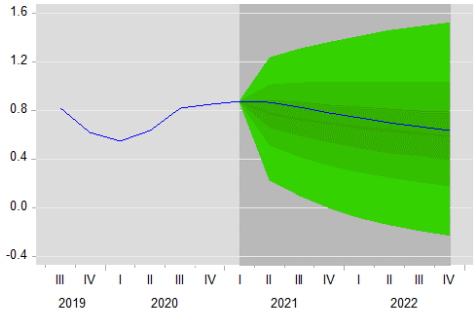
Notes.- The table shows the different measures used to evaluate the forecasts of the financial stress indices. RMSE: Root Mean Square Error, MAE: Mean Absolute Error, MAPE: Mean Absolute Percentage Error and Theil inequality coefficient.
Source: Authors' computation

mean absolute error (MAE), mean absolute percentage error (MAPE) and the Theil coefficient statistic criterias[20]. Table 13 shows that the FSI_EVM has the lowest RMSE (0.090), MAE (0.088), MAPE (11.58) and Theil coefficient (0.062). This indicates that the out-of-sample

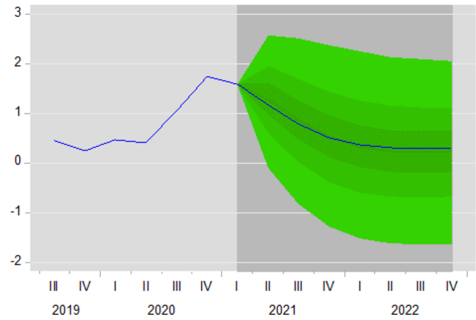
[20]A good forecast that fits the dataset well, has the lowest values of the RMSE, MAE, MAPE and the Theil coefficient (Ilesanmi and Tewari, 2020).

FIGURE 4: Fan Charts for different methods of the FSI

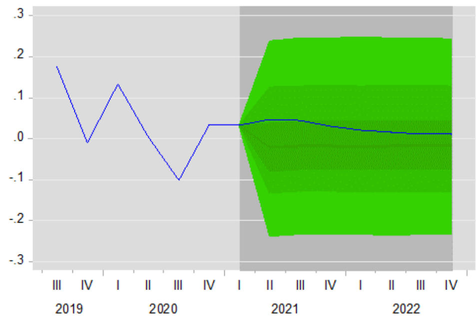
A. Equal-variance weighting method



B. Principal component analysis



C. Dynamic factor model



Notes.- The fan chart shows the realised data for the financial stress indices up to 2020Q4 and the forecasts for 2021Q1 to 2022Q4. The central band (deep green line) depicts the median, while the lighter shades of green that correspond with the widening width of the fan chart, represent increased uncertainty about the financial stress forecasts.

forecasts of the FSI_EVM provide the best fit for the dataset compared to the FSI_PCA and the FSI_FAM. In this case, we therefore conclude that averaging across the different segments of the financial system produces superior forecasts compared to predictions generated from sophisticated financial stress indices. This is possibly because compared to the other methods, the averaging method does not reduce the dimensionality of the dataset and therefore efficiently conveys the variation in the behaviour of all the segments of the financial system.

5 Robustness Tests

5.1 Re-estimation of the financial stress index

As a robustness test, we use an alternative technique of allocating weights to the sectors of the financial system. That is, we apply proportional weights according to the number of financial indicators in each sector of the financial system. This implies that compared to the EVM method (Table 2 in Section 3), the six sectors are unevenly weighted (see Table 14). The aggregate robust financial stress index (RFSI), is constructed as:

$$RFSI = \frac{3Bank_t + 2B_t + 2E_t + 2FX_t + 3M_t + 1P_t}{13} , \tag{28}$$

where Bank denotes the banking sector, B is the bond market, E is the equity market, FX is the foreign exchange market, M is the money market and P represents the property market. The weighting technique reflects the number of financial indicators in each sector. The objective is to confirm if this method is more representative of the proportional contribution of each sector in the financial system.

TABLE 14: Weights for robust financial stress index, RFSI (in percentage)

	Weights
Banking sector	23.08
Bond market	15.38
Equity market	15.38
Foreign exchange market	15.38
Money market	23.08
Property market	7.69

Notes.- The table shows the estimated weights for the sub-components of the robust financial stress index (RFSI), in percentage.
Source: Authors' computation

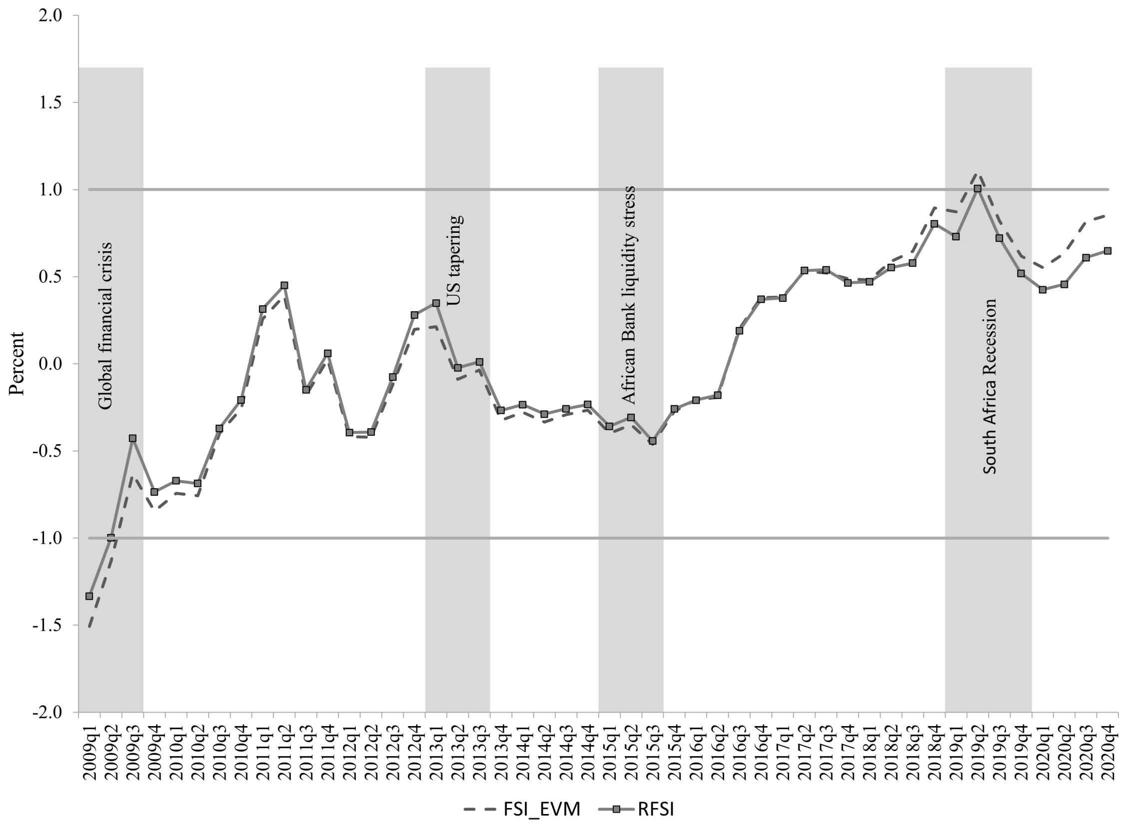
According to Table 14, the banking sector and the money market are heavily weighted at 23.08 percent, while the property market has the least weights (7.69 percent) and the remaining sectors are equally weighted at 15.38 percent. This suggests that the banking sector and the money market capture the majority of the financial stress in the South African financial system, while financial imbalances in the property market are not expected to triger an economic crisis. This is consistent with the research by Ari et al. (2021), which highlights that the banking sector and the money market play a vital role in the transmission of policy changes and the availability of liquidity in the real economy and the financial system. They are therefore crucial in the proper functioning of the economic system.

Interestingly, we find that the robust financial stress index follows a similar trajectory with the FSI_EVM (see Figure 5), which implies that the FSI_EVM is robust to the alternative weighting technique. The results therefore confirm that there is an insignificant difference between the FSIs, when we allocate equal weights to the different sectors and when the weights are allocated according to the proportion of financial indicators in each sector of the financial system.

5.2 Forecast evaluation: Mincer-Zarnowitz regression

We also consider another approach to assess the level of bias in the forecasts. We use the Mincer-Zarnowitz regression of weak forecast rationality, using a Newey-West regression (Mincer and Zarnowitz, 1969). Compared to the test criterias in Section 4, the Mincer-Zarnowitz regression is time-invariant and checks for a constant forecast bias in the

FIGURE 5: Robust FSI (RFSI) and the FSI_EVM



Notes.- The graph shows the robust FSI and the FSI_EVM.

time series. In order to test for the efficiency and unbiasedness of the forecasts, we regress the actual data on the forecasts of financial stress:

$$Y_t = \alpha + \beta F_t + u_t \ , \tag{29}$$

where Y_t is the realised series of financial stress series, F_t is the forecast series, α and β are unknown parameters and u_t is the error term.

The assumption is that the forecasts are unbiased if α is not significantly different from 0 and β is not significantly different from 1. If this condition is satisfied, we conclude that the forecasts are efficient and incorporate all the relevant information.

$$\begin{aligned} FSI\_EVM_t = \underset{(0.031)}{0.00} + \underset{(0.063)}{1.00} F_t + u_t \ , \end{aligned} \tag{30}$$

$$\begin{aligned} FSI\_PCA_t = \underset{(0.078)}{0.00} + \underset{(0.101)}{0.92} F_t + u_t \ , \end{aligned} \tag{31}$$

$$\begin{array}{c} FSI\_FAM_t = 0.00 + 0.87 F_t + u_t \ . \\ \qquad\qquad (0.025) \ (0.562) \end{array} \tag{32}$$

It is clear from the Newey-West regression results that the FSI_EVM satisfies the assumption for the constant and the regression coefficient. This is because compared to the other indices, it accurately depicts a constant and regression coefficient of 0 and 1, respectively, which implies that the model with FSI_EVM gives more efficient and unbiased forecasts. Furthermore, the standard errors (in parentheses) for the FSI_EVM are low, implying that there is a narrow confidence interval, which is a desirable property. This confirms the robustness of the results we obtained in Section 4, which suggests that the out-of-sample forecasts of the FSI_EVM outperform those of the FSI_PCA and the FSI_FAM.

6 Conclusions

The objective of this study is to address the emerging debate about whether FSIs constructed using advanced methods such as the dynamic factor model and the principal component analysis method perform better than those aggregated using simple averages, for the case of South Africa. The performance evaluation exercise extends the existing literature on detecting imbalances in the financial system. It departs from the past literature that heavily relies on early warning indicators such as the credit-to-GDP gap to detect financial imbalances. Instead, we construct and evaluate financial stress indices to measure imbalances in the financial sector. Compared to early warning indicators, which use low frequency variables, financial stress indices are composed of high frequency data, which enhances the timely monitoring of financial crises (Chadwick and Ozturk, 2019a). We compare the performance of financial stress indices constructed using the simple averaging method (FSI_EVM), principal component analysis method (FSI_PCA) and the dynamic factor model (FSI_FAM) for the South African economy. We use four criteria: quantile regressions, ordered probit model, local projections and the autoregressive integrated moving average (ARIMA) forecasting model to evaluate the performance of the indices for the period 2009-2020.

We find that financial stress indices based on sophisticated methods such as the principal component analysis and the dynamic factor model have a significant comparative advantage in predicting financial crises and analysing the spillover effects of monetary policies in the US and China. Furthermore, the econometric evaluation indicates that the benefits of the indices based on simple averaging (e.g., the FSI_EVM) are limited to forecasting stress in the financial system. The results, therefore, suggest that financial stress indices that load heavily on indicators that signal stress in the banking sector and the money market are more helpful in predicting a financial crisis and estimating the transmission of external monetary policy shocks. For instance, Tables 6 and 8 show that compared to the FSI_EVM, the FSI_PCA and the FSI_FAM give a predominant role to the banking sector and the money market, respectively. The FSI_FAM is highly correlated with the money market compared to the other indices and is more reflective of credit costs/interest rates in the South African financial system. It, therefore, gives more sensible estimates of the effects of external monetary policy shocks and is hence more useful for monetary policy monitoring. This implies that compared to the other indices, the FSI_FAM index loads more heavily on financial indicators that efficiently reflect the strains in the South African financial system.

Rigg and Schou-Zibell (2009b) support our findings. They emphasise that compared to the bond and equity markets, the money market is more critical to financial stability as it provides market participants with a significant portion of their funding. They also suggest that money markets play a large role in implementing and transmitting monetary and macroprudential policies since most policy changes are transmitted through interest rate movements. Stress in the money market can therefore impair the financial system and the real economy's access to liquidity during a financial crisis. Financial stress from the money market can also spill over to other parts of the financial sector; for example, US dollar denominated money market funds may spill over to the foreign exchange market. In their study, de Beer and Nhleko (2009) highlight that even though downward movements in South Africa's equity market may reduce the capitalisation of the stock exchange, the effect on the financial system is limited. This can also imply that the effects of the changes in the equity market may take longer to reflect in the financial system.

The results suggest that the aggregation method involved in constructing a financial stress index affects its performance. The findings support the theory that financial stress indices that allocate more weight to indicators more responsive to downside risks in the financial sector are better suited for financial stability monitoring. The conclusion is that the various markets (sub-indices) in the financial system affect the economy in varying ways. Hence, the exercise of allocating weights to the markets is essential. We, however, conclude that there is no single best financial stress index for the South African financial system and that the choice of which index to use depends on the objective that policymakers aim to achieve.

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Appendix A.

TABLE A1: Variables tested for leading indicator properties

	Expected sign	Notation
Current account		
Real exchange rate	+	REER
Current account balance/GDP	+	CA_balance
Financial sector		
M1	+	M1
M3	+	M3
Household Credit	+	Credit
Household debt	+	Debt
Bankruptcy ratio	+	Bankruptcy
Real and public sector		
Real GDP	-	RGDP
CPI	+	CPI
Foreign sector		
Oil prices	+	Oil
Gold prices	+	Gold
MSCI	+	MSCI

Notes.- The table shows the variables that were tested for explanatory power in explaining financial stress.
Source: Authors' computation

TABLE A2: The correlation structure of the principal component analysis financial stress index (PCA) and sub-components

	Banking sector	Bond market	Equity market	FX market	Money market	Property market	FSI PCA
Banking sector	1.00						
Bond market	0.63	1.00					
Equity market	0.15	0.20	1.00				
Foreign exchange market	0.34	0.50	0.21	1.00			
Money market	0.00	0.12	0.61	0.05	1.00		
Property market	0.05	0.53	0.41	0.31	0.40	1.00	
FSI PCA	**0.15**	**0.20**	**1.00**	**0.21**	**0.61**	**0.41**	**1.00**

Notes.- The table shows the correlation structure across the PCA financial stress index and the six market specific sub-indices.
Source: Authors' computation

TABLE A3: The correlation structure of the dynamic factor model financial stress index (FAM) and sub-components

	Banking sector	Bond market	Equity market	FX market	Money market	Property market	FSI FAM
Banking sector	1.00						
Bond market	0.63	1.00					
Equity market	0.15	0.20	1.00				
Foreign exchange market	0.34	0.50	0.21	1.00			
Money market	0.00	0.12	0.61	0.05	1.00		
Property market	0.05	0.53	0.41	0.31	0.40	1.00	
FSI FAM	**0.18**	**0.37**	**0.30**	**0.32**	**0.27**	**0.11**	**1.00**

Notes.- The table shows the correlation structure across the dynamic factor model-based financial stress index (FAM) and the six market specific sub-indices.
Source: Authors' computation

TABLE A4: Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy

	KMO value
Banking sector	0.55
Money market	0.58
Bond market	0.57
Foreign exchange market	0.52
Equity market	0.61
Property market	0.57
Overall	0.57

Notes.- The table shows the KMO measure of sampling adequacy. Values higher than 0.5 indicate that it is appropriate to use the principal component analysis and the factor analysis methods.
Source: Authors' computation

TABLE A5: Dynamic factor model (FSI_FAM)

	Factor 1
Banking sector	0.57
Money market	0.20
Bond market	0.62
Foreign exchange market	0.24
Equity market	0.52
Property market	0.44

Notes.- The table shows the eigen vectors for the corresponding components in the factor analysis method.
Source: Authors' computation

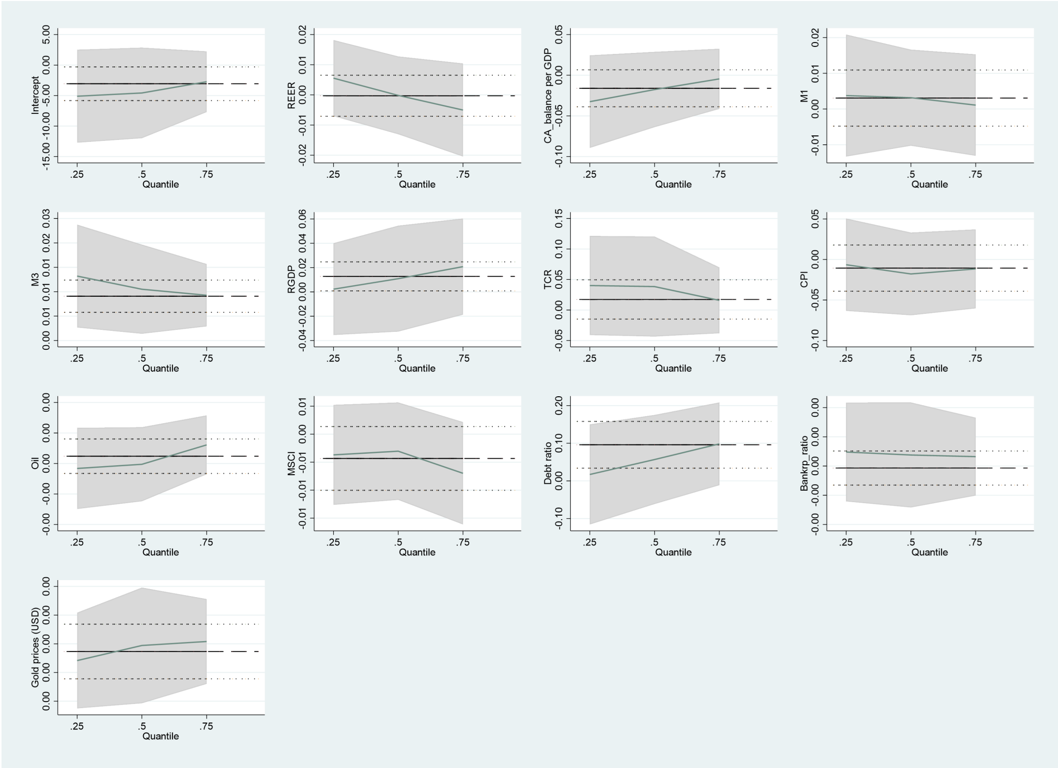
TABLE A6: Eigen Values (FSI_FAM)

	Eigen value	Variance	Proportion	Cumulative value
Factor 1	**1.27**	**0.88**	**1.01**	**1.01**
Factor 2	0.39	0.23	0.31	1.31
Factor 3	0.15	0.18	0.12	1.43
Factor 4	-0.03	0.18	-0.02	1.41
Factor 5	-0.21	0.10	-0.17	1.25
Factor 6	-0.31	…	-0.24	1.00

Notes.- The table shows the eigen values for the corresponding components in the factor analysis method.
Source: Authors' computation

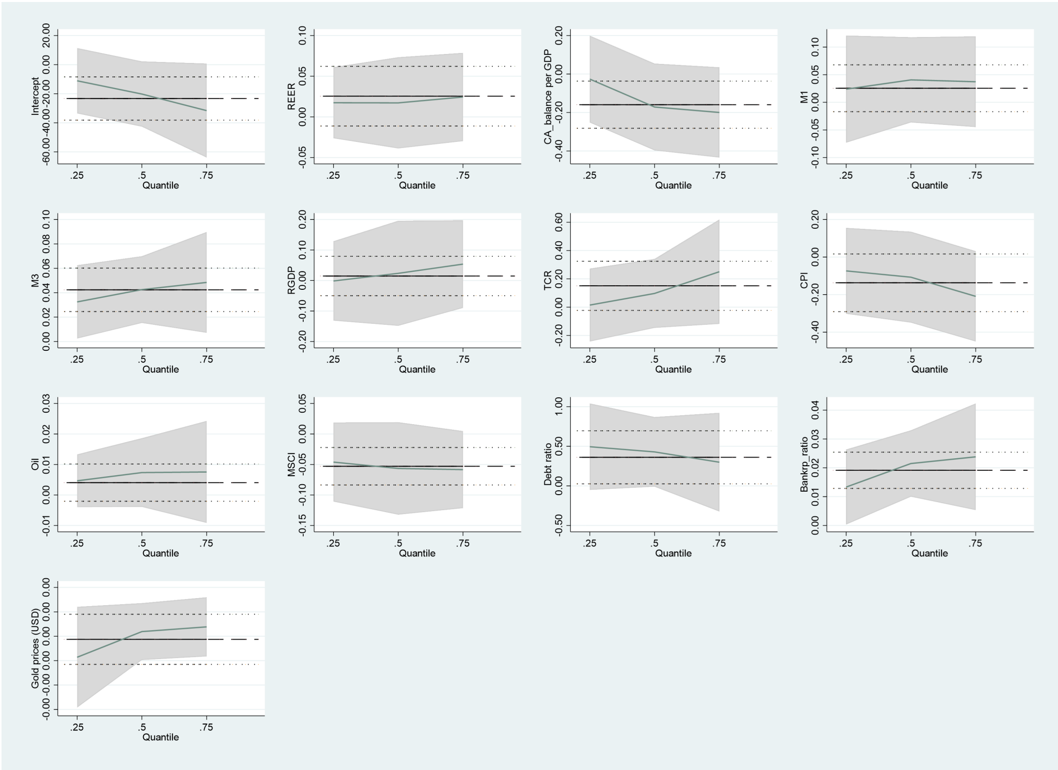
Appendix B.

FIGURE B1: Quantile regression results (Graphical)



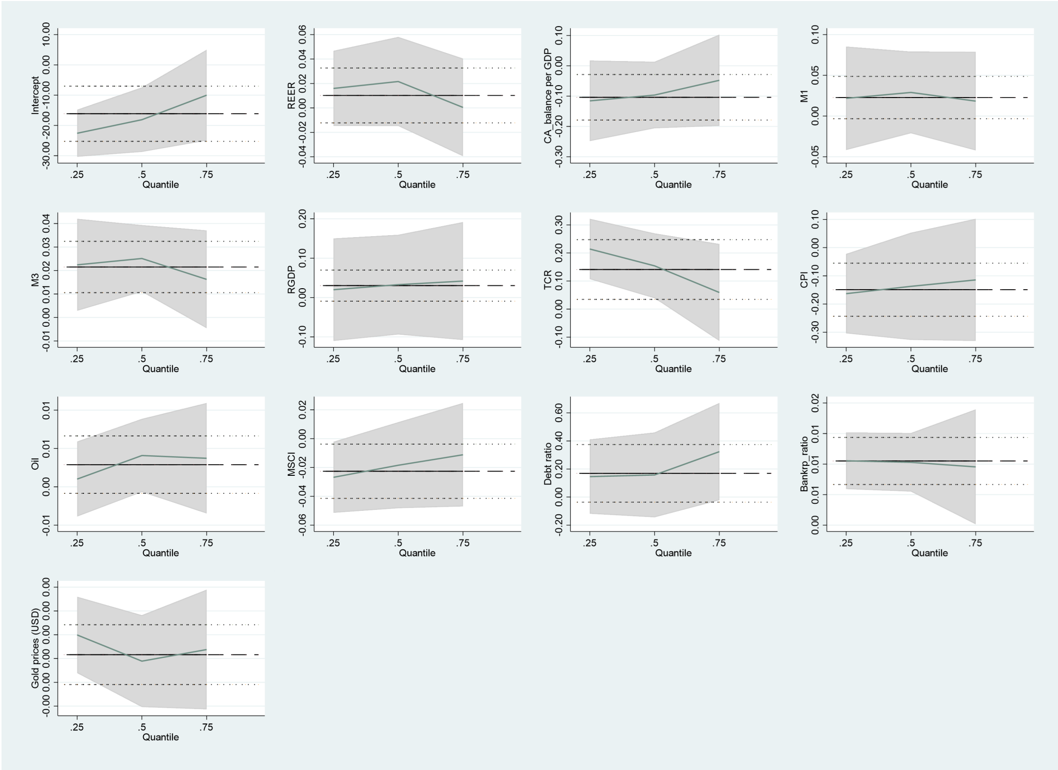
Notes.- Graphical representation of the quantile regression results for the equal-variance weighting method.

FIGURE B2: Quantile regression results (Graphical)



Notes.- Graphical representation of the quantile regression results for the principal component analysis method.

FIGURE B3: Quantile regression results (Graphical)



Notes.- Graphical representation of the quantile regression results for the dynamic factor model.