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ABSTRACT

This paper investigates the relevance of financial conditions indices (FCIs) as an additional gauge of South Africa's economic metabolism. As a starting point, a background is provided on FCIs in terms of evolution, methodologies and uses. In general, FCIs were found to have a very broad definition, are used for different purposes and can be calculated with different statistical techniques.

The first step in developing an FCI for South Africa was to identify a purpose for it. From the purpose followed the data selection, sourced from regular updated financial data since 2003. The selection was differentiated from other South African FCIs by including commodity prices, as well as BER financial survey data. The final selection of indicators was tested for unit roots. The second process was the calculation of weights, in which case the principle components method was used. However, to avoid revising the historical data of the FCI each new month, a real-time principle component series was constructed. This method implies that the weights are recalculated every month, based on a rolling window of 60 months historical data, starting from 2005 onwards. In the third and final step, the real-time principle component series was purged from the real-time nominal GDP growth rate (capturing both output and inflation).

The purged real-time principle component series was taken as the final FCI. The impact of the global financial crisis and the drastic monetary policy that followed is clearly visible in the FCI. The periodical divergence between the FCI and the real economy also served as an indication on the effectiveness of monetary policy. This FCI was found, over shorter horizons, to lead economic growth by nine months, and it improved on a naive forecast of GDP growth.

Keywords: financial conditions, principle components, factor models, leading indicator, financial survey, business cycle
JEL codes: G19, E39, C10

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1. *Introduction*

Following the financial crisis of 2008, policy makers, academics and market analysts realised the need to improve their understanding and tracking of financial conditions. In this endeavour, the financial conditions index (FCI) has been identified as an indicator with the potential to foresee turning points in the business cycle (Thompson, van Eyden, & Gupta, 2013). FCIs summarise the information about the future state of the economy, contained in a range of current financial variables (Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010). A key feature of FCIs is that they are based on regularly updated financial data (Mayes & Virén, 2001), which enable them to signal important changes without a significant time lag.

The aim of this paper is to develop a real-time FCI of a monthly frequency, and investigate its viability as a leading indicator. Most importantly, an attempt will be made to establish the lead/lag of the link between the financial sector and the real economy. With this in hand, users of the FCI will be able to evaluate current financial conditions and make estimates about future economic growth rates. They will also be able to gauge monetary conditions and form opinions on the appropriateness of historical changes in the policy interest rate (Knedlik, 2005).

The first two sections of this paper provide some background on FCIs and the methodologies to derive them. These methodologies are listed, grouped and compared according to their purpose and calculation method. Among them, principle component (PC) analysis, which was the method of choice in this paper, is discussed in more detail. The PC-approach identifies common factors, known as principle components, which capture the maximum common variation within a group of indicators.

Another goal of this paper is to contribute to the literature on FCIs for South Africa through some key innovations. The third and fourth sections deal with the methodology of choice and these innovations. The first innovation is to include the BER's financial sector survey data in the basket of input variables. Key commodity prices such as gold and platinum are also included due to their importance in the South African economy and sensitivity to international financial sentiment. The second innovation is to provide for some dynamics in the FCI by recalculating the weights of the input variables every month, on a rolling 60-month basis. An additional process incorporated in the methodology was to purge the FCI from growth and inflationary influences. Shortly, this is achieved by regressing the FCI on nominal GDP growth and using the residual series as the final FCI.
The third innovation is to use real-time data when the FCI is purged from nominal GDP, such that the purged FCI will not be subjected to future data revisions.

The last two sections analyse the derived FCI in terms of its ability to explain recent economic history, and its GDP growth forecast ability.

2. *Background to FCIs*

First, to understand the decision to develop an FCI and how it can be used, a short background is provided on the history and uses of FCIs. Also, the different methodologies to calculate them are summarised, together with a list of FCIs which is published regularly. The most comprehensive paper on FCIs is probably *Financial Conditions Indexes: a fresh look after the financial crisis* by Hatzius, Hooper, Mishkin, Schoenholtz and Watson (2010). These authors recorded a detailed history of FCIs, reviewed a substantial collection of literature and identified and categorised types of FCIs and methodologies. For a shorter (yet balanced) background, *Identifying a financial conditions index for South Africa* by Thompson, van Eyden and Gupta (2013) is recommended.

2.1. What is a Financial Conditions Index?

The financial sector is complex, riddled with many indicators, sub-sectors and linkages to the real economy. To simplify the noise from all these indicators, the financial conditions index is a blended mix of different financial indices, summarised into a single index (Paries, Maurin, & Moccero, 2014). In the words of Hatzius et al (2010), *a financial conditions index (FCI) summarizes the information about the future state of the economy contained in these current financial variables*. More technically, an FCI is a weighted sum of various financial indices. It sheds some light on the current condition of the financial sector in terms of tightness or looseness.

2.2. Evolution of the FCI

Early research in the 1980s on financial conditions centred on the slope of the yield curve, and found it to be a reliable predictor of economic activity. The Bank of Canada was the first to calculate a monetary conditions index (MCI) in the early 1990s, to serve as a day-to-day target for the conduct of monetary policy (Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010). The FCI emerged around 2001, before the 2008 financial crisis, from the more commonly used MCI. The initial idea was that an FCI could use high frequency data (monthly) as an early indicator to future changes in inflation and output. At that time FCIs were based on a narrower data set, comprising the interest rate, inflation rate and some asset prices. Later on more financial indicators were included. In 2010, Hatzius et al even included survey data in their FCI for the Unites States. The methodologies to estimate FCIs also expanded over the years; it started with the weighted-sum approach, then the principle-component method, followed by the Kalman filter and lastly the dynamic factor model (DFM) (Thompson, van Eyden, & Gupta, 2013).

2.3. Uses and regular published FCIs

These different data selections and calculation methods were partly the result of different uses that economists intended for their FCIs (Kliesen, Owyang, & Vermann, 2012). From a quick scan of the literature, one finds that FCIs can be used as:

1. a real time indicator to assist in the forecasting of economic output,
2. an operational tool to better understand macro-financial linkages,
3. a comparative method to gauge the relative tightness or looseness of financial conditions,
4. an 'early warning system' to business cycle turning points.

Some FCIs were developed for academic purposes, with the aim to determine their relevance as a financial guage. Others were developed for commercial and practical use. Hatzius et al (2010) listed four corporate published FCIs for the United States:

1. Bloomberg Financial Conditions Index (updated daily, equally weighted sum, ten variables, runs from 1991);
2. Citi Financial Conditions Index (weighted sum, six variables, runs from 1983);
3. Deutsche Bank Financial Conditions Index (principle component, seven variables, runs from 1983);
4. Goldman Sachs Financial Conditions Index (weighted sum, six variables, runs from 1983)

For South Africa, only Quantec publishes an FCI every month, accompanied by its respective report. The South African Reserve Bank (SARB) developed an FCI, but they do not publish a periodical index; they only update it on an ad hoc basis for internal use. Thompson, van Eyden, & Gupta (2013) also developed an FCI for South Africa on a once off basis. See the addendum for a literature summary of some international as well as domesitc FCIs.

3. Methodologies to calculate an FCI

When reviewing the academic literature on FCIs, no consistent methodology was found to construct an FCI. Gumata et al (2012), Hatzius et al (2010) and Thomson et al (2013) came to the same conclusion. Similar findings were made regarding financial stress indices (Raputsoane, 2014). To start off, the authors constructed their FCIs for different purposes. This divergence led them to use different criteria to select input variables, and different statistical methods to combine these variables into a single index. It was concluded that there is no best method to construct an FCI and the scope for new approaches is quite large.

Still, a general process to develop an FCI is identifiable from the literature. The first step is to decide on the purpose of the intended FCI. The second step is to select a number of financial variables related to the purpose in step one. The third step is to identify or to calculate the weights for combining these variables into one index. The final step is to assess the relationship between the FCI and its initial purpose.

3.1. Data selection

After a purpose has been identified for the intended FCI, the next step is to collect a dataset of financial variables that would be suitable. In principle, the number of potential indicators to include is substantial. Hatzius et al (2010) subdivide financial indicators into three functional groups:

1. User cost of capital measures (interest rates, the yield curve, credit risk);
2. Prices that affect household wealth (equity & house prices);
3. Credit channels (liquidity, borrower risk, lender willingness, survey data).

The first two groups are measured in the quantitative way such as interest rates or asset prices. The third group is measured in a non-classical way such as quantity indicators or qualitative surveys. The choice among these groups depends to a great extent on the availability of data, especially with regards to historical length. Table 1 depicts a short summary of typical indicators selected for some FCIs, sorted according to the purpose of the FCI. Hatzius et al (2010) tested many indicator types for their "leading indicator" ability.

Table 1: Data selection by some authors, according to purpose.

Purpose	Indicators used	Authors
Forecasting of economic output and inflation	Volatility Interest spreads Stock prices House prices Inflation Money supply growth Consumer sentiment[2] Financial survey	(Gumata, Klein, & Ndou, 2012) (Mayes & Virén, 2001) (Thompson, van Eyden, & Gupta, 2013) (Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010)
Understand macro-financial linkages	Interest rates Exchange rate Corporate spreads Sovereign spreads Oil price	(Goldman Sachs, 2015)
Looseness of financial conditions	Interest rates Exchange rate Money supply growth Earnings yields Yield spreads	(Knedlik, 2005) (Luus, 2008)
Business cycle turning points	Financial survey Consumer sentiment	(Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010) (Thompson, van Eyden, & Gupta, 2013)

Another factor in the choice of data is the frequency. Typically, when the purpose of an FCI is to be a high frequency (daily or weekly) indicator, the underlying data would be from the first two functional

[2] There is some doubt if consumer sentiment truly classifies as a financial indicator.

groups. Monthly and quarterly data can be incorporated in high frequency FCIs, but this will then influence the statistical method (such as using the Kalman-filter).

3.2. Statistical methods

At the same time that the data variables are selected, the appropriate statistical method should be identified. The two processes influence each other. For an unbalanced dataset (with sporadic gaps), some researchers used the Kalman filter. The aim of a real-time FCI can be accomplished by the DFM (Matheson, 2012) or recursive estimation (Thompson, van Eyden, & Gupta, 2013). Most FCIs use the weighted sum method to determine their respective weights, including three of the four corporate indices listed above, as well as that of Quantec. This is followed by the principle component method, which is more favoured with academic FCIs. The main options available to derive the weights can thus be listed in order of use:

1. A weighted sum (such as regression coefficients);
2. Principle component (PC) and factor analysis;
3. The Kalman filter;
4. The Dynamic Factor Model (DFM).

More exotic statistical techniques have been compared with factor analysis, such as impulse response functions and an IS-Curve-based model by Gauthier et al (2003). They favoured the IS-Curve-based model. Gumata et al (2012) compared the PC analysis with the Kalman filter, and found the PC to forecast real economic growth more accurately. In a similar way, Thomson et al (2013) found the PC approach to track recessions better than a simple average FCI. Table 2 below presents a summary of some calculation methods used for different FCIs, according to their purpose.

Table 2: Calculation method used by some authors, according to purpose

Purpose	Calculation method	Authors
Forecasting of economic output and inflation	Regression Impulse response functions Principle component	(Mayes & Virén, 2001) (Gauthier, Graham, & Liu, 2003) (Gumata, Klein, & Ndou, 2012)
Provide for lags and data gaps	Kalman filter Unbalanced techniques	(Gumata, Klein, & Ndou, 2012) (Thompson, van Eyden, & Gupta, 2013) (Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010)
Understand macro-financial linkages	Purge effects of output and inflation	(Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010) (Thompson, van Eyden, & Gupta, 2013)
Looseness of financial conditions	Regression	(Luus, 2008) (Knedlik, 2005)

Purpose	Calculation method	Authors
Business cycle turning points	Principle component Purge effects of output and inflation	(Hatzius, Hooper, Mishkin, Schoenholtz, & Watson, 2010) (Thompson, van Eyden, & Gupta, 2013)
Provide for dynamic weights	Recursive estimation Kalman filter	(Thompson, van Eyden, & Gupta, 2013) (Gumata, Klein, & Ndou, 2012)

An additional step in the statistical calculation process was added by some authors, specifically to isolate pure financial shocks. They regressed economic output and inflation on their initial PCs. Their aim is to strip away any endogenous feedback from the real economy to the financial sector, in order to isolate the effect of only the financial sector. This process is known as purging the FCI from the real economy. Thompson et al (2013) found their purged FCI to be a better forecaster of industrial production growth, interest rates and inflation. However, according to Hatzius et al (2010), their purged FCI was a better leading indicator only in the latter years.

At first glance it might be questionable to use a GDP-purged FCI as a leading indicator to forecast GDP growth. However, the lag-lead difference between the purged GDP and forecasted GDP should avoid this potential problem. In laymen's terms, by purging current GDP movements from the FCI, only current financial movements are isolated, and only they are used to forecast future GDP growth. In this way future GDP is not regressed on its own past, but only on past financial conditions.

4. The methodology

As mentioned above, the first step in the process of developing an FCI is to identify its purpose. To start off, the main intention is to use this FCI for economic now-casting and forecasting. In the case of now-casting, it was observed that no South African FCI incorporated the BER's quarterly financial survey data, and this presented an opportunity. Another observation regarding other FCIs is their frequent use of 'the latest' (most recent) macro-economic time series data. The implication is that they would be prone to change whenever macro-economic data are revised (as often happens). This problem can be addressed by using real-time (first vintage) macro-economic data. With these ideas in mind, this paper set the purpose of its FCI to:

1. evaluate macro-financial linkages,
2. be used as a leading indicator in order to forecast economic growth,
3. incorporate indicators from the BER's quarterly financial survey and
4. be free from data revisions.

4.1. Data selection

Given the purpose set out above, the usefulness of the BER's financial survey data can be established in terms of its impact on the real economy. Financial survey data have not yet been used for any South African FCI. Besides the inclusion of survey data, one would like to capture a wide array of possible financial events that might influence the real economy. Thus, in the spirit of Thompson et al (2013), it was decided to include a whole spectrum of financial data. For the purpose of forecasting, some categories of financial data were identified from Table 1 above. These include yield curves, exchange rates, asset prices (equities and property), volatilities and interest rates (long & short term). To identify business cycles, some indicators from the BER's financial survey were included, and for the macro-financial linkages, some key commodity prices.

One important criterion when selecting an indicator is an extensive time series history. Longer time series allow for a longer window to test and evaluate the significance of the FCI. However, this could be a challenge, as remarked by Hatzius at al (2010). Another is statistical significance; when two indicators are very similar it could lead to statistical problems to determine the weights, such as serial correlation. Hatzius et al (2012) excluded indicators that overlapped in this way. Also, the dataset needs to be parsimonious enough so as to restrict the FCI to one principal component (Thomson et al, 2013).

Initially 41 indicators[3] were selected, most with a monthly frequency which starts in 2000, although some start only in 2002 or 2003. They cover all the categories mentioned above, and more (see Table 3 below). Note that some commodity prices were also included, namely that of oil, gold and platinum (similar to the Goldman Sachs FCI (2015) which includes the oil price). The reason is that commodity production constitutes a major portion of the South African economy, and therefore has a significant impact on the domestic financial sector. Internationally, gold is considered a safe haven asset and therefore its price reacts to the sentiment of financial markets.

Also note that the financial survey data is of a quarterly frequency, while all the other data are used in a monthly frequency. For this reason the quarterly values were applied to each of the current and consecutive two months in order to obtain a monthly series. In the end, the survey data proved to carry a higher weight in the FCI than any of the other data series. The indicators listed below were inspected for unit roots; those indicators in level and volume format were converted into yearly growth rates[4] (12-

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[3] Please note that data from the National Credit Regulator were not included, since the series only started in 2007, which was too short for the intended rolling calculation.

[4] Thompson et al (2013) used month-on-month growth rates. This paper used year-on-year growth rates for the sake of consistency with interest rates which are expressed as yearly rates. It is similar to the FCI developed by

month log difference). Further, none of the indicators were seasonally adjusted as in the case of Thompson et al (2013), specifically to avoid filtering and smoothing out any potential variance. This will also keep the index strictly real-time, thus avoiding the risk of future data revisions. However, researchers still have the option to adjust the final FCI for seasonal factors if desired.

Table 3: Initial indicators selected to build an FCI

Nr	Type	Indicator	Data format	Start	Correl'n	t-Stat[5]	P-Val
1	Flow	Non-resident transactions - Total net purchases of shares and bonds	Level	2000-M1	17%	-6.03	0.0%
2		National government financing of net borrowing requirement	Level	2000-M1	-22%	-2.33	2.0%
3	Monetary	Monetary aggregates - M3	3-month log difference	2000-M4	63%	-3.53	0.0%
4		Private sector credit extension	12-month log difference	2001-M1	66%	-1.88	5.8%
5		Bank and Mutual Banks - Total assets	12-month log difference	2001-M1	37%	-2.11	3.3%
6		Credit impairments in respect of loans and advances	12-month log difference	2001-M1	-57%	-2.62	0.9%
7	Fin market	Number of shares traded	12-month log difference	2001-M1	32%	-3.52	0.1%
8		Value of shares traded	12-month log difference	2001-M1	76%	-3.61	0.0%
9		Value of bonds traded	12-month log difference	2001-M1	22%	-3.10	0.2%
10		Futures - Open interest	12-month log difference	2001-M1	82%	-2.84	0.5%
11	Asset prices	Absa house price index	12-month log difference	2001-M1	78%	-1.86	6.1%
12		JSE Alsi	12-month log difference	2001-M1	81%	-2.93	0.4%
13		JSE Financials	12-month log difference	2001-M1	65%	-2.69	0.7%
14		S&P500	12-month log difference	2001-M1	50%	-3.86	0.0%
15	Commodities	Gold price in R	12-month log difference	2001-M1	1%	-2.59	1.0%
16		Gold price	12-month log difference	2001-M1	32%	-2.44	1.5%
17		Platinum price	12-month log difference	2001-M1	61%	-4.50	0.0%
18		Brent oil price	12-month log difference	2001-M1	57%	-4.44	0.0%
19	Exchange rates	Nominal effective exchange rate	12-month log difference	2001-M1	17%	-3.09	0.2%
20		R/$	12-month log difference	2001-M1	-32%	-3.07	0.2%
21		$/€	12-month log difference	2001-M1	47%	-3.68	0.0%
22	Interest rates	Prime interest rate	Percentage	2000-M1	13%	-2.20	2.7%
23		Treasury bill 3M	Percentage	2000-M1	15%	-2.22	2.6%
24		Gov bond, SA, 10 year	Percentage	2000-M1	5%	-2.94	0.3%
25		US Treasury bill rate -3M	Percentage	2000-M0	83%	-2.31	2.1%
26		Gov bond, US, 10 year	Percentage	2000-M1	72%	-1.88	5.7%
27		India bond index	Percentage	2000-M1	-20%	-2.58	1.0%
28	Interest spreads	Spread Prime & Treasury bill	Percentage	2000-M1	2%	-2.05	3.9%
29		Spread Gov bond & Treasury bill	Percentage	2000-M1	-15%	-3.19	0.2%
30		Spread SA & US PRIME	Percentage	2000-M1	-57%	-2.71	0.7%
31		Spread SA & US Gov bonds	Percentage	2000-M1	-74%	-1.89	5.7%
32		Spread SA & IN Gov bonds	Percentage	2000-M1	16%	-1.65	9.4%
33	Volatilities	Chicago volatility index	Index	2000-M1	-64%	-3.19	0.2%
34		Gov bond volatility	Squared 12m-log difference	2001-M1	0%	-3.18	0.2%
35		House price volatility	Squared 12m-log difference	2001-M1	60%	-1.88	5.7%
36		JSE Alsi volatility	Squared 12m-log difference	2001-M1	29%	-3.60	0.0%
37	Survey	EY-Financial Services Index: Business confidence	Percentage	2003-M9	94%	-2.02	4.2%

the South African Reserve Bank. However, a quarterly growth rate was used for the M3 to solve its unit root problem.

[5] Augmented Dickey-Fuller unit root test results (no trend, no intercept, lags <= 5)

Nr	Type	Indicator	Data format	Start	Correl'n	t-Stat[5]	P-Val
38		Life Insurance: Business Confidence	Percentage	2002-M3	69%	-2.58	1.0%
39		Asset Management: Business confidence	Percentage	2002-M3	81%	-3.25	0.1%
40		Merchant & Investment Banking: Business confidence	Percentage	2003-M3	76%	-2.51	1.2%
41		Retail Banking: Business confidence	Percentage	2002-M3	81%	-2.00	4.4%

Source: DataStream and Quantec

Lastly, in order to have only one significant principle component (Thompson et al, 2013), it was decided to be parsimonious and reduce the dataset above. The final set contains only those indicators which proved to have a relatively significant influence on the FCI. To do this, indicators were excluded which correlated[6] less than 50% with the first principle component series (see the section on methodology) over the whole normalised sample. (Please note that different cut-off values can be chosen, depending on the number of input indicators desired). To exclude some indicators from their FCI, Hatzius et al (2010) only provided the argument that there is *"a fair amount of overlap of very similar but not identical variables"*. Thus, the shaded series in Table 3 above were excluded from the FCI input selection. This left 22 indicators from an original collection of 41. See Figure 7 in the addendum for a graphical comparison between the first principle component series for both selections. There is a 98% correlation between them, thereby confirming that the excluded indicators contributed insignificantly.

4.2. Econometric methodology

The basic approach to an FCI is to blend all the selected indicators into a single time series indicator. This blending is accomplished by allocating weights to each input indicator and then to calculate a weighted average. Different methodologies are used to determine these weights; they have been discussed in the previous section. The literature indicates that principle component (PC) analysis is perhaps one of the favourite methods to do so. However, there are some concerns that these weights might not be dynamic (Gumata, Klein, & Ndou, 2012). To address this issue, the Kalman-filter is sometimes used as an alternative, although this was not found to be as good a predictor of recessions as the PC-method.

In short, the PC-approach identifies common factors, known as principle components, which capture the maximum common variation within a group of indicators. Each PC is calculated as a linear combination of the group of indicators, using a vector of weights. PC-analysis results in a matrix of weights, where each column vector of the matrix represents the weights of different PCs. The first

[6] In the special case where all the input indicators are normalised, their correlations with the common factor (FCI) is the same as their respective weights

column vector captures the most variation in the system, and its PC is then used as an FCI. See the appendix for the mathematical notation.

In the selection of all 41 indicators, the first PC captured only 29% of the variation among them (calculated over a sample from September 2003 to April 2015). In the reduced case of 22 indicators, the first PC captured 51% of the variation among them. The respective weights of the first three principle components are presented in Table 4 below, along with the proportion of the variation all 22 PCs capture.

Table 4: Weights of the PCs and proportion of the variance they capture

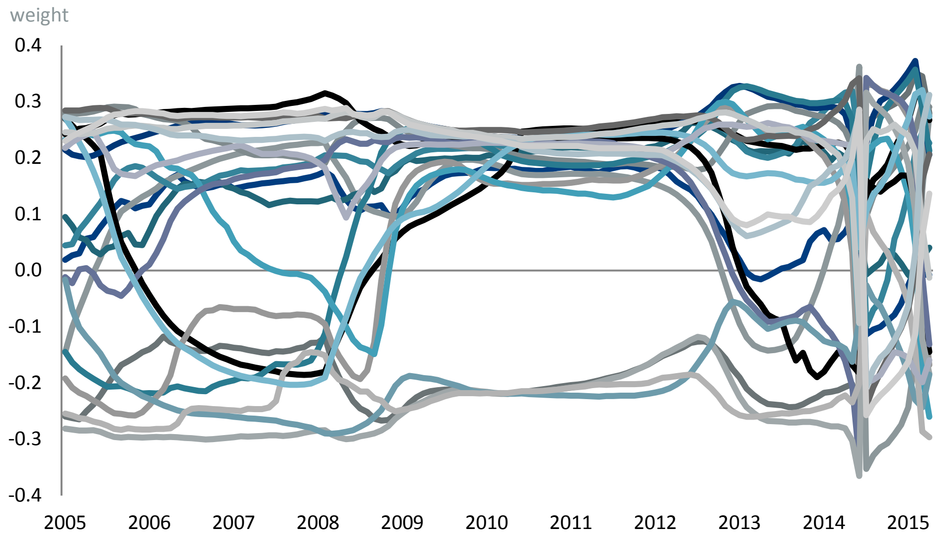
Weights:	PC 1	PC 2	PC 3	Factors	Proportion
M3	0.18	0.25	0.00	PC1	51.5%
CREDIT_EXT	0.18	0.38	-0.07	PC2	14.9%
IMPAIR	-0.19	0.25	0.32	PC3	8.1%
SHARES_VL	0.22	0.04	0.08	PC4	6.7%
OPEN_INT	0.24	0.09	0.02	PC5	4.1%
HOUSE_PR	0.23	0.01	0.11	PC6	2.9%
JSE_ALSI	0.26	-0.22	0.03	PC7	2.4%
JSE_FIN	0.22	-0.29	-0.22	PC8	2.0%
SP500	0.17	-0.41	0.08	PC9	1.6%
PLAT	0.17	-0.15	0.50	PC10	1.5%
OIL	0.17	-0.16	0.48	PC11	1.2%
TB_US	0.24	0.27	-0.08	PC12	0.9%
GB_US	0.19	0.24	0.21	PC13	0.6%
TB_SA_US	-0.20	0.23	0.39	PC14	0.5%
GB_SA_US	-0.22	-0.18	0.24	PC15	0.4%
VIX	-0.21	0.25	0.13	PC16	0.3%
HOUSE_VOL	0.17	0.03	0.10	PC17	0.2%
CONF_FIN	0.28	0.11	-0.01	PC18	0.1%
CONF_INS	0.21	-0.09	0.00	PC19	0.1%
CONF_MAN	0.24	-0.06	0.19	PC20	0.1%
CONF_MERC	0.23	0.17	-0.08	PC21	0.0%
CONF_RETAIL	0.23	0.21	-0.09	PC22	0.0%

Source: Van der Wath

To provide for some dynamic changes in the weights over time, a moving PC was calculated every month, based on the data of the previous 60 months. In this way the weights are adjusted by small amounts every month and in the long run reflect the dynamic changes which might have happened in the financial economy. This method allows for the reconstruction of a real-time PC, month by month, starting in January 2005. (See the addendum for the Eviews code and a graphical comparison in Figure 8). Thomson et al (2013) did something similar; they calculated a recursive FCI by estimating a PC from the first month to the last, every new month.

Figure 1 below shows that in general the magnitude and sign of the respective weights do not change by significant amounts from one month to the next. Rather, they tend to change gradually over the medium term reflecting how volatility shifts over time between the different dimensions of the financial sector. However, there is one month, June 2014, when many of the weights changed suddenly and dramatically. This shock is caused as the tail of the 60-month rolling window drags through the recovery spike of the international financial crisis in July 2009. It might have implications for the robustness of any forecasts based on these results around that time.

Figure 1: Weights of the 22 indicators changing over time



Source: Van der Wath

Lastly, various authors purged their common factors (initial PCs) from the influence of the real economy and inflation, specifically to isolate pure financial shocks. They did this by regressing their initial PCs with GDP-growth and inflation, then using the residual series as their final FCIs. In this case a similar route was followed, but using the real-time[7] nominal GDP instead (which includes the effects of inflation), lagged by four months[8]. The advantage of real-time data is that it is free from revisions, and would thus result in an FCI that will be original and final. For a graphical comparison between the real-time PC and the purged FCI, see Figure 9 in the appendix.

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[7] The first vintage of GDP growth, i.e. a series built-up of all the first values published for GDP growth, thus making it free from any data revisions. The BER constructed such a series and keeps it up to date. In the purging regression, the GDP growth was lagged by four months, since it is published a quarter behind. The regression was repeated every month for a newly calculated PC of the last 60 months, of which the residual for the latest month was then recorded to build up the real-time FCI.

[8] GDP data is published in the 2nd month of the current quarter, for the previous quarter, adding up to 4 months.

Also note that since the current FCI is purged from *nominal* GDP lagged by 4 months, it can be used as a leading indicator for current or future *real* GDP movements. There is no risk that the FCI is regressed on GDP, and the residual series is then used to forecast the very same GDP. In fact, this is done specifically to avoid any GDP forecasts based on the FCI being regressed on past GDP influences.

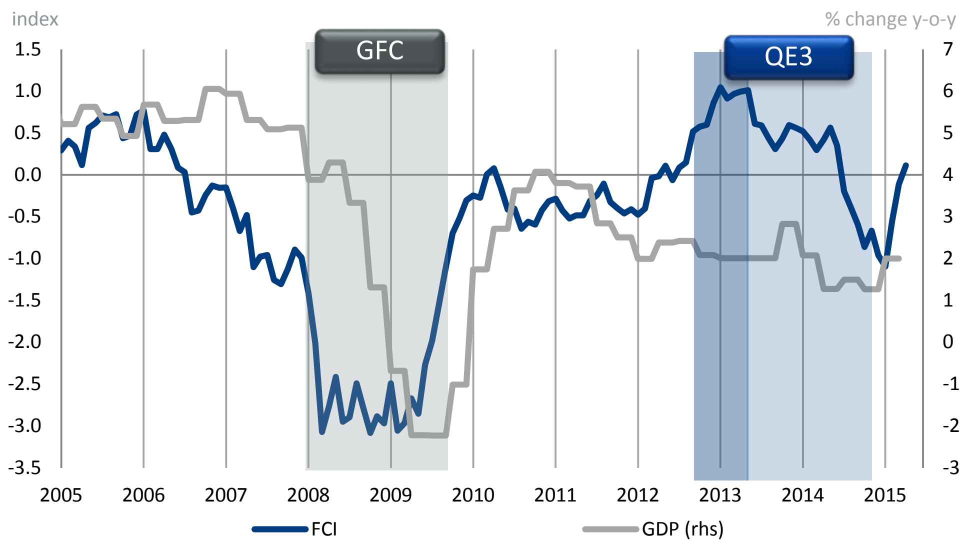
4.3. Forecast evaluation: critique on non-recursive FCIs

When a forecast is done in reality, from a latest data point onwards, that forecast will be out-of-sample. It should not be based on any historical information beyond the latest data point. For this reason, to evaluate the performance of a model, a time series of its historical forecasts needs to be built up in a recursive way. If not, such as when present FCI-weights are used to simulate past forecasts, future information will leak into its past, and the forecast will become in-sample. This leakage would improve the forecast artificially, and create a false sense of accuracy. It is therefore imperative to use real-time FCIs when forecast models are based on them.

5. The FCI

By following the methodology described above, a real-time FCI for South Africa was calculated at a monthly frequency. This FCI starts at January 2005 and, in this paper, has been calculated up to April 2015. A graph of this FCI is presented below, along with real annual GDP growth:

Figure 2: Real time FCI for South Africa, along with annual GDP growth



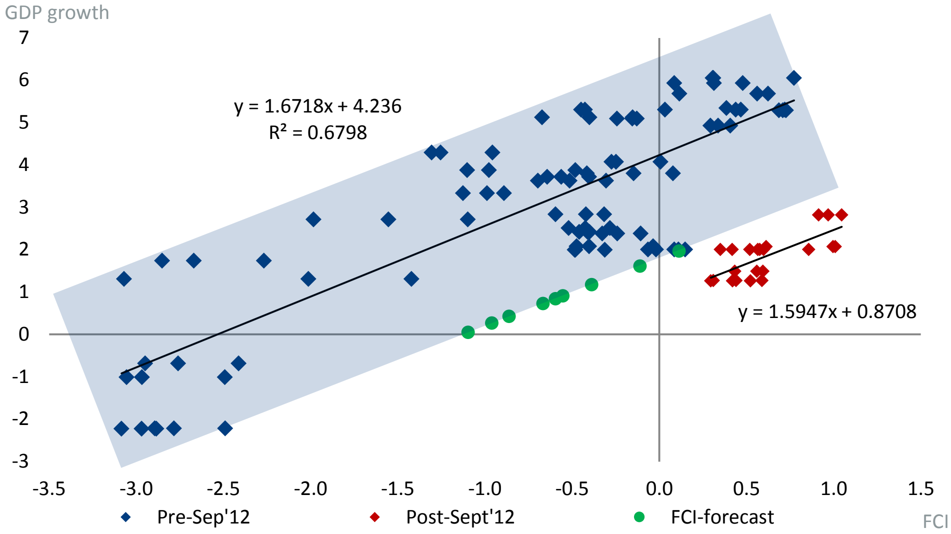
Source: Van der Wath

6. Explaining the real economy from 2005 to 2015

As mentioned in the introduction, one of the potential purposes of FCIs is to serve as a gauge of the real economy. In Figure 2 above it seems that the FCI is to some extent a crude leading indicator of the real economy; it leads real GDP growth by between 6 and 18 months. The FCI pre-empted the global financial crisis (GFC), falling below the neutral 0-line for the first time in the middle of 2006. A dip in real GDP growth only followed 18 months later. A sharp fall in the FCI at the beginning of 2008 was followed by GDP growth plummeting nine months later. The recovery in the FCI also pre-empted the recovery in GDP growth by approximately six months. However, since 2012 the FCI and GDP started to diverge. This divergence intensified during the third wave of asset purchases (QE3[9]) by the Federal Reserve in Washington. It resulted in a gap between the FCI and GDP; in econometric terms – a structural break or change.

Since September 2012, the advent of QE3, it seems that drastic loose monetary policy was not very effective and did not lead to real economic growth as happened in the case of QE1 in 2009. Instead, it only seems to have inflated asset prices. This observation implies that FCIs can perhaps also serve as a gauge of the effectiveness and appropriateness of monetary policies, especially if the policies are very drastic. An XY-plot is a practical tool to present the relationship between the FCI and GDP.

Figure 3: XY-plot of the FCI vs. 9-month lagged GDP growth



Source: Van der Wath

The slope of the fitted trend-line above indicates that for every index point that the FCI *(x)* decreases, annual economic growth *(y)* tends to decline by 1.67 percentage points (% pts) nine months later. The SARB also found positive coefficients in a regression between GDP and their FCIs (Gumata, Klein, &

[9] QE3 was announced on 13 September 2012 and encapsuled bond purchases of $40 billion per month. Purchases were increased to $85 billion per month on 12 December 2012. On 9 June 2013 the tapering of QE3 was announced, but only started in full from February 2014. Purchases were halted on 29 October 2014 after accumulating $4.5 trillion in assets.

Ndou, 2012). The R^2 of 0.68 indicates that financial conditions are indeed correlated with real economic output three quarters later. The period since September 2012 is depicted in red; clearly it lies outside the previous relationship of GDP growth and the FCI in the blue-shaded area. Note that the slopes of the red and blue lines are very close, only their intercepts differ by 3.36. It indicates that since September 2012, future economic growth associated with any specific level of current financial conditions is now 3.4% lower than before.

With the FCI known up to April 2015, a GDP growth forecast can be made up to January 2016 (see green series in Figure 3 above). Note that it is not yet clear if the structural change is still applicable, therefore an add-factor of -2.1 will place the forecast on the border between the blue and red regressions. The FCI predicts year-on-year economic growth of 1.3% in the second quarter of 2015, 0.5% in the third quarter and 0.9% in the fourth quarter. From these, annual economic growth is then predicted to be 1.1% in 2015.

7. Forecast performance

In order to measure the value added by an FCI to a GDP growth forecast, the accuracy of such a forecast will be compared with a naive[10] forecast (Van der Wath, 2013). One method to determine forecast accuracy is to estimate the RMSE (root of the mean squared error) of a forecast (Krainz, 2011). The RMSE measures the average size of the error in a forecast, and therefore a smaller RMSE is preferred. A real-time AR-forecast was calculated of real-time GDP growth from January 2010 to March 2015. In this regression equation, real-time GDP growth is regressed on itself 13 months[11] in the past (AR13). In a second regression equation, the FCI of 9 months in the past was included as an external variable to test if it will improve the naive forecast. As an additional control, a third equation was estimated, based on the All share index (Alsi) of the JSE as exogenous variable, instead of the FCI. This regression was to test if another financial indicator could improve on the FCI as leading indicator.
IMPORTANTLY: all three of these forecast series were compiled from rolling regressions, such that real time forecast series could be used for comparison.

To deal with the structural change discussed above, the sample size of these rolling regressions was reduced from 60 observations (5 years) to 30 observations. Shorter sample sizes allow for more flexible regression coefficients, thus more adaptability around structural changes. Finally, the RMSEs for these

[10] A pure auto regressive (AR) forecast

[11] 13 months were used instead of 9, since GDP is published by a lag of 4 months, and the FCI is leading by another 9 months.

three forecasts were calculated, as well as that of the BER's quarterly macro-economic forecast for three quarters ahead. The results are presented in the table below:

Table 5: RMSEs of the different 9-month-ahead forecasts at different sample sizes

RMSE	60 Obs	30 Obs
AR(13)	1.01	1.74
AR(13) FCI(-9)	1.34	**0.72**
AR(13) ALSI(-9)	1.09	1.06
BER	0.88	

Source: Van der Wath

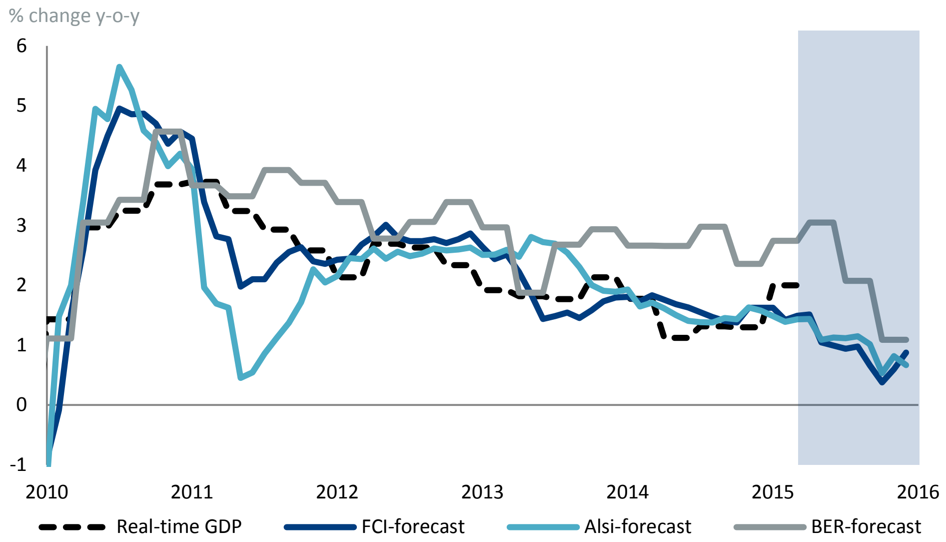
In the case where the rolling regressions were based on 60 observations, the RMSE of the naive forecast was the smallest among the three models, indicating it was more accurate than the others. However, it did not perform better than the BER's quarterly model forecast. This result indicates that over a 5-year sample, the FCI did not contribute to forecasting annual economic growth.

However, in the case where the rolling regressions were based on only 30 observations, the rankings changed considerably. Now the FCI-forecast has the smallest RMSE by far; it is 102 basis points below the naive forecast. It roughly indicates that the FCI-forecast for 9 months ahead will miss the actual growth rate (first vintage) by 0.72 percentage points (% pts). This forecast is 0.34% pts closer to the actual growth rate than the Alsi-forecast, and 0.16% pts closer than that of the BER. It can thus be concluded that, in the case of the 30 observation sample, this FCI does indeed contribute to forecasting GDP growth more accurately.

The large difference in accuracy of the FCI-forecasts between the two sample sizes might present an opportunity to identify the presence of structural changes. Differently asked, do FCI-forecasts, which differ significantly between a short and long regression sample, perhaps imply that monetary policy is ineffective in its impact on the real economy? The example above does not prove anything conclusively in this regard, but triggers the question that might be answered by some future research paper. Another hypothesis from this observation, for later testing, is that the structural relationship between the financial sector and the real economy is fluid in the medium to long term.

A comparison is presented in Figure 4 below of the three different 9-month-ahead forecasts and real-time GDP growth. The FCI- and Alsi-forecasts are based on a regression sample size of 30 observations. No conclusion can be made on the ability of turning points in the business cycle, since the window of evaluation is too short. Going forward, the FCI-model forecasted that annual economic growth will decline from 2.0% registered in the first quarter of 2015, to only 0.6% in the fourth quarter. The Alsi-forecast was very similar, expecting a growth rate of 0.7% in the fourth quarter. The BER seems the most optimistic regarding three quarters ahead; they forecasted 1.1% growth for the same period.

Figure 4: Comparison between different 9-month-ahead forecasts and actual GDP growth



Source: BER

Finally, this result points out that the FCI developed above can be used as a gauge of economic growth over a short horizon rather than a long horizon. Thus, its last 30 months of history can be used to forecast future GDP growth. Using more historic data, without providing for structural changes, could compromise the forecast. Knowing in advance when the structural changes will start and end is a challenge, and therefore a risk.

8. Conclusion

In conclusion, it was found that FCIs are still in a process of evolution. Different methods are used to derive them, based on different data selections and different uses. Some existing FCIs have been discussed, both for South Africa and other economies. They are mostly used as indicators of financial conditions, linking through to the real economy.

In this paper an FCI of a monthly frequency was developed, which includes some of the BER's survey data, and is purged of real-time nominal economic growth. The recalculation of the weights every month also lends a dynamic property to this FCI. Some of these properties differentiate it from other FCIs.

From the FCI developed here, it can be visually seen that the international financial crisis had a profound impact on financial conditions in South Africa. Besides the recovery from the financial crisis, financial conditions improved considerably since 2012, the year in which the QE3 programme of the Federal Reserve in Washington was initiated. Still, a positive spillover into the real economy remained absent.

Of interest is the structural change in the relationship between this FCI and economic growth since 2012. It is perhaps an important indication that drastic monetary policy does not always influence the real economy later on. This property might make the FCI useful as an indicator of the effectiveness of monetary policy. These hypotheses provide an opportunity for further future research.

Regardless of the structural changes, on shorter analysis horizons the linkage between the FCI and the real economy intensifies. In the case of the 30-month regression sample, this FCI was found to be a much better predictor of economic growth than a naive forecast.

APPENDIX

9. Factor models

The factor model aims to extract from a table of variables, X_t, a similar sized table of variables, F_t, which captures the variation of the original set. The columns of F_t are called common factors, and the mean of each column is 0. In principle components analysis, the first column of F_t captures most of the variance. Each column of F_t is a weighted average of the columns of the original table X_t. The weights can be written in a smaller table of their own, called the coefficient matrix β. We can write the mathematical formula as follows:

$$X_t - \mu = \beta F_t - U_t$$

where μ is a vector (column) of the means of the variables in X_t, and U_t is a matrix (table) of residuals (error values). In the special case where all the variables in X_t are normalised, their coefficient weights in β is the same as their correlations with F_t.

10. International examples from the literature

10.1. Mayes & Virén (2001)

Mayes and Virén use panel datasets for the European Union countries to explore how stock and house prices can provide indicators of future changes in output and inflation. The authors distinguished between two methodologies to derive an FCI. The first is an atheoretical regression estimation (Stock & Watson, 2001), where financial variables are included in an explanatory equation of output, regardless of theory. The second is a theory based estimation, which they did. They used panel data regression to etimate an IS-equation (with lagged exogenous variables) to explain the output gap. They found that house prices are a good predictor, but stock prices are not. In general, their article is unclear on the meothodology, and hard to understand.

10.2. Gauthier, Graham and Liu (2003)

These authors constructed several FCIs for Canada based on three approaches: an IS-Curve-based model, generalised impulse response functions and factor analysis. Each approach was intended to address one or more criticisms applied to MCIs and existing FCIs. They evaluated their various FCIs based on their weights, dynamic correlation with output and inflation, their in-sample fit in explaining output and their out-of-sample forecast performance. Based on the IS-Curve method with monthly data, they found that housing prices, equity prices and bond yield risk premia are significant in explaining output from 1981 to 2000. In addition to these, short- and long-term interest rates and the exchange rate were found to also be significant. In both the HP-filter and first difference specifications, housing prices have a higher absolute-value coefficient than that of the exchange rate. Finally, they found that the FCI outperformed the MCI in many criteria considered in this paper.

10.3. Hatzius, Hooper, Mishkin, Schoenholtz and Watson (2010)

Hatzius et al explored the link between financial conditions and economic activity. They built a quarterly FCI for the US that features three key innovations: first, it includes a broad range of quantitative and survey-based indicators (45). Second, they used unbalanced panel estimation techniques, which resulted in a longer time series (back to 1970) than available for other indices. Third, they purged their measures of endogenous movements related to the business cycle. The authors used principle components to estimate the weights, and compared its forecasting capability with that of an AR-model as benchmark (by comparing relative RMSEs[12]). They found their FCI to show a tighter link with future economic activity than existing indexes. In addition, the authors presented a useful history on FCIs. Generally this article is thorough, practical and useful.

10.4. Matheson (2012)

This author developed an FCI for the United States as well as the Eurozone (EZ). He took his methodology one step further than the papers presented above by using a dynamic factor model (DFM). This methodology estimated both a principle component and then used a Kalman filter to model the dynamic effects. The author converted all series to monthly frequency, made sure they were all stationary and standardised them. His sample ran from 1994 to 2011. To compare the forecasting capability of his FCIs, he made some real time forecasts using vector auto regressions (VARs) including the FCIs and excluding the FCIs. The cases when he included the FCIs had a significantly smaller RMSE for both the US and EZ, indicating that the FCIs do have forecasting capabilities. He also estimated cross-region FCIs for both the US and EZ, and found them to have significant value.

11. South African examples from the literature

11.1. Tobias Knedlik (2005)

Tobias Knedlik developed a monetary conditions index (MCI) for South Africa. He followed the methodology of Korhonen to estimate the relative weights of interest and exchange rates in the MCI. This methodology uses least squares to determine an equation with interest and exchange rate indicators as independent variables and the output gap as dependent variable. The equation he regressed for 1994 to 2003 was:

$$y_{gt} = \beta_0 + \beta_1 y_{gt-1} + \sum \beta_{2i}\Delta r_{t-i} + \sum \beta_{3i}\Delta e_{t-i} + u_t$$

with the following quarterly data used:

1. Y_g – Output gap, the difference between the log of GDP and potential GDP (smoothing the log of GDP data by the Hodrick-Prescott filter with *parameter = 1600).*

---

[12] RMSE: root mean squared error

2. *r* – Real interest rate, the difference between the real 6-month money market rate and its smoothed version (by Hodrick-Prescott filter).
3. *e* – Real exchange rate, the difference between the log of the SARB's real exchange rate and its smoothed version (by Hodrick-Prescott filter).

He then summed the coefficients of all the lags for *r* and *e* respectively, and from this calculated the relative ratio (1.9:1).

To calculate an MCI, he followed these steps:

1. He chose a base period to serve as a reference point when monetary conditions were in equilibrium (not too loose or too tight).
2. He then calculated the deviations in the interest and exchange rates from the base period.
3. Finally, he summed these deviations for each period according to the weight ratio of 1.9:1 to obtain an MCI for South Africa.

Knedlik concluded that an MCI for South Africa can be regarded as economically meaningful, and should be part of the analysing tools of the monetary authorities as well as of public observers.

11.2. Thompson, Van Eyden and Gupta (2013)

Perhaps the most technical and detailed article on FCIs for South Africa is the one written by Thompson, Van Eyden and Gupta in 2013. The authors did a thorough literature study on FCIs developed in other regions of the world, and identified some gaps in those developed for South Africa. One of their aims was also to evaluate whether the resulting FCI can act as an 'early warning system' to business cycle turning points. Their study claims to add value to the literature of FCIs on three grounds:

1. They used more than three decades of monthly data (1966 – 2012).
2. Their FCI comprises a wider coverage of financial variables than others.
3. They make use of recursive estimation techniques, allowing them to account for parameter instability.

Thompson et al used 16 monthly financial variables to construct their FCI, covering asset prices, liquidity, credit, financial activity and volatility measures. The variables were seasonally adjusted, differenced (if not stationary) and lastly standardised. They constructed four different FCIs, all permutations of each other. Their main methodology is based on principle component analysis (PCA), to which they added two options:

1. Recursive calculations of the PCA (vs. non-recursive)
2. A purged FCA, where they exclude endogenous variables such as inflation, interest rates and the economic growth rate (vs. non-purged).

First, they estimated an FCI by deriving a principle component from a vector of financial variables. Then, they purged this FCI from any endogenous feedback effects such as interest rates, inflation and output. They did this by regressing the FCI on these three variables and then using the error vector as their new purged FCI:

$$\widehat{FCI_t} = \alpha + \beta MANUFN\_GR_t + \delta INFL_t + \theta TBILLN_t + \epsilon_t$$

They did the recursive estimation of the FCI due to the differences between FCIs obtained from shortened sub-samples and the total long sample. To derive a recursive FCI, they estimated a principle component for a longer sample each period, starting with 2 periods (n=1 to n=2), then gradually extending it to all 552 periods (n=1 to n=552). The recursive FCI is then built up by the end values of each new FCI, in effect simulating what the FCI would have looked like in real time. *(The Kalman filter is an alternative way to provide for time-varying parameters.)*

They evaluated the performance of the four FCIs by graphically comparing their ability to pick up turning points in the South African business cycle, decade-by-decade. To do the graphical comparison, they had to use a 12-month moving average of each FCI, since the monthly volatility made direct FCI graphical comparisons too difficult.

Besides the graphic comparison, they also conducted in-sample causality tests (Wald test) to determine the FCI's usefulness as an early warning system. They found that the recursive FCIs had a better ability to forecast output and inflation. In forecasting the Treasury bill-rate, both the recursive and non-recursive had the same forecasting qualities. The authors concluded that the recursive FCI, purged from endogenous effects, turned out to be the best forecaster of industrial production growth, the Treasury bill rate and inflation to a lesser extent.

11.3. Quantec (2008)

In 2008, Christo Luüs of Ecoquant developed an FCI for South Africa. One point which makes his FCI different from that of the SARB is its monthly frequency (as opposed to a quarterly frequency). Luüs used monthly data from 1990 to 2007, and he indexed, standardised and debased the data into five input variables. He ran a regression of these five variables against manufacturing production and took the respective coefficients as an indication of the weights:

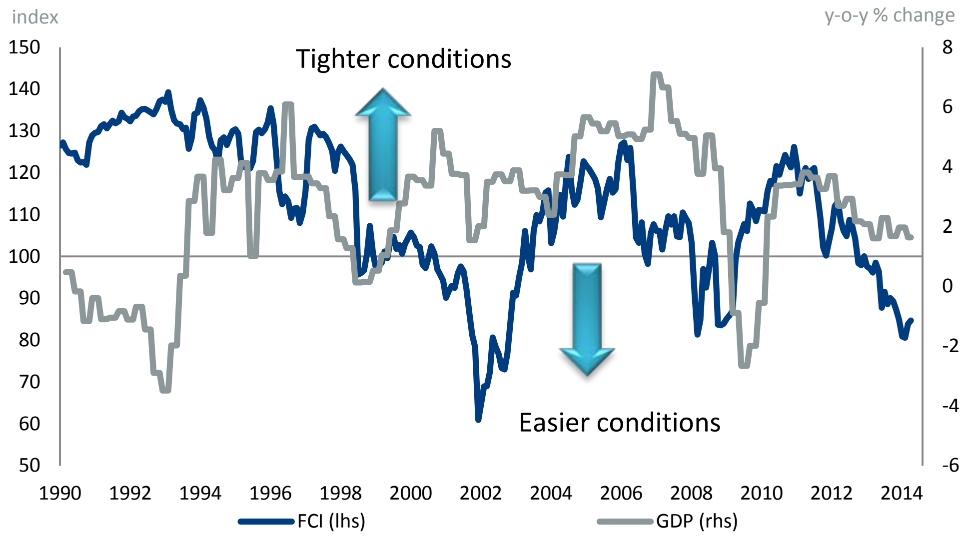
1. Real interest rate: 30%
2. Excess money supply growth: 30%
3. Real effective exchange rate: 25%
4. Company earnings yield: 10%
5. Yield spread: 5%

Luüs used this FCI to make some conclusions about the historical path of financial conditions in South Africa from 1990 to the beginning of 2008. Based on the looseness of financial conditions in early 2008, his recommendation was that interest rates should have increased more at that time (Luüs, 2008).

Quantec now publishes the Luüs-FCI on a monthly basis on their website, available for download by Quantec's clients. The monthly report of three pages starts off with a summary of the latest financial conditions and implications. Then the report presents a table of all five indicators and a graph of the FCI compared to inflation. This is followed by five graphs of each of the input variables. The reports also contain some economic comment at each graph.

Figure 5 below depicts Quantec's FCI since 1990. According to Luüs, above 100 the index indicates tighter monetary and financial conditions, and below 100 reflects easier financial conditions. For example, during the onset of the global financial crisis in 2008, the FCI quickly moved from levels above 100 to below 90 as credit dried up, real interest declined and the rand weakened substantially. Since the end of 2012, the FCI moved below 100 again and kept on declining up to 2014, indicating looser financial conditions. However, the weak correlation to GDP growth is also visible in Figure 5. This is an expected problem of FCIs that tend to gauge economic growth as well as inflation.

Figure 5: Quantec's FCI



Source: SARB & Quantec

11.4. FCI of the South African Reserve Bank (2012)

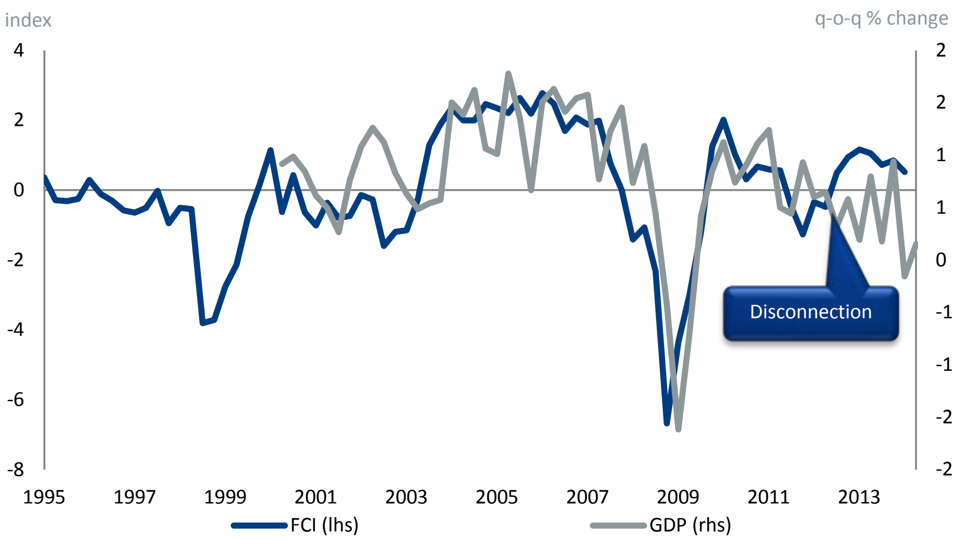
In August 2012, the SARB constructed two financial conditions indices (FCIs) for South Africa (Gumata, Klein, & Ndou). In the first approach they used PC analysis and for the second the Kalman filter. Both of them are based on the same indicators, with the aim of comparison. Their sample of quarterly data stretched from 1999 to the end of 2012-Q1. As input indicators, they selected the following data series:

1. S&P500 volatility index (VIX)
2. S&P500 stock price index (SP500)

3. JP Morgan EMBI total return index (EMBI)
4. Spread between the 3-month LIBOR and US Treasury bills (TED)
5. Total loans and advances to the private sector (LOANS_ADV)
6. South African sovereign spread (SOVEREIGN)
7. Non-performing loans (NPL)
8. Negotiable certificates of deposit (NCD)
9. Nominal effective exchange rate (NEER)
10. JSE All share index (JSE)
11. ABSA house price index (ABSA)

As an exercise attempt, the SARB's FCI (which they estimated using the first principle component) was reconstructed. A very similar result was obtained, though not exactly. Figure 6 below presents the recalculated FCI along with annual GDP growth. Some level of correlation is visible, especially around the global financial crisis. Note the disconnection that happened between the FCI and GDP-growth since 2012, most probably due to the Fed's third wave of quantitative easing (QE3).

Figure 6: SARB's FCI (recalculated by BER)



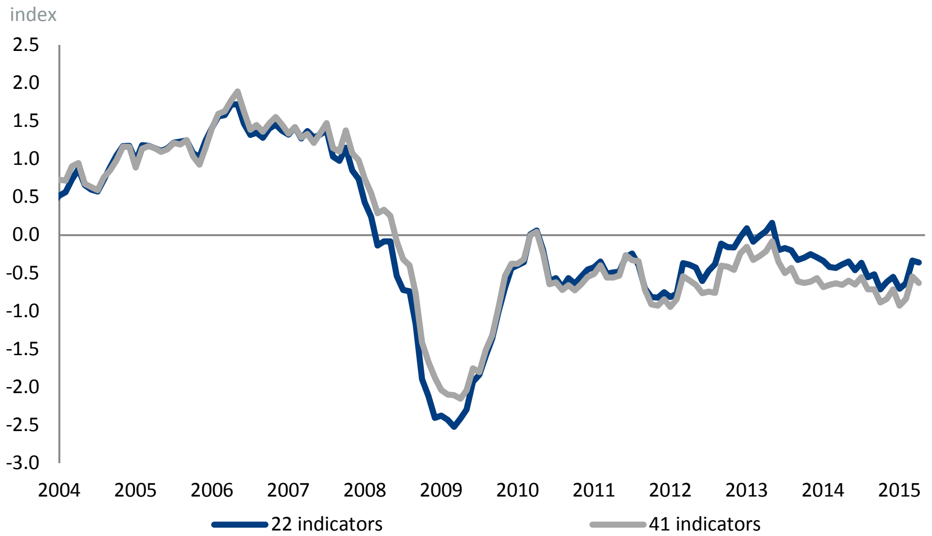
Source: SARB and recalculated by BER

The SARB found that their PC-FCI performed better as a predictor of economic growth than the Kalman-FCI, though the latter was more robust. They also compared these with the forecasts of the SARB's leading economic indicator, as well as each of the separate input indicators. The VIX, which correlates more than 80% with the PC-FCI, is nearly as good a predictor of economic growth as the respective FCI. The authors concluded that joint movements in financial variables effectively contain relevant information regarding future outcomes in real activity.

12. Graphs

The first PC (PC1), based on the full basket of 41 indicators, explained 29% of the variance in its basket. The first PC of the reduced basket of 22 indicators explained 51% of the variance in its basket. In Figure 7 below, the principle components of both versions are compared, and they are seemingly similar, indicating that the additional indicators do not add significant value.

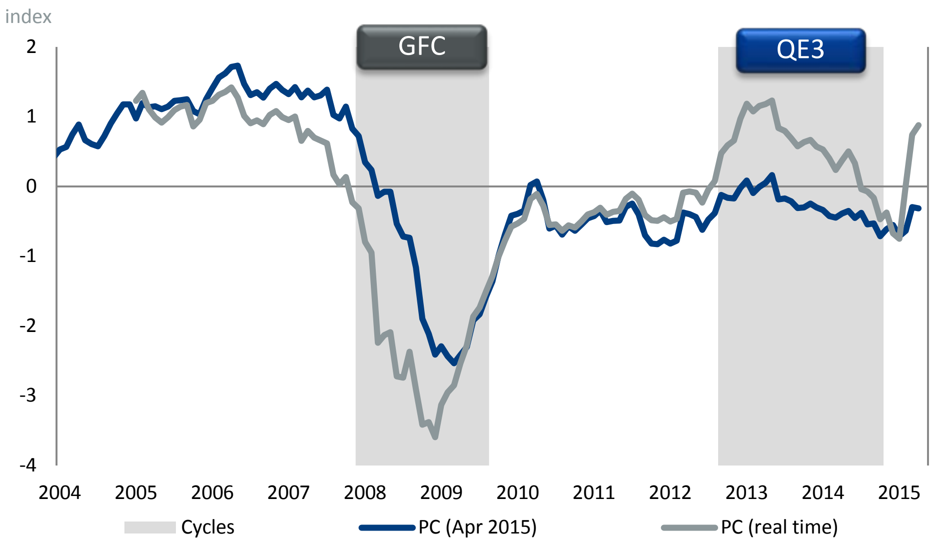
Figure 7: First principle components on the full and reduced baskets



Source: Van der Wath

Figure 8 below compares the first principle component, as calculated over the entire sample (125 months), with that of the real-time principle component, calculated over a rolling 60-month period. Clearly, the real time-PC started to decline much earlier, pre-empting the global financial crisis of 2008. The real time-PC also emphasise the impact of the third wave of quantitative easing in the US.

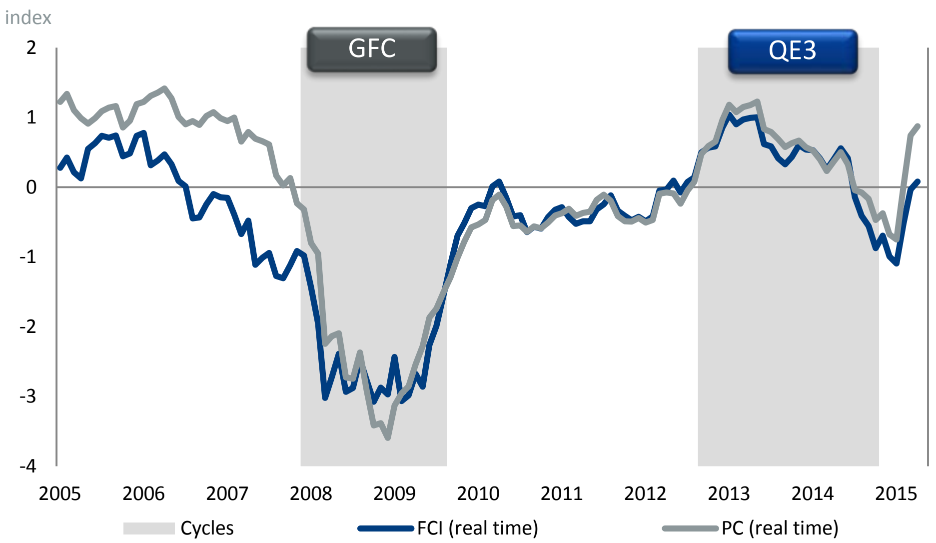
Figure 8: First principle components: real time vs. Apr 2015



Source: Van der Wath

Figure 9 below compares the real time principle component (PC) with its purged counterpart, the FCI. In comparison, the FCI pre-empted the financial crisis of 2008 slightly sooner, already declining below the 0-line in the middle of 2006. Yet, the FCI recovered in tandem with the real time-PC from the GFC in 2009.

Figure 9: Purged (FCI) vs. non-purged (PC) indices



Source: Van der Wath

13. Eviews code to create a real-time FCI and forecast

'Create realtime FCI

```
matrix(22,1) pc_series
For !obs =  60 to 183
smpl 2000M01+!obs-59  2000M01+!obs

group02.pcomp(eigvec=eigenvecs) score
vector v_loop = @columnextract(eigenvecs,1)
matrix pc_series = @hcat(pc_series, v_loop)
matrix weight=@transpose(pc_series)

group02.makepcomp(scale=normscores) pc1
equation eq_fci.ls pc1 rt_ngdp(-4)  c
series fci=resid

smpl 2000M01+!obs 2000M01+!obs
series rt_pc1=pc1
series rt_fci=fci
next
smpl @all
```

'Forecast comparison

```
For !obs =  0 to 71
smpl 2010m01+!obs-29  2010m01+!obs
equation eq_gdp_ar.ls rt_gdp rt_gdp(-13) c
eq_gdp_ar.fit gdp_ar_f
equation eq_gdp_ar_fci.ls rt_gdp rt_gdp(-13) rt_fci(-9) c
eq_gdp_ar_fci.fit gdp_ar_fci_f
equation eq_gdp_fci.ls rt_gdp rt_fci(-9) c
eq_gdp_fci.fit gdp_fci_f
equation eq_gdp_alsi.ls rt_gdp jse_alsi(-9) rt_gdp(-13) c
eq_gdp_alsi.fit gdp_ar_alsi_f

smpl 2010m01+!obs 2010m01+!obs
series rt_gdp_ar_f=gdp_ar_f
series rt_gdp_ar_fci_f=gdp_ar_fci_f
series rt_gdp_fci_f=gdp_fci_f
series rt_gdp_ar_alsi_f=gdp_ar_alsi_f
next
smpl @all
```

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Data

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South African Reserve Bank Quarterly Bulletin, various years.

Thomson Reuters' DataStream

Quantec's Easydata