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A Financial Conditions Index for South Africa

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Abstract

The main purpose of this paper is to construct a financial conditions index (FCI) for South Africa. The analysis extracts the index by applying two alternative approaches (principal component analysis and Kalman filter), which identify an unobservable common factor from a group of external and domestic financial indicators. The alternative estimated FCIs, which share a similar trajectory over time, seem to have a powerful predictive information for the near-term GDP growth (up to four quarters), and they outperform the South African Reserve Bank's (SARB) leading indicator as well as individual financial variables. Their recent dynamics suggest that following a strong recovery in late-2009 and 2010, reflecting in part domestic factors such as systematic reductions in the policy rate, the rebound in real economic activity, and a benign inflationary environment, the financial conditions have deteriorated in recent months, though not as sharply as in end-2008. Given their relatively high predictive power regarding GDP growth, a further deterioration may imply that economic activity is likely to slow in the period ahead.

JEL Classification Numbers: E5, E17, E44

Keywords: Financial conditions index, factor analysis

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I. INTRODUCTION

The response of real economic activity to the recent global financial crisis and the ongoing sovereign debt crisis highlighted the importance of macro-financial linkages and demonstrated how severe the impact of financial markets' stress on real activity can be. But more generally, financial conditions are known to have an important influence on business cycles because they reflect not only the feedback of current and past economic conditions but also the markets' expectations about the economic outlook. Thus, the assessment of the financial conditions on an ongoing basis has become critical for policymakers, regulators, market financial participants, and researchers, who have increasingly worked to construct financial conditions indices that can be used as operational tools to better understand the macro-financial linkages and also to obtain a historical perspective in comparing the relative tightness or looseness of financial conditions.

A wide range of methodologies for constructing the financial conditions indices have been developed over time, but the most popular are the weighted-sum approach and the principal component approach.[1] In the first approach, the weights of each financial indicator are assigned according to the estimated impact on real GDP growth in a vector autoregressive (VAR) or structural macroeconomic models.[2] In the second approach, the financial conditions index (FCI) reflects a common factor, which is extracted from a group of financial indicators and captures the greatest common variation among them.[3] The models in this group differ by the estimation methods and by the statistical processes, in which the unobserved common factor is specified.

This paper aims at constructing an FCI for South Africa, which can be used as a leading indicator for short-term economic activity and as a tool to assess financial conditions across time. The analysis uses the methodology proposed by Hatzius and others (2010) and applied in Osorio, Pongsaparn, and Unsal (2011). This approach strips the unobservable principal component factor from the feedback of economic activity. Acknowledging the limitations of the principal component approach, the analysis also applies an alternative methodology–Kalman filter–which provides the estimated FCI with greater auto-correlation over time.

The results indeed show that the financial conditions started deteriorating in 2007Q3 and worsened in 2008, and ultimately affected real economic activity. While recovering strongly in late-2009 and 2010, the financial conditions have tightened in recent months, although not

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[1] Hatzius and others (2010) provide an extensive survey on financial conditions indices, which were constructed in recent years.

[2] Examples of a weighted-sum approach are the FCIs of the Organization of Economic Co-operation and Development (OECD), Goldman Sachs, Bloomberg and Citigroup. In South Africa, the Quantec financial conditions index regresses real short-term interest rates, the yield spread, excess money supply growth, company earnings yield, and the real effective exchange rate on manufacturing production. Each variable's coefficients are then used to give an approximation of the relative weights.

[3] Such indices are used by Deutsche Bank and the Federal Reserve Bank of Kansas City.

as sharply as in 2008. Moreover, the estimated FCIs were found to have powerful predictive information for near-term GDP growth by up to four quarters and outperform the current South African Reserve Bank (SARB) leading indicator as well as other individual financial indicators. Based on this, the recent deterioration in the financial condition indices suggests that economic activity in South Africa is likely to moderate in the period ahead.

This paper is structured as follows: Section II describes the principal component approach (PCA) and presents the financial indicators used to construct the FCI under this methodology. Section III offers an alternative approach (Kalman filter), which allows for auto-correlation and thus gives the estimated FCI greater dynamics over time. Section IV looks at the alternative indices and compares their evolution over time; Section V evaluates the financial conditions indices by performing Granger causality tests and by looking at the explanatory power for near-term GDP growth and compares them to that of the SARB's leading indicator; Section VI assesses the impact of the recent deterioration of the financial conditions on GDP growth by presenting dynamic simulations under three different scenarios for 2012. Section VII concludes.

II. Principal Component Approach (PCA)

The principal component methodology aims at extracting a common factor (F_t) that captures the greatest common variation in a group of P variables (X_t). Analytically, the model can be presented as follows:[4]

$$X_t - \mu = \beta F_t + U_t \tag{1}$$

Where μ is a $p \times 1$vector of the variables' means. β is a $p \times m$ matrix of coefficients, and F is a vector of $m \times 1$ unobserved variables, termed as common factors, and U_t is a $p \times 1$vector of errors. The model assumes that errors are orthogonal to the common factors, $[E(FU') = 0]$, and that the common factors have zero mean $E(F) = 0$.

We calculate a common factor for the period of 1999q1 and 2011q4 based on both financial indicators that are entirely exogenous to South Africa and reflect the global financial conditions as well as indicators that relate specifically to South Africa. The variables selected cover measures of market risk and liquidity, with implications for monetary policy, financial stability and economic activity.

The variables are divided into global and domestic factors. The global factors include the S&P500 volatility index (*VIX*), which reflects international investors' appetite for risk; S&P500 stock price index (*SP500*) indicates general market risk; JP Morgan EMBI total return index (*EMBI*) is a measure of risk aversion and tracks returns for actively traded

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[4] The main benefit of the principal component approach (PCA), is its ability to determine the individual importance of a large number of indicators so the weight allocated to each indicator is consistent with its historical importance to fluctuations in the broader financial system. For extensive discussion on the PCA, see Johnson and Wichern. (1992).

external emerging market debt; and the spread between the three-month LIBOR and the yield on a three-month US Treasury bill (*TED*), which measures the perceived credit risk, global liquidity conditions and uncertainty surrounding the projected path of U.S. monetary policy.

The domestic (South Africa-related) indicators are: total loans and advances to the private sector (*LOANS_ADV*) that capture the demand factors affecting the economic outlook and supply constraints not captured by interest rates; the South African sovereign spread (*SOVEREIGN*) indicates risk of the government's funding ability in the capital markets, nonperforming loans (*NPL*) indicate the health of the banking sector and the building up of risks in the banking sector; the negotiable certificates of deposit rate (*NCD*) measures the cost of financing for firms and households; the nominal effective exchange rate (NEER) captures the magnitude of capital flows to and from South Africa; the all-share Johannesburg Stock Exchange index (*JSE*); and the ABSA house price index (*ABSA*), which captures asset prices, the wealth and collateral channels, and expectations about inflation and other macroeconomic conditions.[5]

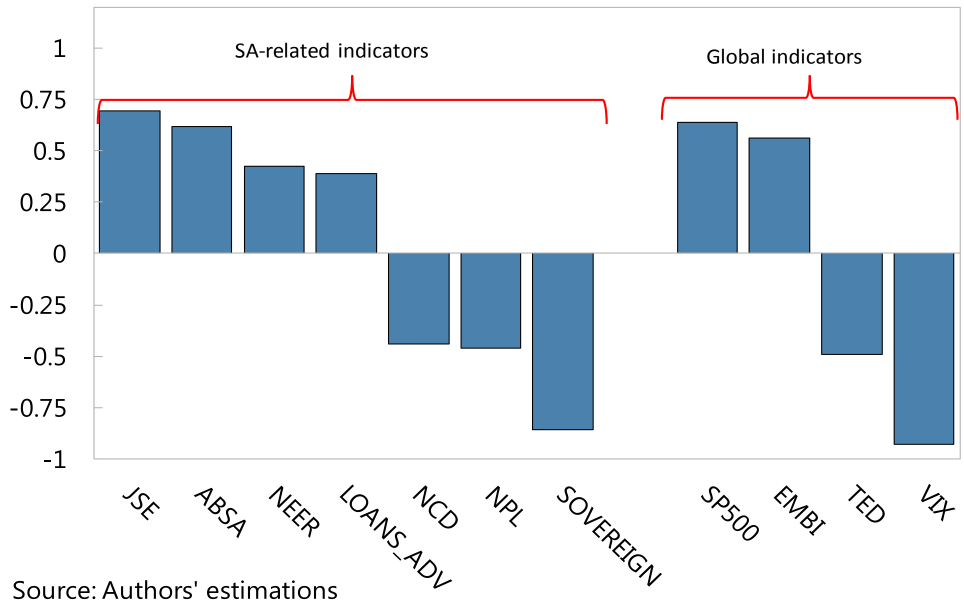
While many variables were considered in the first round, the selection of the final variables was based on their factor "loadings," i.e., correlation coefficients. For this exercise, we set the threshold at 30 percent. All variables are demeaned and transformed to I(0). In this regard, the variables *NEER, JSE, ABSA, LONS_ADV, EMBI*, and *SP500* are measured on a y-o-y basis while the rest of the variables are measured at their levels (Figure 3A in the appendix).

Figure 1 shows the factors "loadings". These loadings reveal the signs and magnitudes of variables included in the index. The signs and magnitudes are important in capturing and assessing the systematic relationships with the identified common factor. The more correlated the factor is with other variables, the higher the allocated weight. In particular, Figure 1 shows that, among the global indicators, the common factor is negatively correlated with the *VIX* and the *TED* movements, whereas, it is positively correlated with the *SP500* and the *EMBI.* The loadings' values suggest that the common factor is highly affected by the *VIX's* movements because the factor explains more than 80 percent of the *VIX* variation.

As for the South Africa's specific indicators, the loadings' values suggest that the common factor is positively affected by the *JSE*, *ABSA* house price index, credit to the private sector, and the *NEER*. The latter suggests that an appreciation of the rand, which is also correlated with higher capital inflows, reflects better (looser) financial conditions. The common factor is negatively affected by the short-term interest rate (*NCD*), the nonperforming loans (*NPL*), and the sovereign spread (*SOVEREIGN*).

[5] It is worth noting that despite the emphasized importance of the inclusion of credit availability surveys in the construction of FCIs in the literature, we are not able to include such qualitative variables in our index because the available series only start in 2002 Q1.

Figure 1. Factor "Loadings"



Source: Authors' estimations

Because the FCI should reflect information about the future state of the economy, it should be "stripped" from the feedback of economic activity. The intention is to capture pure financial shocks and not the influence of past economic activity. This endogeneity problem is therefore, addressed in the second stage of the estimation, when we purge the estimated common factor of this feedback by regressing $\widehat{F}_t$ on current GDP growth (Y_t) as follows:

$$\hat{F}_t = \gamma Y_t + V_t \qquad (2)$$

Where V_t is uncorrelated with Y_t. We can now refer to V_t as the estimated FCI, which reflects only the exogenous shifts in the financial conditions and thus should have a predictive power for future economic activity.[6] This will be examined in subsequent sections.

III. Extracting the Common Factor by a Kalman Filter

One of the main drawbacks of the principal component estimator is that the factor is constructed as a stationary variable with a zero mean, thus it lacks a dynamic (autocorrelation) pattern, which, in the context of estimating an FCI, is important given that the aim is to predict the near-term GDP growth, which, in general, is characterized by more gradual shifts. Therefore, in this section we expend the factor structure to include a more dynamic specification. This is done by using the following state-space form:

[6] The unpurged factor is presented in Figure 1A in the appendix.

$$X_t - \mu = \delta F_t + \varphi Y_t + \epsilon_t \qquad (3)$$
$$F_t = \alpha F_{t-1} + \eta_t \qquad (4)$$

Where Eq. (3) is the signal equation that includes the vector of the observable variables, X_t, their mean, μ, and the estimated common factor, F_t. Eq. (4) is the state equation, which describes the statistical process of the estimated common factor. Here, we simultaneously strip the observable variables from the feedback of economic activity by including the current GDP growth in the signal equation. The error terms ϵ_t and η_t are independent disturbances with zero mean.

For comparison, we used the same set of financial indicators in both methodologies to construct the financial conditions indices. The comparison of the dynamics of the two alternatives FCIs is presented in the next section.

IV. THE ESTIMATED FINANCIAL CONDITIONS INDICES: A COMPARISON

The estimated FCIs by the two methodologies are presented in the Figure 2. An upward movement of the index implies more accommodative overall financial conditions, whereas a decline indicates tighter financial conditions. The two indices broadly follow a similar trajectory, though the Kalman filter-based FCI is smoother owing to its “built-in” auto-correlation. The simple correlation between the two indices is positive and around 0.4 for the whole period; however, in the first half of the sample (1999–2006), the correlation was much higher (0.68) than in the second half of the sample (0.2), suggesting the two indices responded somewhat differently to the financial crisis and to the recovery that followed. To explore this aspect further, the comparison is divided into three parts, namely, pre-crisis period, the financial crisis, and post crisis period.

Pre-crisis period

In the early-2000s the two indices show slightly negative levels reflecting the elevated volatility in the stock markets, which accompanied the Internet bubble burst, the rand crisis, and a relatively high sovereign risk. The improvement in financial conditions that followed (2004–07) is associated with the upturn in the global economic activity and the high GDP growth in South Africa. During this period, South Africa’s international economic standing also improved as shown by reduced sovereign risk spreads and better debt ratings.

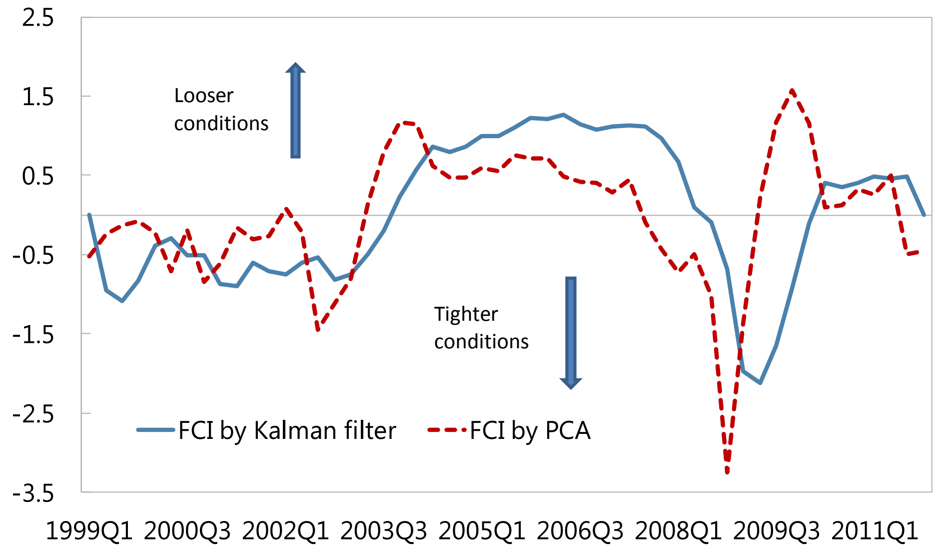
Financial crisis period

During the financial crisis and the period that followed, the PCA-based FCI seems to exhibit sharper swings: it deteriorated faster than the Kalman filter-based FCI as it reached its low point of -3.2 already in 2008q4, and it recovered quite strongly in the subsequent quarters, reaching its high point in 2009q4. The Kalman filter-based FCI seems to react two quarters later to the financial crisis as it reached its record-low level in 2009q2.

Post-crisis period

The Kalman filter-based FCI also recovered more gradually than the PCA-based FCI, and its level in the post-crisis period remained below its pre-crisis level. While the PCA-based FCI showed a gradual deterioration in 2010 and 2011, entering a negative territory in recent months, the Kalman filter-based index remained flat from 2010q2 to 2011q3. In 2011q4, however, it has somewhat deteriorated to just below zero.

Figure 2. The Estimated Financial Conditions Indices (FCIs)

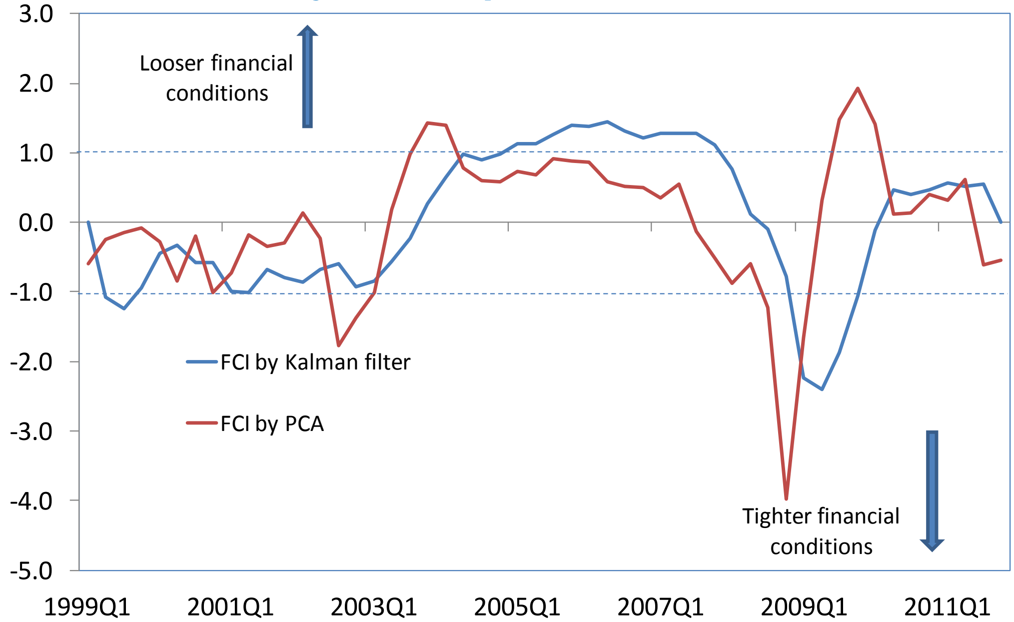


Source: Authors' estimates.

Hatzius and others (2010) and Hakkio and Keeton (2009), suggest that an FCI can also serve as a guide to the effectiveness of the monetary policy stance because it could identify periods in which the normal monetary policy transmission channels may be impaired on account of increased financial market frictions. To identify the periods in which conditions showed large changes, we scaled the FCI by the sample's standard deviation. Measured this way an index value of -1 is associated with financial conditions that are tighter than on average by one standard deviation, while an index value of 1 indicates that financial conditions are looser than average by one standard deviation (Figure 3).

Figure 3 indicates looser conditions that exceed one standard deviation in 2003q3 to 2004q2 and 2009q3 to 2010q1 whereas the dynamic Kalman filter FCI points 2004q1 to 2007q4. That said, the PCA and Kalman FCIs indicate that financial conditions were significantly tighter and exceeded one standard deviation in 2008Q3 to 2009Q1 and 2009q1to 2009q4, respectively. This may suggest that the deterioration in financial conditions during these periods was not conducive for efficient/effective transmission of monetary policy changes through certain traditional channels. In particular, during this period, house prices plummeted by a larger proportion than historic averages, stock prices lost significant value, nonperforming loans and other measures of impaired loans and advances outside the banking sector increased, and credit extension to the private sector shrank significantly. The high illiquidity of disposable assets and price devaluation weakened the role of the wealth and collateral channels in facilitating access to credit and thereby possibly adding frictions to already imperfect markets and further impairing the transmission of monetary policy changes into the real economy. Although not at a significant level, the latest deteriorations coincide with lingering European sovereign debt problems, which affect sovereign risk and risk appetite.

Figure 3 . The Estimated Financial Conditions Indices (FCIs) Scaled by the Sample Standard Deviations



V. Evaluation of the Financial Conditions Indices

This section conducts various tests to ascertain the effectiveness of financial conditions indices as a policy tool by performing Granger causality tests and two forecasting exercises. First, we conduct Granger causality tests of the two alternative FCIs and GDP. Second, we evaluate and determine which of the estimated FCIs has greater ability to explain and predict GDP growth over the near-term, and compare it to that of the SARB's composite leading business cycle indicator.[7] Third, we assess the relative predictive performance of the FCI to various variables included in the index.

Table 1 shows the results of the Granger causality tests of the two alternative FCIs and GDP. In these tests, the results show unidirectional causality from the estimated FCIs to GDP.

[7] The SARB leading indicator comprises several economic indicators, including jobs advertisements, labor productivity in manufacturing, surveys of business confidence, average working hours, orders and inventories in the several sectors, and commodity prices. It also includes some financial variables such as the spread between short and long rates, M1 growth rate, and shares' prices.

Table 1. Granger Causality tests of Alternative FCIs and GDP		
Null Hypothesis	**F-Statistic**	**P-value**
FCI by Kalman filter does not Granger Cause GDP	4.15663	0.0219*
GDP does not Granger Cause FCI by Kalman filter	1.99865	0.14710
FCI by PCA does not Granger Cause GDP	9.67749	0.0003*
GDP does not Granger Cause FCI by PCA	1.79838	0.17700

(*) represents significance at 5 percent.

For testing the relative predictive performance of the FCIs, we estimate the following equation:

$$growth_{t+h} = \alpha + \sum_{i=1}^{q} \beta_i growth_{t+1-i} + \omega INX_t + \varepsilon_t \qquad (5)$$

Where *INX* refers to the examined indices (PCA, Kalman filter, and the SARB's leading indicator).[8] The forecast horizon (h) is set to 1, 2 and 4 quarters ahead and the estimation is based on 1999q1–2011q4. The optimal lag of the GDP growth is determined by Akaike Information criterion (AIC) by first estimating Eq. (5) without the financial conditions/leading indices.[9] The explanatory power of the indices is assessed by the estimations' Sum Squared Residuals (SSR). The results are presented in Table 2.

Table 2. The Explanatory Power of the Indices [1]						
	Full sample (1999q1-2012q1)			Sub-sample (1999q1-2007q4)		
	h=1	h=2	h=4	h=1	h=2	h=4
	SSR	SSR	SSR	SSR	SSR	SSR
AR model with FCI (PCA)	11.309*	33.959*	89.817*	5.426*	10.483*	10.148*
AR model with FCI (Kalman filter)	14.943*	52.164*	141.412*	5.112*	8.764*	11.306*
AR model with Leading indicator	16.439	60.527	117.152	7.069	21.438	29.819*
AR model w/o indices	17.036	63.009	118.328	7.261	21.951	36.525

[1] *h* reflects the number of quarters ahead.
(*) indicates that the index's coefficient is significantly different from zero with a confidence level of 95 percent.

The results show that, overall, the two alternative financial conditions indices help in explaining the near term GDP growth because their coefficients are significantly different from zero with a positive sign, as expected. Moreover, the results show that the two FCIs outperform the SARB's leading indicator as their SSR are substantially lower for all three

[8] The SARB's leading indicator is introduced on y-o-y basis.

[9] This ensures that the optimal lag, which was found to be 2, is equal in all estimations and thus allowing a fair comparison of the Sum Squared Residuals (SSR).

horizons. Between the two FCIs, the PCA-based FCI seems to have a greater explanatory power over the entire sample. For robustness check, we estimate Eq. (5) for the sub-sample of 1999q1–2007q4 to examine the explanatory power of the variables before the global financial crisis. The estimation results suggest that the Kalman filter-based FCI has a slightly smaller SSR compared to the PCA-based FCI for 1 and 2 quarters ahead. In this sub-sample the SARB's leading indicator turned out to be significant only with a four-quarter horizon.

We also explore whether the FCIs' explanatory power is higher than each of the variables that are included in them by estimating Eq. (5) and comparing the resulting SSR. The results, which are presented in Table 3, show that the PCA-based FCI has the lowest SSR, although the VIX seems to perform well, especially for 1 and 2 quarters ahead. The Kalman filter seems to outperform some financial variable, but falls short compared to the VIX, ABSA housing prices, sovereign spread, and the JSE.

Table 3: Comparison of SSR for 1,2, and 4 Quarters Ahead, 1999q1-2011q4 [1]

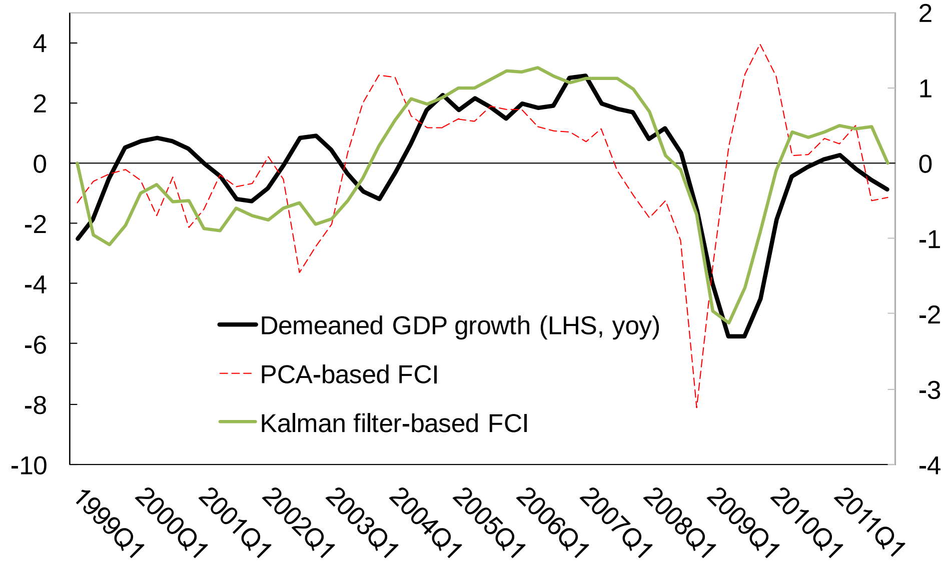
	h=1	*h=2*	*h=4*
PCA-Based FCI	11.309*	33.959*	89.817*
Kalman filter-based FCI	14.943*	52.164*	141.412*
VIX	11.594*	36.728*	105.849*
EBMI	16.377	60.194	154.043
SP500	15.392	54.012*	139.536*
SOVEREIGN	13.944*	46.405*	115.836*
TED	14.637*	49.062*	101.064*
NPL	15.391*	56.495*	154.604
JSE	13.339*	45.056*	126.362*
ABSA	14.449*	46.354*	90.063*
NEER	16.551	60.474	142.815
NCD	16.641	59.438	145.169
LOANS_ADV	15.574*	57.408*	160.291

[1] *h* reflects the number of quarters ahead.
(*) indicates that the index's coefficient is significantly different from zero with a confidence level of 95 percent.

The global financial crisis and the predictive power of the indices

Figure 4 indeed shows a relatively high correlation between the alternative FCIs and GDP growth (demeaned, y-o-y basis). The figure also indicates that the two FCIs contain some predictive information regarding the near-term path of GDP growth, particularly given that in some periods the two FCIs move in advance to the trajectory of the GDP growth.

Figure 4. Demeaned GDP Growth and the Alternative FCIs



Source: Authors' calculations

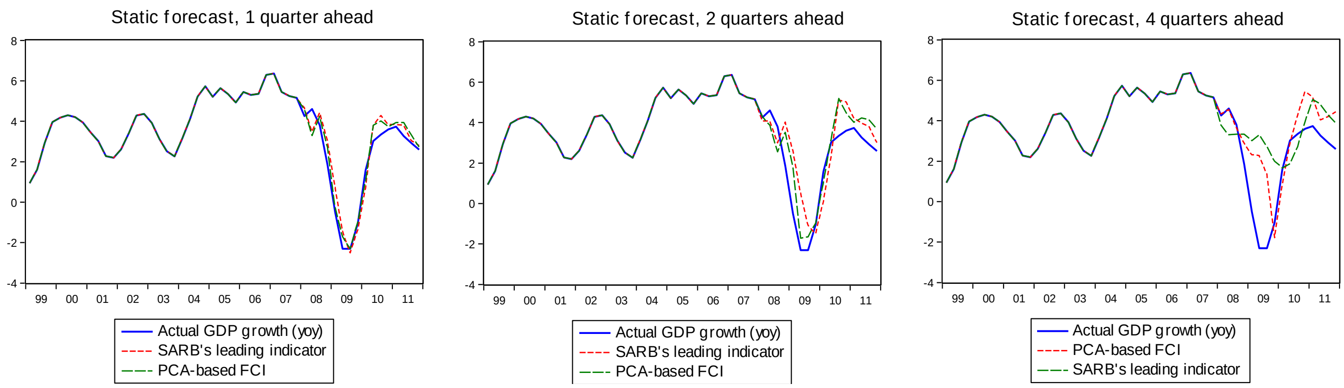
To evaluate the indices' predictive power before and during the global financial crisis, we use Eq. (5) and perform an in-sample static forecast for 1,2 and 4 quarters ahead for the period of 2008q1–2011q4, and compare the forecasts' deviations from the actual GDP growth by focusing on the Root mean squared error (RMSE) indicator. The results, which are presented in Table 4 and Figure 5, suggest that the PCA index performs significantly better than the other indices for all horizons. The results also show that the Kalman filter-based FCI is marginally better than the SARB's leading indicator, though both indicators provide a higher predictive power compared to a simple AR model that does not include any form of leading/financial conditions indicators.

Table 4. The Predictive Power of the Indices, 2008q1-2011q4

	h=1	*h=2*	*h=4*
	RMSE	RMSE	RMSE
AR model with FCI (PCA)	0.575	1.096	1.877
AR model with FCI (Kalman filter)	0.703	1.405	2.400
AR model with Leading indicator	0.721	1.467	2.400
AR model w/o indices	0.740	1.508	2.505

Figure 5 illustrates the forecast dynamics. It shows that while in the first and second quarters ahead the differences are relatively small between the PCA-based FCI and the SARB's leading indicator, there is a substantial difference in the four-quarter forecast. The FCI seems to almost fully capture the contraction of GDP while the leading indicator forecast only envisages a modest slowdown. In the course of 2010, both indices seem to overshoot the economic recovery mainly because of the inertia introduced by the AR specification.

Figure 5. Static Forecast, 2008q1–2011q4



VI. What Can the Financial Conditions Index Tell About the Near-Term GDP Growth?

The implications of the financial conditions for the near-term GDP growth are assessed by a dynamic forecast for the next three quarters (up to 2012q4) using Eq. (5). The dynamic forecast implies that, for every quarter, the starting point is the model's prediction. For this exercise we use the FCI under the principal component approach, which was found to outperform the Kalman filter-FCI and the SARB's leading indicator. In light of the ongoing sovereign crisis in the euro-area and the potential repercussions on South Africa's financial conditions, we focus on three main scenarios for the remainder of the year.[10] The first scenario assesses the impact of current financial conditions (2012q1) while the last two scenarios focus on tighter or more restrictive financial conditions. The assumed three scenarios are-

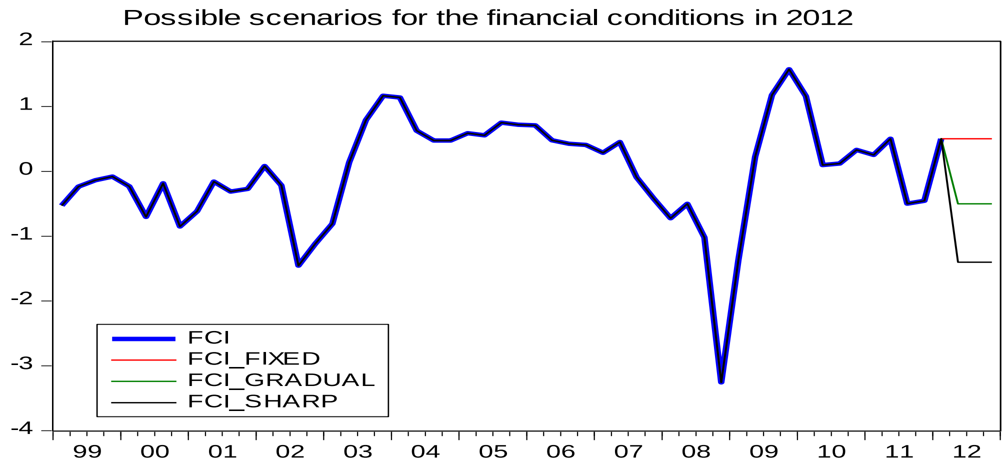
1. Financial conditions remain at their current level (as of 2012q1) throughout the forecast horizon (0.5).

2. Financial conditions gradually deteriorate, and return to the average level of the second half of 2011 (-0.5).

3. Financial conditions sharply deteriorate and reach the average level that was observed in 2008 (-1.4).

[10] For this exercise, we updated the FCI using the 2012q1 GDP figure that was published at end-May 2012.

Figure 6. Dynamic Forecast, 2012q1-2012q4



The FCI trajectories under the three scenarios and the dynamic forecasts are presented in Figure 6. While the impact on GDP growth largely depends on both the magnitude and the pace at which the financial conditions deteriorate, the forecast results suggest that they have a substantial effect on economic activity. More specifically, under the "no change" scenario, GDP growth is projected to gradually accelerate to 3.4 percent in 2012q4, suggesting that the average 2012 GDP growth will be 2.7 percent, which is consistent with the growth projection of the 2012 budget. If the financial conditions deteriorate and return to the level observed in the second half of 2011, the quarterly GDP growth is projected to remain broadly stable compared to the 2012q1 growth figure (2.1 percent) for the rest for the year, which implies that the average rate for 2012 would decelerate to 2.3 percent compared to 3.1 percent in 2011. The last scenario, which assumes the FCI deteriorates sharply, envisages a sharp deceleration of GDP growth to 1.4 percent in 2012q4, leading to an average rate of 2 percent for 2012. The quarterly pattern of the three scenarios is presented in Table 5.

Table 5. Forecast Results under Three Scenarios

	FCI remains constant	***FCI gradually deteriorates***	***FCI sharply deteriorates***
	GDP growth (yoy)	GDP growth (yoy)	GDP growth (yoy)
2012Q1 (Actual)	2.1	2.1	2.1
2012Q2	2.3	2.3	2.3
2012Q3	2.9	2.4	2.0
2012Q4	3.4	2.4	1.4
2012 growth (average)	**2.7**	**2.3**	**2.0**

VII. CONCLUSION

The paper constructs FCI for South Africa. The analysis extracts the index by applying two alternative approaches, namely, the principal component analysis and Kalman filter), which identify an unobservable common factor from a group of external and domestic financial indicators. We tested the predictive power of the FCI using out-of-sample forecasting and an in-sample exercise. This forecasting exercise compares the performance of both FCIs against the autoregressive model of GDP growth, the SARB's leading indicator, and the predictive capacity of various key financial market variables at one, two, and four quarters ahead.

The results indicate that both the PCA and Kalman filtered FCI performed better as a leading indicators of real activity relative to the SARB's leading indicator, and to an autoregressive model of GDP growth. The PCA-based FCI also outperforms the individual financial indicator that it includes. These findings suggest that joint movements in financial variables effectively contain relevant information regarding future outcomes in real activity. Among the two alternative FCIs, the PCA-based FCI seems to have greater explanatory power over the entire sample, though during the pre-crisis period, the Kalman filter-based FCI seems to have performed better in predicting GDP growth, particularly for one and two quarters ahead.

The dynamics of the FCIs suggest that, following a strong recovery in late-2009 and 2010, the financial conditions have deteriorated in recent months, though not as sharply as in 2008. Because the estimated FCIs were found to have powerful predictive information for the near-term GDP growth (up to four quarters), further deterioration may imply that economic activity is likely to slow in the period ahead.

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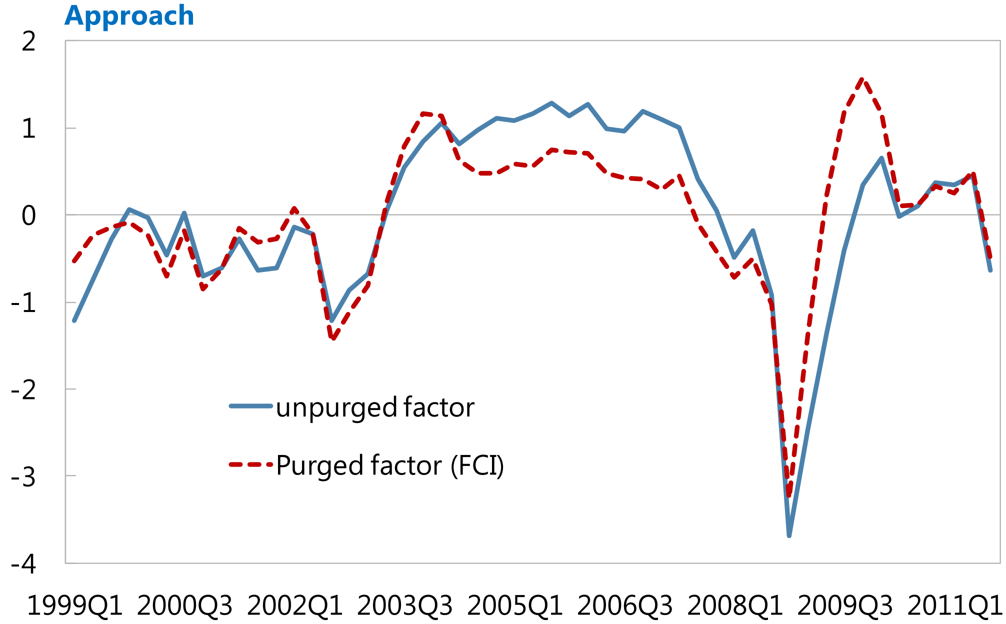
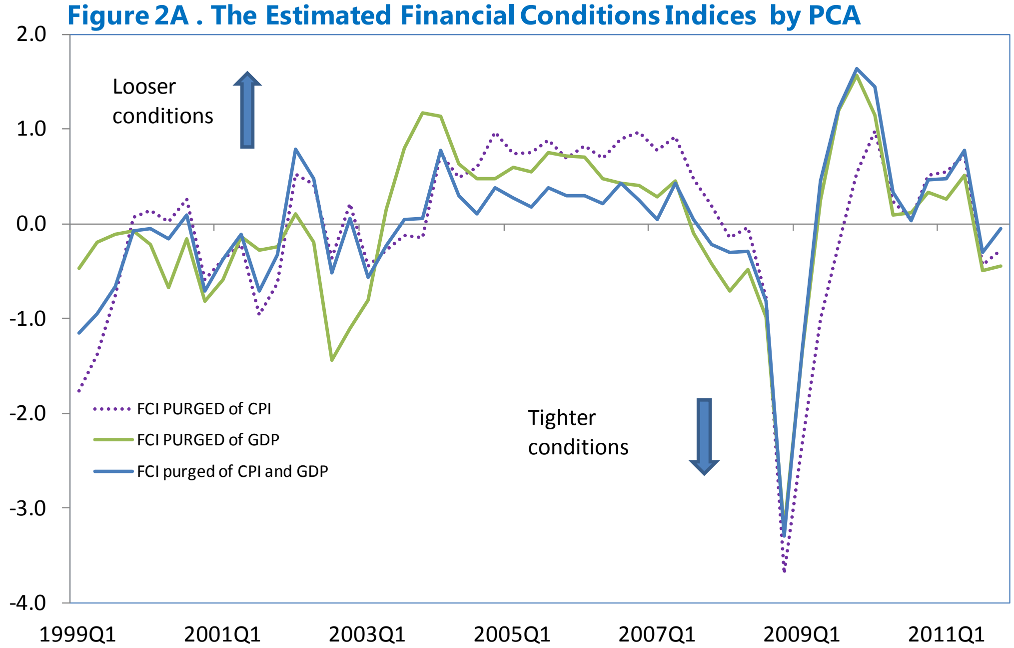
Appendix

Figure 1A. Calculated Common Factors under the Principal Component Approach



Source: Authors' calculations.

Figure 2A . The Estimated Financial Conditions Indices by PCA



Sources: Authors' estimates.

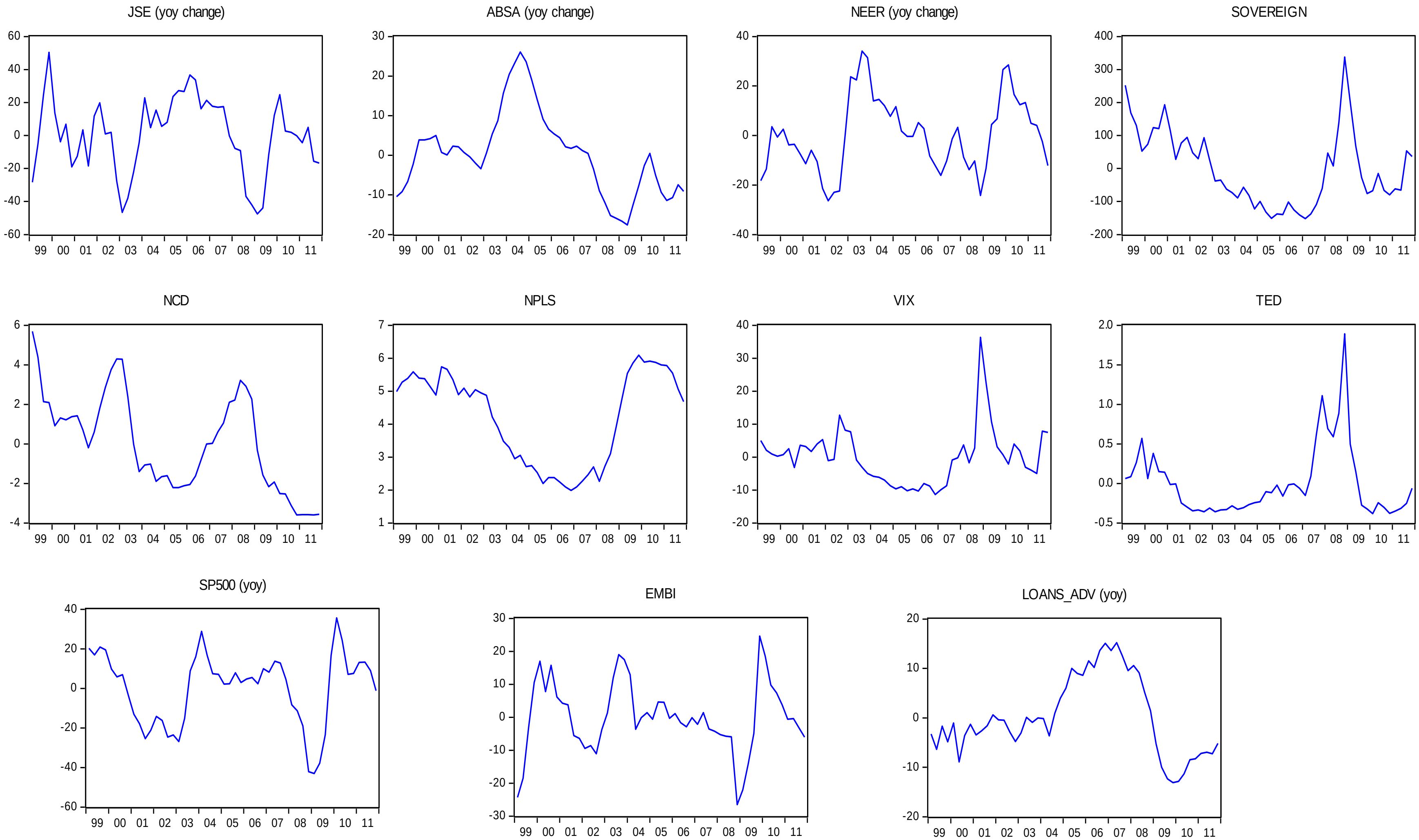
Table 1A. Correlation Matrix

	JSE	*ABSA*	*NEER*	*SOVEREIGN*	*NCD*	*NPLS*	*VIX*	*TED*	*SP500*	*EMBI*	*LOANS_ADV*
JSE	1.000	0.437	0.051	-0.549	-0.312	-0.289	-0.677	-0.213	0.633	0.383	0.339
ABSA	0.437	1.000	0.356	-0.493	-0.192	-0.441	-0.591	-0.398	0.362	0.437	0.304
NEER	0.051	0.356	1.000	-0.490	-0.427	0.079	-0.315	-0.388	0.426	0.701	-0.290
SOVEREIGN	-0.549	-0.493	-0.490	1.000	0.550	0.496	0.794	0.480	-0.429	-0.473	-0.399
NCD	-0.312	-0.192	-0.427	0.550	1.000	0.016	0.338	0.388	-0.315	-0.345	0.141
NPLS	-0.289	-0.441	0.079	0.496	0.016	1.000	0.469	-0.227	-0.103	0.099	-0.913
VIX	-0.677	-0.591	-0.315	0.794	0.338	0.469	1.000	0.479	-0.625	-0.491	-0.437
TED	-0.213	-0.398	-0.388	0.480	0.388	-0.227	0.479	1.000	-0.265	-0.397	0.285
SP500	0.633	0.362	0.426	-0.429	-0.315	-0.103	-0.625	-0.265	1.000	0.526	0.020
EMBI	0.383	0.437	0.701	-0.473	-0.345	0.099	-0.491	-0.397	0.526	1.000	-0.137
LOANS_ADV	0.339	0.304	-0.290	-0.399	0.141	-0.913	-0.437	0.285	0.020	-0.137	1.000

Table 2A. Descriptive Statistics

	JSE	*ABSA*	*NEER*	*SOVEREIGN*	*NCD*	*NPLS*	*VIXL*	*TED*	*SP500*	*EMBI*	*LOANS_ADV*
Mean	0.23	0.27	0.12	0.22	0.07	4.21	0.08	0.00	-0.01	-0.01	0.07
Median	2.36	0.56	-0.35	-31.12	-0.01	4.85	-0.47	-0.14	5.67	-0.50	-1.18
Maximum	50.48	26.07	34.12	337.38	5.69	6.09	36.32	1.89	35.61	24.66	15.19
Minimum	-47.54	-17.58	-26.33	-151.62	-3.60	1.99	-11.39	-0.38	-43.04	-26.56	-13.11
Std. Dev.	22.77	10.54	14.82	115.27	2.44	1.39	8.55	0.44	18.22	10.71	7.88
Skewness	-0.36	0.57	0.36	0.73	0.27	-0.31	1.69	2.06	-0.59	-0.12	0.36
Kurtosis	2.64	3.03	2.59	2.98	2.14	1.48	8.00	8.07	2.69	3.36	2.15
Observations	52	52	52	52	52	52	52	52	52	52	52

Figure 3A. Financial Condition Indicators*



SP500, EMBI, ABSA, NEER, LOANS_ADV, and *JSE* are presented on y-o-y basis, while others are shown at their levels. All variable are demeaned.