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Estimating a time-varying financial conditions index for South Africa*

Alain Kabundi[†] Asi Mbelu[‡]

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Abstract

This paper uses 39 monthly time series of the financial market observed from January 2000 to April 2017 to estimate a financial conditions index (FCI) for South Africa. The empirical technique used is a dynamic factor model with time-varying factor loadings proposed by Koop and Korobilis (2014) based on the principal component analysis and the Kalman smoother. In addition, we estimate a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model, which includes, in addition to the FCI, two observed macroeconomic variables. The results show the ability of the estimated FCI to predict risks in the financial market emanating from both the domestic market and the global market. Furthermore, the TVP-FAVAR model outperforms the constant-loadings factor-augmented vector autoregressive (FAVAR) model and the traditional vector autoregressive (VAR) model in the out-of-sample forecasting of the inflation rate and the real gross domestic product (GDP) growth rate. Finally, tighter financial conditions contract the real economy and are deflationary at the same time. Importantly, the responses of macroeconomic variables vary over time.

JEL Classification Numbers: B26, C32, C53, G01, G17.

*Keywords:*time-varying parameters FAVAR, time-varying factor loadings, forecasting, financial conditions index.

*The views expressed in this paper are those of the author(s) and do not necessarily represent those of the South African Reserve Bank, South African Reserve Bank policy.

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1 Introduction

Since the Global Financial Crisis (GFC) of 2007-2008, there has been an emergence of interest in monitoring the financial market. However, the main issue with the financial market is its size and complexity. For example, a crisis in the banking sector does not necessarily spill over to another sector, like equity. It is also worth emphasising that not all financial crises become systemic. But some crises, like the GFC, do become systemic where the entire financial system is affected, which in turn affects the entire economy. It is therefore necessary to monitor each sector of the financial market as well as the system as a whole.

It is along the lines of Oet et al. (2012) that we construct an index which encompasses the six main sectors of the financial system, namely the credit market, the funding market, the real estate market, the foreign exchange market, the equity market, and the global financial market. One of the advantages of this approach is that it uses different weights associated with different sectors of the financial market, such that it is relatively easy to identify a sector that is under stress. Hence, the index serves as a warning signal of an imminent crisis which is still in its early stage when the index is persistently above a certain predetermined threshold.

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

Since the GFC, many countries have embarked on the construction of a financial stress index which assists in monitoring the financial system and hence serves as a warning signal. Nevertheless, the literature is still in its infancy in South Africa, where the work of Gumata, Klein, and Ndou (2012) is an exception. These authors use a constant weighting method in the construction of the index. However, this assumption is too restrictive in that it does not account for evolving relationships between macroeconomic and financial variables, as demonstrated by by Aceomglu, Ozdaglar, and Tahbaz-Salehi (2015). The approach adopted in this note is flexible enough that it nests the constant-loadings approach of Gumata, Klein, and Ndou (2012). Importantly, with constant weights, we can hardly estimate the index in real time.

Against this backdrop, this paper estimates a time-varying financial conditions index (FCI) for South Africa using 39 monthly financial time series observed from January 2000 to April 2017. The financial system comprises six main sectors, namely the credit market, the funding market, the real estate market, the foreign exchange market, the equity market, and the global financial market. The empirical method used is the time-varying factor model of Koop and Korobilis (2014), which uses the two-step estimation procedure based on the principal component analysis and the Kalman smoother. To assess how good the estimated FCI is in predicting macroeconomic variables, we estimate a time-varying parameter factor-augmented vector autoregressive (TVP-FAVAR) model which includes, besides the FCI, the annual headline inflation rate and a measure of real activity based on the nowcasting of gross domestic product (GDP) growth proposed by Kabundi, Nel, and Ruch (2016). It is possible with this framework to assess the impact of an FCI shock on macroeconomic variables at different points in time of our sample.

The results show that the constructed FCI captures instances of global and idiosyncratic financial risks which affect the financial market in South Africa during the period under investigation. For example, the maximum value reached by the FCI during the crisis of 2001 which came from the foreign exchange market was less than the level attained at the GFC of 2007-2008. The results also show evidence of a tranquil period from 2003 to 2006 and from 2009 to the end of the sample. Furthermore, the results depict evidence of time-varying loadings for a few selected variables. The TVP-FAVAR model outperforms the traditional vector autoregressive (VAR) model with two observed variables in the out-of-sample forecasting for all the forecasting horizons for both macroeconomic variables. Similarly, the TVP-FAVAR outperforms the constant-loadings FAVAR of Gumata, Klein, and Ndou (2012) in the out-of-sample forecasting for all the forecasting horizons except for the first three months where the latter model does well. The performance is comparable with the 12-month horizon for GDP growth. The results based on impulse response functions (IRFs) show that tighter financial conditions affect both GDP growth and the inflation rate negatively. The effects die out with a longer forecasting horizon. Interestingly, the GDP growth depicts relatively weaker effects before the exchange rate crisis of 2001. But the effects increase with the crisis and then fade away gradually. For inflation, the effects seem stronger in 2001 compared to the GFC period. Both variables show weaker reaction towards the end of the same period, which coincides with an environment of loose financial conditions both globally and domestically.

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

2 Literature review

Over the years, the literature has distinguished between financial stress indicators (FSIs) and FCIs. Both indicators focus on instances when financial markets are under strain, which in turn make them unstable and vulnerable to shocks. Financial markets may be subject to spells of volatility, with spillovers into the real economy. The difference between the two indicators is that FSIs predominantly rely on prices while FCIs use quantities, prices, and other macroeconomic indicators like GDP growth and inflation. By construction, FCIs are a mapping of financial conditions onto macroeconomic conditions. They serve primarily as a channel through which monetary policy affects the real economy. More than just movement in the policy rate, Brave and Butters (2012) argue that FCIs represent stress in the financial market.

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

In the aftermath of the GFC, there arose a strong need for advanced economies (AEs) to provide a measure of financial and macroeconomic stability. This gave rise to an extensive literature on financial conditions, in particular for AEs. Even though consensus has emerged regarding their ability to predict the real economy, empirically, the approach to measure FCIs has been contested. For example, Goodhart and Hofmann (2001) use a reduced-form VAR model containing short rates, exchange rates, house prices, and share prices to estimate FCIs for the Group of Seven (G7) countries. Gauthier, Graham, and Liu (2004) propose three approaches for constructing the FCI using different weighing techniques such as weights derived from an I-S curve, weights from the VAR model's IRFs, and weights based on the principal component analysis (PCA) approach. They prefer the weighted sum approach over the PCA technique. On the other hand, Swiston (2008) finds that an FCI obtained using the weights of the impulse responses of a reduced-VAR model captures quite well the macro-financial linkages and serves as a leading indicator of the business cycle. When comparing their measure of the FCI to alternative measures proposed in the literature, Hatzius et al. (2010) conclude that expanding the coverage to a higher number of financial variables improves the forecasting performance of the FCI.

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

The literature is less extensive for emerging market economies (EMEs) than it is for AEs, mainly due to data availability. Moreover, many of these indicators rely on a static specification, which overlooks problems related to high-frequency updates of financial data. For instance, Park and Mercado (2014) construct an indicator for 25 EMEs, including South Africa, using a static PCA. They sum up the first three components to create this indicator and compute missing values by using the average of the preceding and succeeding monthly values. Similarly, Osorio et al. (2011) construct a quarterly FCI for 13 developed and developing countries from the Asia Pacific region from the period 2001-2011. To derive this index, the authors rely on two methodologies, namely a VAR model and a DFM similar to that of Koop and Korobilis (2014).

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

Evidence for South Africa is limited. Excluding the cross-country analysis of FCIs above, only a few additions to the existing body of work in constructing FCIs for South Africa can be found. Gumata, Klein, and Ndou (2012) construct an FCI from 11 nominal indicators by applying two alternative approaches, the PCA and the Kalman filter with constant loadings and homoscedastic errors, over the period 1991Q1-2011Q4. The authors demonstrate that their indicator has predictive information for near-term GDP growth and that it outperforms the South African Reserve Bank's (SARB) leading indicator. Thompson, Van Eyden, and Gupta (2015) re-evaluate the FCI derived by Gumata, Klein, and Ndou (2012) by applying a recursive PCA with constant loadings to 16 monthly financial variables and 3 macroeconomic variables (output, inflation, and interest rates, where industrial production is used as a proxy for output) over the period 1966-2011. The causality tests reveal that their FCI is a good out-of-sample prediction of industrial production growth but a weak forecasting tool for inflation and interest rates. Closely related to our approach is the analysis by Balcilar et al. (2016) who extracted the FCI using the Koop and Korobilis (2014) approach. They then include it in a nonlinear logistic smooth transition VAR (LSTVAR) model to account for the asymmetric effects on the real economy caused by change in volatility. Their results indicate that manufacturing growth and interest rates react more forcefully in the upswing phase, whereas inflation tends to respond more in a recession.

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

3 The time-varying parameters of the FAVAR model

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

$$y_t = \lambda_t f_t + \beta_t z_t + v_t \tag{1}$$

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

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

$$\begin{bmatrix} z_t \\ f_t \end{bmatrix} = \Theta_t(L) \begin{bmatrix} z_{t-1} \\ f_{t-1} \end{bmatrix} + \psi_t \tag{2}$$

where $\psi_t \sim N(0, \Psi_t)$ is a vector of disturbances with time-varying covariances Ψ_t and $\Theta_t(L) = I - \Theta_{t,1}L - \cdots - \Theta_{t,p}L^p$ is a time-varying matrix polynomial of order p. As Equation (2) links the financial system with macroeconomic variables, the FCI can be used to forecast macroeconomic variables included in z_t.

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

$$\begin{aligned} \gamma_t &= \gamma_{t-1} + \varepsilon_t \\ \delta_t &= \delta_{t-1} + \omega_t \end{aligned} \tag{3}$$

where $\varepsilon_t \sim N(0, \Xi_t)$ and $\omega_t \sim N(0, W_t)$ are uncorrelated error terms with time-varying co-variances Ξ_t and W_t respectively. Koop and Korobilis (2014) clearly demonstrate that this TVP-FAVAR with time-varying loadings represented by (1), (2), and (3) is general enough, such that the VAR with the observed macroeconomic variables ($f_t = 0$), the constant-factor loading FAVAR ($\Xi_t = W_t = 0$), and the homoscedastic FAVAR ($V_t = V$ and $\Psi_t = \Psi$) are its special cases. Hence, the FCI estimated by Gumata, Klein, and Ndou (2012) – using the FAVAR with constant loadings, constant coefficients of the VAR, and homoscedastic errors – is nested in the current framework.

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

Note that the vector of the observed macroeconomic variables, z_t, contains the annual inflation rate and the economic growth rate. We use the monthly information consistent with financial variables. However, the real GDP, which is the proxy of economic activity, is only available at a quarterly frequency. We follow the recent study of Kabundi, Nel, and Ruch (2016), who estimate the nowcasting of real GDP growth, to construct a monthly series of the real GDP growth from a panel of monthly and quarterly economic indicators. We start by extracting common factors for monthly indicators as follows:

$$x_t = \mu_1 + \Lambda f_t^m + \xi_t \tag{4}$$

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

$$f_t^m = C + A_1 f_{t-1}^m + \cdots + A_p f_{t-p}^m + u_t \tag{5}$$

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

$$\xi_t = \rho_1 \xi_{t-1} + \eta_t \tag{6}$$

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

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

$$G_t^q = \frac{1}{3}\left(G_t^m + G_{t-1}^m + G_{t-2}^m\right) \tag{7}$$

where $t = 3,\ 6,\ 9,\ \ldots,\ G_t^q = 100 \times \ln(GDP_t^q)$ is the natural logarithm of quarterly GDP, and $G_t^m = 100 \times \ln(GDP_t^m)$ is the natural logarithm of monthly GDP. Taking the three-period difference yields:

$$G_t^q - G_{t-3}^q = \frac{1}{3}(G_t^m - G_{t-3}^m) + \frac{1}{3}(G_{t-1}^m - G_{t-4}^m) + \frac{1}{3}(G_{t-2}^m - G_{t-5}^m) \tag{8}$$

Let $y_t^q = G_t^q - G_{t-3}^q$ and $y_t = \frac{1}{3}G_t^m + G_{t-1}^m)$, then (8) becomes:

$$y_t^q = y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4} \tag{9}$$

We use Equation (9) to link the observed monthly values of GDP to the unobserved values. This yields the following expression:

$$y_t^q = \begin{cases} G_t^q - G_{t-3}^q & \text{for } t = 3, 6, 9, \ldots \\ \text{unobserved} & \text{otherwise} \end{cases}$$

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

$$y_t = \mu_2 + \Gamma f_t^m + \zeta_t \tag{10}$$

and

$$\zeta_t = \rho_2 \zeta_{t-1} + \varphi_t \tag{11}$$

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

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

$$\begin{aligned} y_t^+ &= \mu^+ + Z(\theta)s_t + e_t \\ s_t &= T(\theta)s_{t-1} + w_t \end{aligned} \tag{12}$$

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

4 Data and data transformation

This paper uses monthly data for South Africa from the period January 2000 to April 2017, collected from Bloomberg and the SARB. The dataset comprises 39 financial variables and 2 macroeconomic variables, namely the GDP growth rate and the year-on-year headline inflation rate. The financial variables are grouped according to the major markets of the financial system in South Africa, namely the equity, funding, foreign exchange, credit, real estate, and global financial market. The list of variables, their sources, and the treatment are included in the Appendix. We use the natural logarithms for all the variables, except those in rate. We use spreads for most of short- and long-term interest rates, expressed as a difference from the 91-days Treasury bills. Particularly, the South African TED spread, which is simply the difference between the JIBOR and the 91-days Treasury bill rate, provides evidence on liquidity risk in interbank lending.[1] We transform all the series accordingly to induce stationarity.

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

$$FXcrash_t = \frac{x_t}{\max\left[x_t \in (x_{t-i} | i = 1, \ldots, 12)\right]} \tag{13}$$

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

Equivalently, the stock market crash describes expectations about the state of banks and indicates the extent to which the All-Share Index has collapsed over the past 12

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

months. Like the FX crash, it yields the following expression:

$$Stockcrash_t = \frac{x_t}{\max\left[x_t \in \left(x_{t-i} | i = 1, \ldots, 12\right)\right]} \tag{14}$$

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

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

$$\beta_{fin} = \frac{cov\left(r_{fin,t}|_{t-1}^{t}, r_{JSE,t}|_{t-1}^{t}\right)}{var\left(r_{JSE,t}|_{t-1}^{t}\right)} \tag{15}$$

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

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

$$\beta_{bank} = \frac{cov\left(r_{bank,t}|_{t-1}^{t}, r_{JSE,t}|_{t-1}^{t}\right)}{var\left(r_{JSE,t}|_{t-1}^{t}\right)} \tag{16}$$

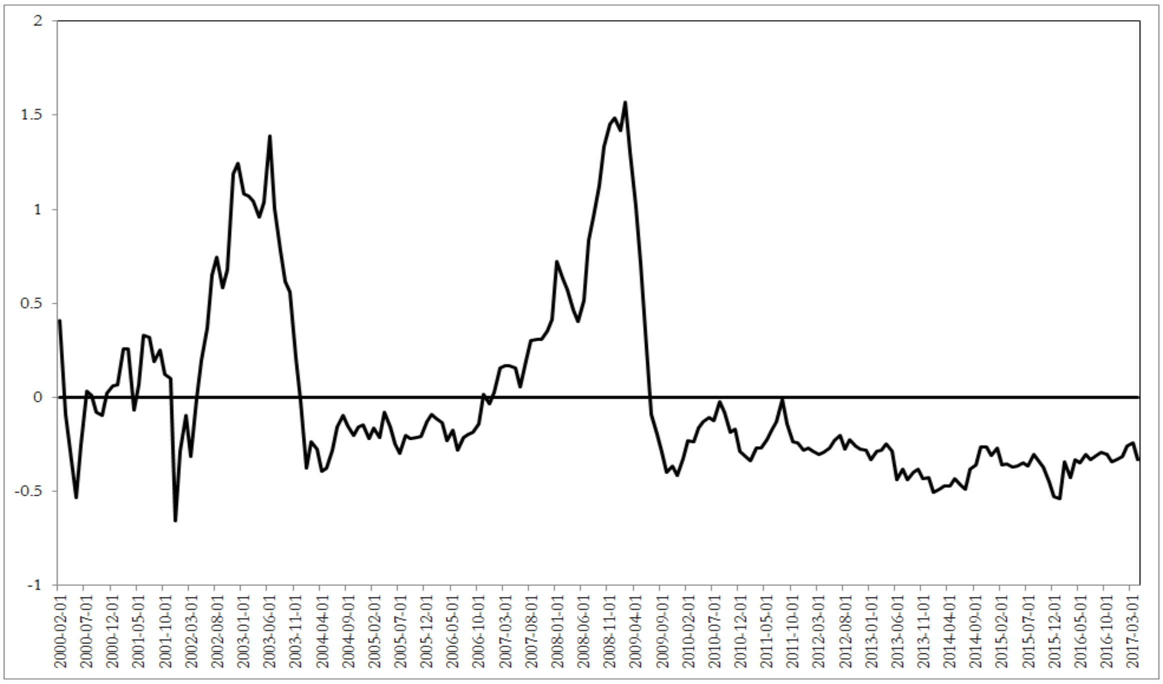
Finally, all the series are standardised by subtracting the mean and dividing by their respective standard deviations before estimating the FCI, which implies that the FCI itself is standardised.

5 Empirical results

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

Figure 1 shows the extracted FCI based on the PCA and the Kalman smoother. Since the FCI is standardised, 0, which is the mean of the FCI, can be interpreted as the financial system at the average level of risk. We use it as the threshold, such that values above 0 exceed the average and hence send a signal of a plausible crisis in the financial market. Positive values that are close to 0 represent the low probability of a crisis whereas values strictly greater than 0 indicate an imminent crisis in the financial market.

Figure 1: FCI



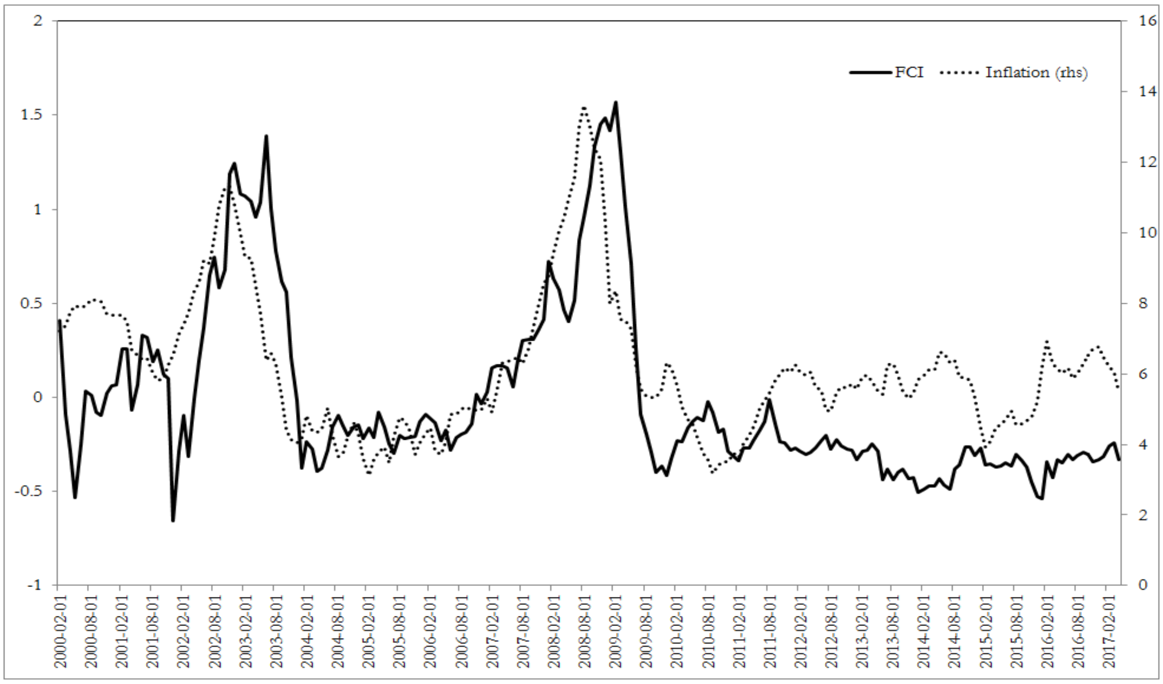
With that in mind, the FCI was above 0 from 2000 to 2001, from 2002 to 2003, and from 2006 to 2009. The increase in the FCI in 2000 was caused by the depreciation of the domestic currency, originating from stress in the global financial market owing to the burst of the Dotcom bubble in the US. The second period, which was somewhat idiosyncratic to South Africa, coincided with the massive depreciation of the rand in 2001. The last breach of the threshold captured the stress from the most recent GFC which started in 2006, way before the 2008 crash in the US and the 2009 crash in South Africa.

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

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

Figure 2 shows the correlation between the extracted FCI and headline inflation. It is clear that the two series trend together throughout the sample, but headline inflation appears more volatile than the FCI. Evidence of co-movement between the two series is exemplified by a correlation coefficient of 67%.

Figure 2: FCI and Headline Inflation



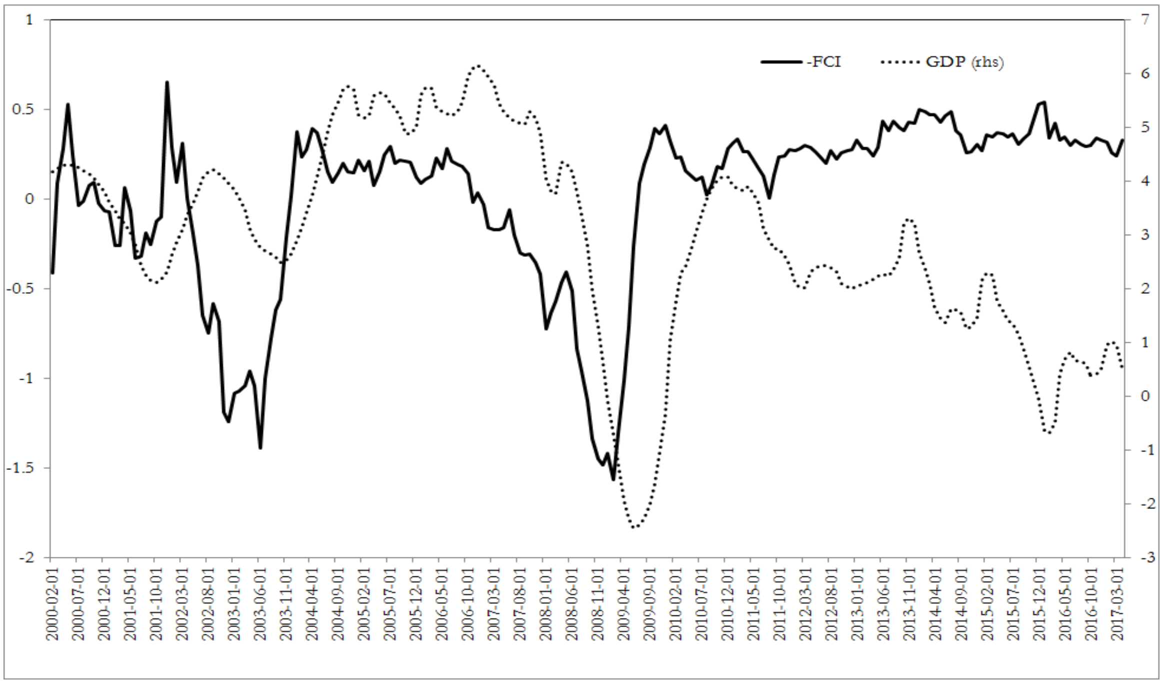
The increases in both the FCI and inflation in 2000 were caused by a depreciation of the rand together with contractionary monetary policy. A further depreciation of the rand in 2001 pushed inflation even higher, from 5.88% in October 2001 to 11.33% in November 2002. This also created stress in the FX market, with the FX crash variable attaining its lowest level ever. The SARB reacted to inflationary pressure by increasing the policy rate. The FCI reached its peak a month later, then decreasing and increasing again before a sharp drop in June 2003. Interestingly, the highest level it attained was lower than its highest level during the GFC. In addition, the market risk increased considerably, contracting the stock market.

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

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

Similarly, Figure 3 represents the relationship between the FCI and the constructed monthly GDP growth rate. Note that we use the negative value of the FCI for a better comparison. In general, the two series co-move, except in the aftermath of the GFC. The relationship is not contemporaneous like with the inflation case in Figure 2. Instead, the FCI tends to lead the GDP growth rate by at least four months.

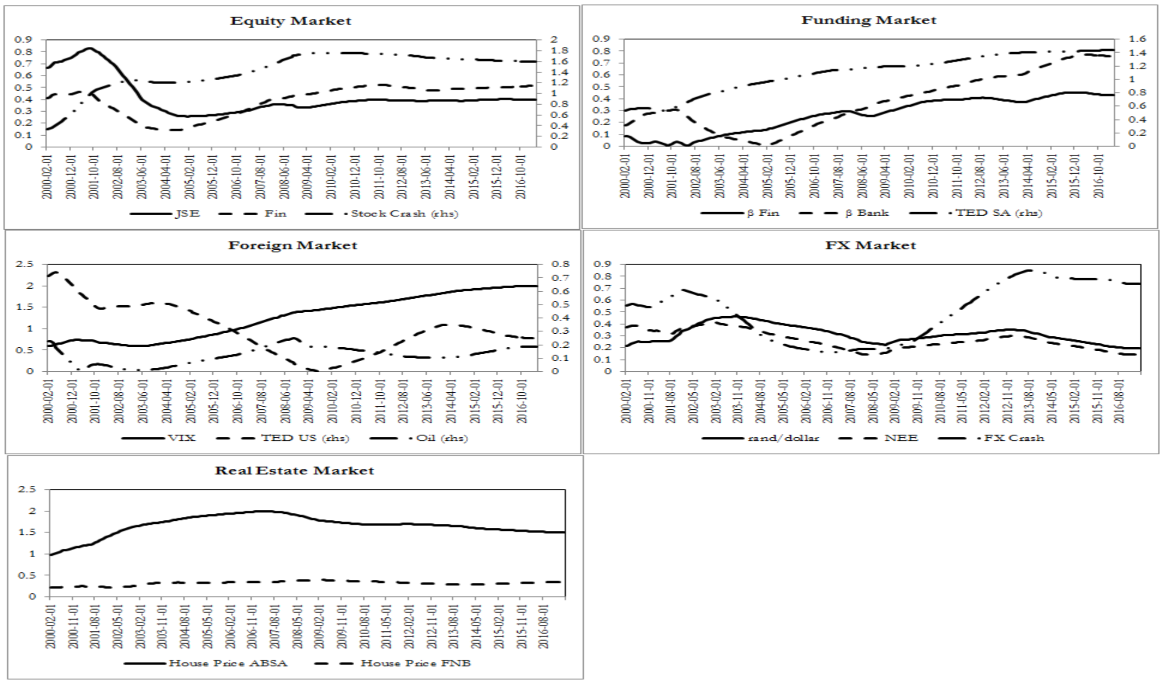
Figure 3: Negative FCI and GDP growth



In general, stress in the financial market can be perceived as a warning signal of possible future weaknesses in the real economy. It helps to predict dynamics in the business cycle, especially the turning points. For example, the FCI in Figure 3 passed the threshold in May 2002 – approximately six months before the economic growth rate reached its peak. And its downward trend commenced in April 2006, followed by a decline in economic activity in February 2007. Finally, the FCI reached a trough in February 2009, four months before the real economy did.

From Figure 4, it is clear that factor loadings are not constant. Hence, using constant loadings like Gumata, Klein, and Ndou (2012) is too restrictive. The top-left graph shows selected variables representing the equity market. Notice that the All-Share Index of the JSE and the financial index of the JSE move together. They score highest values during the Dotcom crisis of 2000 and then decrease gradually. The financial-index loading increases slowly before the GFC and then remains constant throughout the rest of the sample. The loading of the stock crash shows a different pattern. After reaching its lowest level in 2000, it increases rapidly from 0.34 to 1.25 during the currency crisis. It then stays constant at around 1.20 until 2006 and reverts its upward trend, reaching the maximum of 1.75 in 2009. It has been constant ever since.

Figure 4: Selected Factor Loadings of Variables Different Markets



The top-right graph presents the loadings of the two βs as well as the South African TED spread. These series represent the funding market. The banking β shows a pattern that is similar to the financial index of the JSE. Its upward movement, which coincides with the Dotcom crisis, is followed by a slow decline, which is in turn followed by a persistent increase until the end of the sample. Both the financial β and the South African TED spreads are trending upward, albeit with different slopes.

The middle graph on the left represents the foreign market. The weight of the VIX trends upward from the beginning to the end of the sample. But the US TED spread and the oil price exhibit a different pattern. While the loading of the US TED depicts a V-shaped pattern, the picture of the oil price is an inverted V-shape. The V-shape of the US TED captures both the Dotcom and the GFC crises. The inverted V-shape of the oil price represents the contribution of the rise in the oil price in the wake of the GFC. Notice that the middle graph on the right depicts the same V-shape pattern like the US TED, but for these series, in addition to the Dotcom crisis and the GFC, it also captures the currency crisis.

Lastly, the bottom-left figure shows a slow increase in the loading of house price, which reaches its maximum in October 2007. This period coincides with the adoption of the National Credit Act, which curbed the growth in credit extended to households and caused growth in house prices. Interestingly, the two series do not contribute equally to the estimation of the FCI.

To evaluate the predictability of the FCI, we compare the out-of-sample prediction of the economic growth rate and the inflation rate using the TVP-FAVAR. We use a two-variable vector VAR model, which includes the economic growth rate and the inflation rate, as a benchmark model. The main difference between the VAR and the TVP-FAVAR models is that the latter contains the estimate FCI in addition to the two macroeconomic variables. Furthermore, we use the FAVAR model with constant loadings – like Gumata, Klein, and Ndou (2012) – as an alternative model. Table 1 exhibits the relative root mean squared forecast errors (rRMSFEs) of the out-of-sample forecasts from January 2005 to April 2017.

Table 1: rRMSFE

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

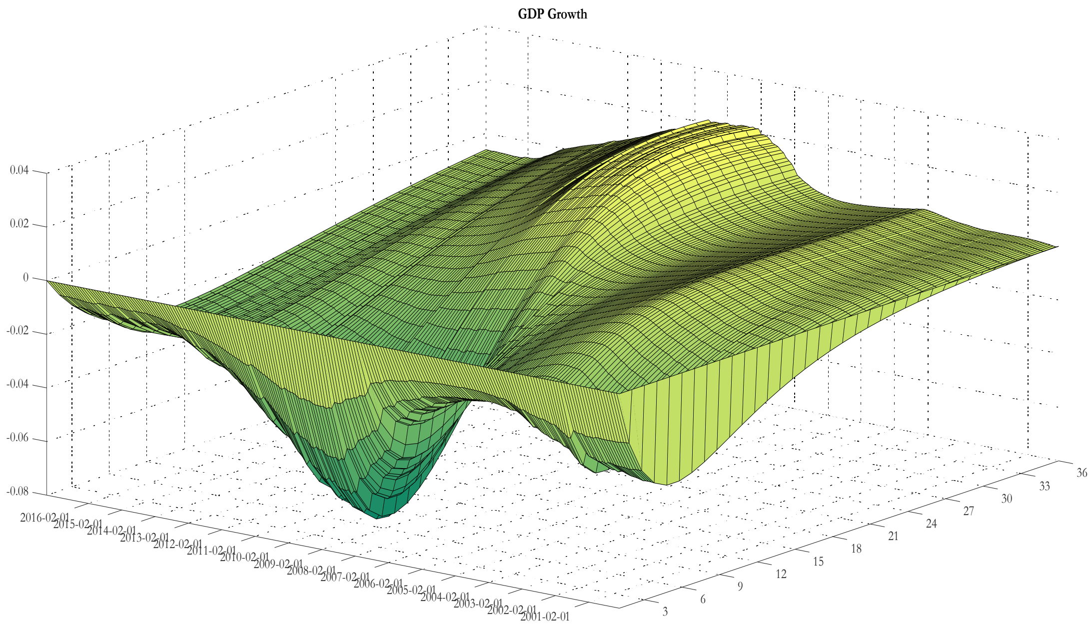
In general, the TVP-FAVAR, depicted in columns 2 and 3 of Table 1, outperforms the VAR for both variables for all the forecast horizons. The results are roughly the same when we use the constant-loading FAVAR.[2] Like the TVP-FAVAR, the forecast of GDP growth outperforms the small VAR over the entire forecasting horizon.

Finally, when we compare the rRMSFEs of the TVP-FAVAR and the FAVAR, the former surpasses the latter throughout the forecast horizon for both macroeconomic variables, except for the first three months where the latter scores lower rRMSFEs. It is worth mentioning that the two models of GDP growth for the 12-month horizon show comparable performance. These results point to the important contribution of financial variables in predicting macroeconomic variables.

Figure 5 illustrates a three-dimension response of the GDP growth rate, which changes with time and over a forecast horizon of 36 months to a percentage tightening of financial conditions. The identification scheme of the tighter financial conditions is based on the Cholesky restriction where the FCI is ordered last after GDP growth and the inflation rate. We use two lags in the FAVAR, based on the Bayesian information criteria, and the IRFs are calculated over 36 months. Figure 5 exhibits the expected sign: the real economy reacts negatively to financial conditions tightening.

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

Figure 5: Time-Varying IRFs of GDP growth

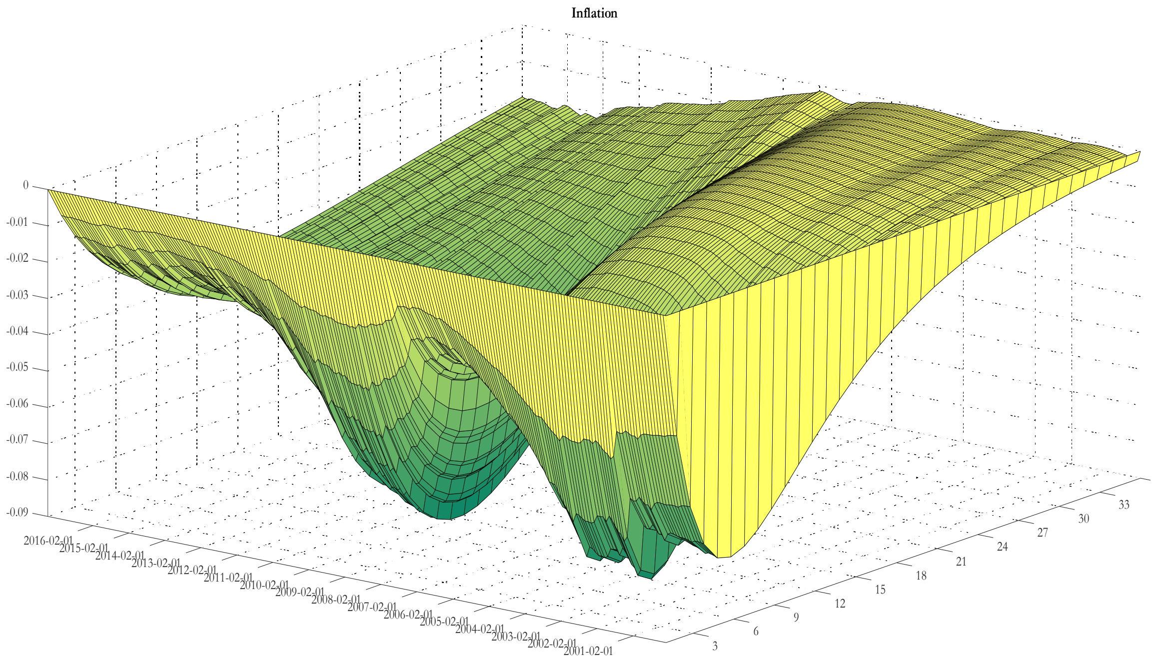


It is clear from the picture painted in Figure 5 that the effects of the FCI on the real economy vary over time. We observe two episodes of contraction of the real economy caused by tight financial conditions, namely at the beginning of the sample and during the GFC. Recall that, during these two periods, the FCI is above 0. The monetary policy authority reacted to the depreciation of the currency in 2001 by raising its policy rate, which in turn put downward pressure on the real economy.

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

Note that Figure 6 is based on the same identification as Figure 5. The picture is somewhat similar to that of GDP growth.

Figure 6: Time-Varying IRFs of Inflation



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

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

6 Conclusions

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

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

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

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Appendix

List of variables

No.	Description	Tcode	Source
	Credit Markets		
1	All monetary institutions : Credit extended to the domestic private sector: Total loans and advances	5	S
2	R186 10.5% (2026) - Government stock	2	S
3	Spread: Yield Market: Eskom bonds - daily (ES33) and 91 day treasury bill	1	S
4	Spread: Yield Market: 0-3 year government bond - daily (R203) and 91 day treasury bill	1	S
5	Spread: Yield Market: 3-5 year government bond - daily (R207) and 91 day treasury bill	1	S
6	Spread: Yield Market: 5-10 year government bond - daily (R2023) and 91 day treasury bill	1	S
7	Spread: Yield Market: Long-term government bond - daily (R186) and 91 day treasury bill	1	S
8	Secondary Market: JSE All Bond yield - daily	2	S
9	Differential between repurchase rate and 91 day treasury bill rate	1	S
10	Margin between prime rate and 3-months NCD's	1	S
11	Margin between 3-months NCD's and Reserve Bank debentures	1	S
	FX Markets		
12	S.A. rand against U.S. dollar (ZAR)	5	S
13	Nominal effective exchange rate of the rand - 20 trading partners: Effective Jan. 2010 - Trade in manufactured goods	5	S
14	Fx crash	1	A*
	Real Estate Markets		
15	South Africa: ABSA House Price Index (S.A., 2000=100)	5	S
16	South Africa: FNB Average House Prices	5	S
	Foreign Data		
17	3m LIBOR (U.S.)	2	B
18	90 day T-bill rate (U.S.)	2	B
19	TED (U.S.)	1	A*
20	VIX - last price	1	B
21	S&P500 stock in gold index	5	B
22	Oil price - U.S. dollar (Brent crude)	5	S
23	Gold price - London (U.S. dollar)	5	S
24	Global Total Return index	5	B
	Funding Markets		
25	Negotiable certificates of deposits (NCDs): 3 months	2	S
26	Negotiable certificates of deposits (NCDs): 6 months	2	S
27	Negotiable certificates of deposits (NCDs): 12 months	2	S
28	Spread: Prime overdraft rate and 91 day treasury bill	1	S
29	Spread: Inter-bank funds rate and 91 day treasury bill	1	S
30	Bankrate and average/fixed repo rate	2	S
31	TED (S.A.)	1	A*
32	beta_fin1yr	1	A*
33	beta_bank1yr	1	A*
	Equity Markets		
34	Stock crash	1	A*
35	All share (J203) Price index	5	S
36	Financials (J580) Price index	5	S
37	Banks (J835) Price index	5	S
38	All share total return (J203T) Price index	5	S
39	General Mining (J154) Price index	5	S

Source: A* = Author's calculation, B = Bloomberg, S = South African Reserve Bank; Tcode: 1 = Level, 2 = First difference, 5 = Log difference