Identifying a financial conditions index for South Africa

Kirsten Thompson[a,*], Reneé van Eyden[a], Rangan Gupta[a]

[a] Department of Economics, University of Pretoria, Pretoria 0002, South Africa
[*] Corresponding author. Email address: kirsten.thompson@lantic.net

---

Abstract

The global financial crisis that began in 2007-08 demonstrated how severe the impact of financial markets' stress on real economic activity can be. In the wake of the financial crisis policy-makers and decision-makers across the world identified the critical need for a better understanding of financial conditions, and more importantly, their impact on the real economy. To this end, we have constructed a financial conditions index (FCI) for the South African economy, to enable the gauging of financial conditions and to better understand the macro-financial linkages in the country. The FCI is constructed using monthly data over the period 1966 to 2011, and is based on a set of sixteen financial variables, which include variables that define the state of international financial markets, asset prices, interest rate spreads, stock market yields and volatility, bond market volatility and monetary aggregates. We explore different methodologies for constructing the FCI, and find that recursive principal components analysis (PCA) yields the best result. We furthermore investigate whether it is beneficial to purge the FCI of the real effects of inflation, economic growth and interest rates, and use the identified FCI in causality testing with three macroeconomic variables.

Keywords: financial conditions; financial crisis; principal components

JEL Classification: C32, C52, C53, G01

---

1. Introduction

The global financial crisis that began in 2007-08 demonstrated how severe the impact of financial markets' stress on real economic activity can be. In the wake of the financial crisis policy-makers and decision-makers all over the world identified the critical need for a better understanding of financial conditions, and more importantly, their impact on the real economy. Indeed, Borio and Lowe (2002) forcefully make the point that even during times of sound and credible economic policy, financial instability remains a threat. In order to allow for a timely assessment of economy-wide financial conditions and their impact on the macro economy, we construct a financial conditions index (FCI) for the South African economy. We also evaluate whether the resulting FCI can act as an 'early warning system'. This in turn may indicate whether monetary policy should take broader financial conditions into account. This study offers three main contributions to the existing literature on financial conditions in South Africa: (i) we construct an FCI over a sample period that is three decades longer than existing indices; (ii) our FCI comprises a wider coverage of financial variables than others; and (iii) we make use of recursive estimation techniques, that allow us to account for parameter instability and to capture the real-time constraints faced by a policymaker[1]. We evaluate the performance of our constructed FCIs by comparing their ability to pick up turning points in the South African business cycle, and by running in-sample causality (forecast) tests.

The usefulness of an FCI stems from its ability to summarise the impact of a central bank's policy decision "on financial prices, which can be related to future output and inflation" (Mayes and Viren, 2001). An FCI is more comprehensive than a monetary conditions index (MCI) which typically only includes interest rates and real exchange rates, while an FCI additionally incorporates data on asset prices and/or financial activity measures. The early literature on FCIs (see for example Goodhart and Hofmann (2001), Mayes and Viren (2001), Goodhart and Hofmann (2002), Lack(2003), Montaglioni and Napolitano (2004), and Castro (2008)) suggested the use of a narrow data set incorporating an interest rate, an exchange rate and asset prices – usually house prices and share prices. These ideas have recently been broadened to include a multitude of financial indicators.

One of the desired characteristics of an FCI is that it comprises high-frequency data which can easily be updated, thereby providing timely estimates (and forecasts) at much shorter intervals than typical economic forecasts based on macroeconomic variables. In South Africa especially, a monthly FCI would be most valuable in an environment where macroeconomic forecasts are generally restricted to a quarterly basis, at best.

Due to the need for estimating and monitoring FCIs, a number of different methods for constructing these indices have been developed in the recent literature. Hatzius, Hooper, Mishkin, Schoenholtz, and Watson (2010) split these into two broad methodological categories: a

[1] As discussed later in this paper, the recursive nature of the FCI is representative of economic agents having only the information available until time *t* when making a decision in time *t*, as opposed to a non-recursive FCI which has the full set of information at all points in the sample.

weighted-sum approach and a principal components approach. We can add to this list the Kalman filter approach (Gumata, Klein and Ndou (2012) and Koop and Korobilis (2013)).

Hatzius, et al. (2010) have compiled an FCI for the USA from a sizeable set of 45 quarterly financial variables, which are split into five categories of data encompassing prices, quantities, surveys, liquidity and credit measures. The factors of the FCI are estimated through iterative least squares regressions of the unbalanced panel on level and lagged values of real GDP and GDP inflation.

Indices estimated according to the weighted sum approach include the Bloomberg FCI (Rosenberg, 2009), which is a daily FCI estimated as an equal weighted average of three sub-indices, themselves equal-weighted averages of 10 variables in total. Goodhart and Hofmann (2001) estimate FCIs for the G-7 countries comprising short-rates, exchange rates, house prices and share prices (i.e. an extension of an MCI). The weights of these variables are determined by reduced-form coefficients in an aggregate demand equation as well as impulse responses from a VAR. Gauthier, Graham and Liu (2004) construct FCIs for Canada using three approaches: weights derived from an IS-Phillips curve; weights from a VAR's impulse-response functions; and by taking the first principal component from a PCA approach. They find that the two weighted-sum approaches present better FCIs than the PCA approach. Swiston (2008) estimates an FCI for the US by obtaining weights from the impulse responses from a VAR. Citi's FCI is a weighted average of six monthly financial variables, where the weights are determined by the reduced-form parameters of the chosen variables regressed on the Conference Board's coincident index (Diclemente, Schoenholtz and D'Antonio, 2008). Oet, Bianco, Gramlich and Ong (2012) construct a financial stress index (FSI) for the USA using a weighted average approach applied to 16 spread measures, as opposed to using volatility measures, so as to create an index capturing stress in six financial markets.

The principal components approach to estimating an FCI has been pursued by English, Tsatsaronis and Zoli (2005), who estimate FCIs for Germany, the UK and the USA, using principal components analysis, with 35 financial variables making up the FCI in the case of Germany, 37 for the UK and 47 for the USA. Similarly, Hakkio and Keeton (2009) compile the Federal Reserve Bank of Kansas City's FCI by taking the first principal component of 11 monthly financial indicators. Brave and Butters (2011) estimate an FCI for the USA based on an unbalanced panel of 100 financial variables of differing frequencies, using a combination of PCA and the Kalman filter. Rapach and Strauss (2011) create FCIs for the G-7 nations to assess the empirical relevance of financial sector shocks on business-cycle fluctuations. They do so by taking the first principal component of a set of 10 quarterly financial variables, and perform tests using structural VARs and a factor-augmented VAR (FAVAR).

Koop and Korobilis (2013) estimate a number of alternative FCIs for the USA using both principal components analysis (PCA) and the Kalman filter approach, and apply dynamic model averaging (DMA) and dynamic model selection (DMS) on time-varying parameter FAVARs (TVP-FAVARs) and on constant parameter FAVARs which incorporate these FCIs. The FCIs are estimated from

20 quarterly financial variables. Montaglioni and Napolitano (2004) estimate FCIs for the USA, Canada and the Euro area applying a Kalman filter; and use these estimated FCIs to test the interactions between financial conditions and monetary policy through the augmentation of forward-looking Taylor rules. Castro (2008) does the same for the UK, the USA and the Euro area.

The literature on FCIs for South Africa is rather limited. Gumata, et al. (2012) estimate an FCI for South Africa using the alternative approaches of PCA and a Kalman filter; applied to quarterly data over the period 1999Q1 to 2011Q4. Our research represents an improvement on the data frequency and length of this sample. Kasai and Naraidoo (2011) estimate an FCI for the purposes of including it in a monetary policy reaction function for the South African Reserve Bank (SARB). Their index is constructed as the average of monthly data spanning five variables, over the period January 2000 to December 2008. Quantec (2007) estimates an FCI for South Africa over the period 1997 to 2007 as the weighted average of a short rate, a yield spread, excess money supply growth, company earnings yield and an exchange rate.

Koop and Korobilis (2013) indicate that there are three issues involved in the construction of an FCI: (i) the selection of financial variables; (ii) identifying/calculating the weights for combining these variables into an index; and (iii) assessing the relationship between the FCI and the real economy. The layout of the remainder of this paper is roughly in line with these processes and is as follows: Section 2 provides a brief overview of the econometric methodology we use in estimating the indices; followed by a discussion of the data we use in Section 3; while Section 4 presents the results of the estimated FCIs; and causality testing is conducted in Section 5. Section 6 concludes the paper.

2. Econometric methodology

The indices estimated in this study are compiled using PCA[2]. PCA has the useful objective of combing many variables into a few linear combinations or principal components (factors), and is thus widely used in index number generation. PCA extracts a common factor, in this case FCI_t, from a group of p variables, X_t:

$$\boldsymbol{X_t} = \boldsymbol{\beta FCI_t} + \boldsymbol{U_t} \qquad (1)$$

where $\boldsymbol{X_t}$ is a vector of p standardised financial variables, $\boldsymbol{\beta}$ is a $p\ x\ m$ coefficient matrix, $\boldsymbol{FCI_t}$ is a vector of $m\ x\ 1$ unobserved variables, and $\boldsymbol{U_t}$ is a $p\ x\ 1$ error vector.

Similarly to Koop and Korobilis (2013), Gumata et al. (2012), Brave and Butters (2011) and Hatzius et al. (2010) we purge the FCI of any potential endogenous feedback effects, so as to ensure that it captures only information about pure financial shocks and not past economic activity. However, where Gumata et al. (2012) purge only economic activity, we, similar to Hatzius et al. (2010), also purge inflation; and, like Koop and Korobilis (2013), also purge interest rates from the FCI, so as to fully remove monetary policy influences. This is achieved by

[2] PCA is discussed in further detail in the appendix.

regressing the FCI on the growth in the index of manufacturing production ($MANUFN\_GR_t$), CPI inflation ($INFL_t$)[3] and the nominal 3-month Treasury Bill rate ($TBILLN_t$) as follows:

$$\widehat{FCI}_t = \alpha + \beta MANUFN\_GR_t + \delta INFL_t + \theta TBILLN_t + \epsilon_t \qquad (2)$$

In equation (2) $\widehat{\epsilon_t}$ is regarded as the estimated purged FCI, and is uncorrelated with MANUFN_GR, INFL and TBILL. The next section provides an overview of the data used in the models.

3. Data

There is a trade-off between the breadth of coverage for an extended time period and the frequency of the data. Financial variables are available at a higher frequency but often over shorter time periods than macroeconomic variables. Another distinguishing feature of financial variables is that they tend to exhibit greater volatility. However, an FCI that incorporates a large variety of financial data may not necessarily suffer from increased volatility, since the inclusion of each additional series will decrease the weights of all of the variables included, some of which may be volatile.

Our dataset contains 16 monthly financial variables which encompass domestic and global financial measures, shown in Table 1.The aim is to have a dataset sizeable enough to cover the spectrum of financial indicators (including asset prices, liquidity, credit, financial activity and volatility measures), and which is parsimonious enough so as to restrict the FCI to one principal component, as well as being of a significant sample length. However, as noted by Hatzius, et al. (2010), there is significant tension between wide variable coverage and long history when it comes to financial data. The chosen series encompass measures in levels, as well as volatility measures.

The data series include: South African financial asset prices; South African property prices; global asset prices; the real Dollar-Rand exchange rate to capture global effects; the yield on the Johannesburg Stock Exchange (JSE); a global indicator of confidence; four South African interest rate spread measures, namely the bond spread, mortgage spread, treasury bill spread and term spread; US monetary policy measured by the Federal Funds rate; South African M3 money supply growth; credit extended to the South African private sector; and South African asset price volatility. The data set covers the significant sample of 1966M02 – 2012M01. The US Census X-12 procedure is used to seasonally adjust the data for series not already seasonally adjusted. Unit roots are tested for using the Ng-Perron (2001) procedure[4], and non-stationary series are differenced to be made stationary. Finally, all data is standardised[5] before compiling the alternative FCIs.

[3] Manufacturing growth and CPI inflation are calculated as the rate of change between successive months.
[4] Unit root test results are available from the authors upon request.
[5] Standardising the data enables analysis and comparison of the sizes of the impacts of the FCIs.

Table 1. Variables used to construct the FCI

Name	Description	Transformation(s)
ALSI_VOL	Stock exchange volatility (South Africa)	Square of the first log difference of the All-Share Index
CONFUSN	University of Michigan US Consumer Sentiment Index	N/A
D_LALSI	FTSE/JSE All-Share Index (South Africa)	Seasonally adjusted, deflated, first log difference
D_LHOUSEP	Absa House Price Index (medium house size 141m^2–220m^2) (South Africa)	Deflated by South African CPI, first log difference
D_LPSCE	Credit extended to domestic private sector (South Africa)	Deflated by South African CPI, first log difference
D_LRD	Rand-Dollar exchange rate	Seasonally adjusted, deflated, first log difference
D_LSP500	S&P500 Composite Price Index	Seasonally adjusted, deflated, first log difference
DIVN	Johannesburg Stock Exchange dividend yield (South Africa)	Seasonally adjusted
FED	US Federal Funds market rate	Deflated by US CPI
GBINDEX_VOL	Government bond volatility (South Africa)	Square of the first log difference of Government Bond Return Index
HOUSEP_VOL	House price volatility (South Africa)	Square of the first log difference of House Price Index
INFL	Month-on-month growth in CPI (South Africa)	Seasonally adjusted, month-on-month rate of change
M3_GR	Month-on-month growth in M3 money supply[6] (South Africa)	Seasonally adjusted, deflated, month-on-month rate of change
MANUFN_GR	Month-on-month growth in Manufacturing Production Index (South Africa)	Month-on-month rate of change
SPREADN_BOND	Long-term bond spread between Eskom Corporate Bond yield and 10-year Government Bond yield (South Africa)	N/A
SPREADN_MORT	Mortgage spread between mortgage loan borrowing rate and 3-month Treasury Bill yield (South Africa)	N/A
SPREADN_TBILL	Short-term spread between prime overdraft rate and 3-month Treasury Bill yield (South Africa)[7]	N/A
SPREADN_TERM	Term spread between 10-year Government Bond yield and 3-month Treasury Bill yield (South Africa)	N/A
TBILLN	3-month Treasury Bill Yield (South Africa)	N/A

Notes: All data is extracted from the Global Financial Database (https://www.globalfinancialdata.com).

[6]We tested the inclusion of M1 growth vs. M3 growth through graphical comparison and correlation coefficients between the two FCIs and found that they were very similar, nearly identical in fact, so we chose the FCI including M3 since it is theoretically a more inclusive measure.

[7]This short spread captures the profitability of commercial banks.

4. Empirical Results

4.1 FCI Indices

In choosing the best available FCI for South Africa, a number of different methods are used to compile indices, and these are compared graphically to isolate a subset of indices, which are then compared with each other using causality tests. The original set of indices is compiled using two techniques: a simple averaging procedure, and various permutations of PCA. A comparison of these indices indicates that the simple average did not perform as well as the PCA-FCI, especially with regard to tracking recessions in the economy. We tested different PCA approaches resulting in four different FCIs from which to choose: recursive vs. non-recursive; and for each of these, we tested whether it is preferable to purge the index of the endogenous feedback effects of output, inflation and interest rates (i.e. purged vs. un-purged).

The idea of estimating a recursive FCI arises from comparing the PCA-estimated FCI over shorter time periods with the one estimated for the full sample. This comparison highlights that their performance varies significantly over time. This evidence calls for an assessment of the relevance of the individual components of the FCI over shorter ten-year sub-samples. This is done using a procedure similar to Ludvigson and Ng (2009 and 2010), namely regressing the individual financial variables (X_t) on the FCI, one at a time, over sub-samples, and using the resultant R^2 statistics to determine the importance of each variable.

The results in Table 2 indicate quite conclusively that not only are the chosen variables relevant within the FCI[8], but also that these variables' importance varies over time, due to the substantial size of our sample providing a case for estimating a recursive FCI to capture time variation of the weights assigned to the financial variables within the index. A recursive FCI is also relevant when considering that not only the relative importance of the individual data series within the index is time-variant, but also the impact of the FCI on the real economy changes over time. Goodhart and Hofmann (2001) noted the potential problem of not accounting for time-varying parameters, especially over a sample as long as ours, due to, for example, changing exchange rate regimes, changing monetary policy stances, oil shocks, labour disputes, changing macroeconomic policy paradigms, political shifts, and asset price bubbles. Gauthier, et al. (2004) criticise FCIs for ignoring dynamics and for parameter instability. Gumata, et al. (2012) also note that a PCA-constructed FCI will lack a dynamic pattern due to the assumption of the factor being stationary with zero mean – hence they constructed an alternative FCI using the dynamic and recursive Kalman filter approach. Koop and Korobilis (2013) estimate TVP-FAVARs to incorporate time-variation. We choose to address the issue of parameter non-constancy through the implementation of recursive PCA.

[8]An R^2 value of 0.1 or above is regarded as acceptable.

Table 2. Marginal R^2 from sub-sample regressions, with *t* as depicted in table

X_t	Full-sample	1966M02–1969M12	1970M01–1979M12	1980M01–1989M12	1990M01–1999M12	2000M01–2012M01
CONFUSN	0.14	0.004	0.0002	0.05	0.31	0.50
D_ALSI	0.13	0.012	0.13	0.07	0.26	0.19
D_LHOUSEP	0.67	0.79	0.64	0.66	0.59	0.78
D_LRD	0.001	0.0001	0.007	0.0003	0.06	0.003
D_LSP500	0.06	0.27	0.04	0.007	0.09	0.11
DIVN	0.20	0.01	0.44	0.04	0.19	0.09
FED	0.018	0.0007	0.02	0.01	0.002	0.002
M3_GR	0.27	0.05	0.29	0.34	0.36	0.24
SPREADN_BOND	0.12	0.0002	0.34	0.004	0.16	0.50
SPREADN_MORT	0.05	0.02	0.05	0.20	0.20	0.003
SPREADN_TBILL	0.36	0.47	0.41	0.33	0.61	0.02
SPREADN_TERM	0.50	0.16	0.67	0.81	0.41	0.17

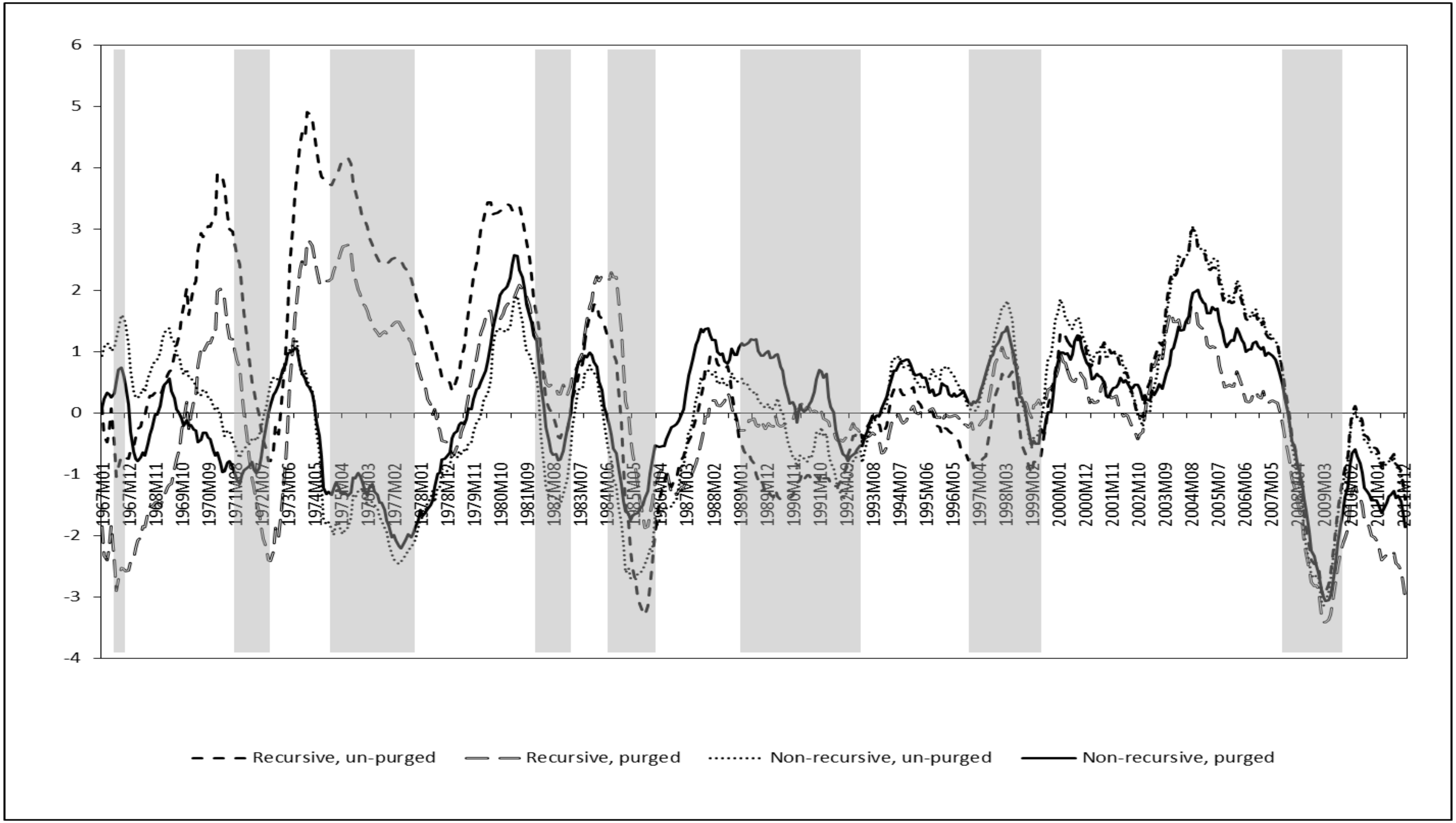
In deriving a recursive FCI, the first principal component is once again selected. This time, however, PCA is run on our set of 16 variables from n=1 until n=2 to obtain the first element of our factor vector; then we re-estimate from n=1 until n=3 to obtain the next elements of our factor vector; and continue this iterative process until we finally estimate from n=1 to n=552. In other words, the FCI is compiled from the main diagonal elements of an upper triangular matrix of *PC1s*, where the first column comprises one element – the PC for the first period; the second column comprises two values – the PCs for the first two periods; etc.

This recursive estimation of the FCI allows us to account for time-varying conditions, which is important given that our sample spans 552 observations. The usefulness of this recursive estimation becomes more apparent when one considers that economic agents make decisions based only on the information they have available at a particular point in time. The non-recursive FCI is estimated using full information at all times throughout the sample, whereas the recursive FCI is estimated at each point in time, *t*, using only the information available until time *t*. It is for this reason that the performance of the recursive FCI improves over the sample period, as more and more information becomes available. This recursive FCI is also purged of the effects of economic activity, interest rates and inflation.

Figure 1 shows trends in the 12-month moving averages of the various estimated FCIs. We look at moving averages graphically since the volatility of the high-frequency monthly data makes graphical interpretation difficult. The grey vertical bars represent periods of recession in the South African economy. An upward movement in the estimated FCI represents an improvement (loosening) in financial conditions, and a downward trend indicates a worsening (tightening) of financial conditions. The estimated FCIs are discussed later in this section in a decade-by-decade comparison.

Table 3 provides the correlation coefficients between the four estimated FCIs over the full sample and decade-long sub-samples. It is evident that over the full sample as well as the shorter sub-samples, the most similar FCIs are the non-recursive-purged and non-recursive-un-purged; as well as the recursive-purged and recursive-un-purged. Therefore, we will treat two FCIs as representative of all four for which we conduct further testing in section 5: the non-recursive-purged and recursive-purged indexes.

Figure 1. Performance of various FCIs



Notes: The grey vertical bars represent periods of recession in the South African economy.

Table 3. Correlation coefficients between estimated FCIs

Correlation coefficients Full sample	Non-recursive -un-purged	Recursive-un-purged	Recursive-purged	Non-recursive -purged
Non-recursive-un-purged	1	0.343	0.254	0.840
Recursive-un-purged		1	0.866	0.262
Recursive-purged			1	0.302
Non-recursive-purged				1
1966M02 – 1969M12				
Non-recursive-un-purged	1	-0.021	-0.016	0.944
Recursive-un-purged		1	0.999	-0.020
Recursive-purged			1	-0.007
Non-recursive-purged				1
1970M01 – 1979M12				
Non-recursive-un-purged	1	-0.129	-0.264	0.790
Recursive-un-purged		1	0.983	-0.044
Recursive-purged			1	-0.134
Non-recursive-purged				1
1980M01 – 1989M12				
Non-recursive-un-purged	1	0.701	0.516	0.895
Recursive-un-purged		1	0.880	0.585
Recursive-purged			1	0.352
Non-recursive-purged				1
1990M01 – 1999M12				
Non-recursive-un-purged	1	0.691	0.519	0.799
Recursive-un-purged		1	0.814	0.369
Recursive-purged			1	0.298
Non-recursive-purged				1
2000M01 – 2012M01				
Non-recursive-un-purged	1	0.970	0.925	0.936
Recursive-un-purged		1	0.965	0.901
Recursive-purged			1	0.901
Non-recursive-purged				1

4.2 Evaluating the performance of FCI indices

In this section we conduct a period-by-period analysis to assess whether the proposed FCIs are in line with important events in South Africa, in particular whether they can pick up recessionary episodes in a satisfactory way. This evaluation helps us to identify the FCI that performs best and to gauge whether FCIs are a good early warning indicator for financial turmoil.

The 1960s and 1970s

A brief recession in 1967 (bottoming at -7.1 per cent GDP growth in the fourth quarter of 1967) is picked up by both the recursive-purged and recursive-un-purged indices, but not by the non-recursive FCIs. The recursive-purged FCI is lower (i.e. indicates more severity) than the recursive-un-purged. This recession precedes a period of growth in South Africa, driven by stability and gold exports. A recession from January 1971 to August 1972 (quarterly GDP growth was lowest at -3.2 per cent in the second quarter of 1971) is captured by all of the FCIs, but at a slightly lagged interval – possibly due to the devaluation of the South African Rand by 12 per cent due to the Smithsonian agreement only entering the FCIs towards the end of this recessionary period. The recursive-purged FCI is once again the lowest of the group. Following on from this period, all of the FCIs rise after an increase in the gold price, with the recursive-un-purged and recursive-purged indices being the highest.

All of the FCIs exhibit the recession of 1974 to 1977 (when GDP growth hit a low of -7.7 per cent in the second quarter of 1976), which was characterised by the after-effects of the first oil price shock, double-digit inflation, the collapse of the Angolan and Mozambican colonies in 1975 and the Soweto uprising in 1976. The recursive-purged and recursive-un-purged indices lagged the recession slightly, and at higher levels than the two non-recursive indices.

The 1980s

Driven by record gold prices and exchange rate and current account improvements, the economy boomed in the late 1970s and early 1980s, reflected in all of the FCIs reaching a peak (at a similar level, except for the higher recursive-un-purged index) during that period. This boom was however immediately followed by a recessionary period between September 1981 and March 1983 (average quarterly GDP growth over the period was -3.1 per cent and a trough of -8.2 per cent was reached in the fourth quarter of 1982), caused in part by excessive inflation, large current account deficits and rapid exchange rate depreciation. All of the FCIs reach a minimum during this period, the most severe of which is the non-recursive-un-purged index and the mildest of which is the recursive-purged index. A brief recovery followed this recession, where both of the recursive FCIs exhibit higher peaks than the non-recursive indices.

The recession of 1984 to 1986 (average quarterly GDP growth over the period was -1.8 per cent), a result largely of international sanctions and a debt standstill agreement to limit burgeoning current account deficits, is captured by all of the FCIs. The recursive-un-purged index exhibits the deepest trough while the recursive-purged and non-recursive-purged indices are the mildest during this period. This is followed by an upswing, which all of the indices reflect.

The 1990s

All of the FCIs go on to enter a mild recessionary period, led by political uncertainty, between March 1989 and May 1993 (average quarterly GDP growth amounted to -0.6 per cent over the period), preceding a slight upswing in the three years that follow. The four FCIs lag the mild recession of 1996 to 1999 (GDP growth was -0.9 per cent in the third quarter of 1998), which was driven by high crime levels, uncertainty, net capital outflows, weakened domestic demand, the Asian crisis and high debt levels. The indices track this period at a similar level, except for the recursive-purged index which is at a marginally higher level.

The 2000s[9]

Following a recovery in commodity prices and improving Asian and European outlooks in 1999, along with capital inflows and increased confidence, all of the FCIs recovered and increased at similar levels in 2000. The FCIs for South Africa estimated by Gumata, et al. (2012) do not exhibit the same upswing as ours, but are rather flat during this period; whilst Kasai and Naraidoo's (2011) index does show a similar upswing. This is followed by a slight dip, albeit not during a recession, due to the IT boom-bust of the early 2000s (and its associated stock market volatility) and the Rand crisis of late 2001 – a dip which is also captured by Kasai and Naraidoo (2011) and by Gumata, et al.'s (2012) FCIs. Our four indices (as well as Gumata, et al.'s (2012) and Kasai and Naraidoo's (2011)) pick up again in the mid-2000s on the back of higher commodity prices, emerging market growth and increased expenditure growth; with both the non-recursive-un-purged and recursive-un-purged FCIs at the highest levels.

All of the FCIs capture the trough in 2007 to 2009 at equal levels, the lowest levels in fact of the entire FCI sample (quarterly GDP growth bottomed at -6.3 per cent in the first quarter of 2009). Gumata, et al.'s (2012) and Kasai and Naraidoo's (2011) FCIs also pick up this crisis period in South Africa. This is in line with the timing of the global financial crisis as well as a domestic electricity supply crisis. The indices recover again in early 2010 due to the increased confidence and construction associated with the FIFA World Cup™ hosted in South Africa in that year. However, this is followed by a sharp drop again in late 2010 and 2011, the result of the Euro crisis and continuing domestic uncertainty and credit down-grades. At the end of our FCI sample, the recursive-purged index is at its lowest (most severe) level.

In section 5 we use causality testing to determine which of the non-recursive or the recursive FCI (both purged) is the best predictor of economic activity.

5. In-sample causality testing

We conduct a series of in-sample causality tests to assess whether the estimated FCIs are indeed adequate indicators of economic activity, and whether they can in fact be regarded as an 'early warning system'.

Similar to Rapach and Weber (2004), we set up an ARDL model:

$$\sum_{i=1}^{h} \Delta y_{t+i} = \alpha + \sum_{i=0}^{q_1-1} \beta_i \Delta y_{t-i} + \sum_{i=0}^{q_2-1} \gamma_i FCI_{t-i} + \varepsilon_{t+h} \qquad (3)$$

where y_t is the variable of choice (manufacturing growth, treasury bill and inflation), q_1 and q_2 are the ARDL lags, and h is the in-sample forecast horizon (set to 24 months in this instance). This model is used to conduct a Wald test[10] by using the full sample of observations to test the null hypothesis of $\gamma_0 = \cdots = \gamma_{q_2-1} = 0$. If the null hypothesis is rejected, we can conclude that the FCI

[9] Gumata, et al.'s (2012) and Kasai and Naraidoo's (2011) samples begin at this time, so comparison between our FCIs with theirs can only take place from this part of the sample.

[10] Inference of this Wald statistic is based on a bootstrapping procedure described in Rapach and Weber (2004), originally found in Kilian (1999).

has forecasting ability (therefore, has causality) with respect to y_t. The results of these tests are found in Table 4, and indicate that there is stronger in-sample predictability (or causality) between the recursive FCI and industrial production growth than for the non-recursive FCI[11]. With respect to the Treasury Bill rate the recursive and non-recursive FCIs present similar results and appear to be equally strong predictors. There is no evidence of causality between the non-recursive FCI and the inflation rate, whereas the recursive FCI exhibits predictability of inflation at a horizon of 24 months.[12] These causality results lead to two broad conclusions: 1) The estimated FCIs are good predictors of economic activity; and 2) the results point toward the recursive FCI being the 'best' performing index, over and above the non-recursive FCI. Specific conclusions related to the chosen recursive FCI's results are that: 1) it best Granger-causes industrial production growth at longer horizons (especially the 12th, 15th, 18th, 21st and 24th months); and 2) the recursive FCI Granger-causes the Treasury Bill rate equally well at all forecast horizons.

6. Conclusions

The aim of this paper was to identify an appropriate FCI for South Africa – one which adequately captures trends in economic activity, and one which can be used as an early-warning system for predicting downswings in the economy. We tested a variety of approaches, but settled on applying recursive PCA to a set of sixteen monthly financial variables, and then purging this index of endogeneity from output, inflation and interest rates. Causality tests indicated that this FCI is a good in-sample predictor of industrial production growth and the Treasury Bill rate, but a weak predictor of inflation.

The FCI identified in this paper opens a number of interesting avenues for future research which are subject to on-going work: we construct two vector autoregression (VAR) systems – one with constant parameters, and one with time-varying parameters (a TVP-VAR) – in the spirit of Rapach and Strauss (2011) and Koop and Korobilis (2013). These VARs will be used to perform impulse response analyses, which will provide us with the dynamic behaviour of the three key macroeconomic variables of output growth, inflation and an interest rate in response to a shock to the FCI. The constant-parameter structural VAR will provide us with the average responses over time, whilst the TVP-VAR will provide the responses at each point in time. The FCI constructed in this paper will then be used to conduct out-of-sample forecasting of the three key macroeconomic variables of output growth, inflation and an interest rate.

[11] These results are similar in a sense to Gumata, et al. (2012), who found that their two FCIs for South Africa do Granger Cause GDP growth.

[12] English, et al. (2005) also found through forecasting exercises that financial factors are less effective in predicting inflation than is the case with output.

Table 4. Wald causality test results

Horizon (h) months ahead:	1m	3m	6m	9m	12m	15m	18m	21m	24m
Non-recursive FCI as independent variable									
y_t: Industrial production growth									
q_1	2	12	12	11	11	11	11	8	11
q_2	2	1	3	3	2	1	1	1	5
Wald (p-value)	21.723 (0.012)**	8.0009 (0.158)	8.007 (0.216)	5.413 (0.324)	2.664 (0.518)	0.560 (0.794)	0.005 (0.982)	0.143 (0.920)	25.912 (0.020)**
y_t: Treasury bill									
q_1	12	12	12	12	12	12	12	12	12
q_2	2	2	9	9	12	12	12	12	12
Wald (p-value)	12.826 (0.076)*	23.666 (0.006)***	26.314 (0.006)***	26.664 (0.008)***	27.304 (0.000)***	25.882 (0.004)***	25.558 (0.01)**	25.904 (0.014)**	26.038 (0.018)**
y_t: Inflation									
q_1	4	6	12	12	12	12	12	12	12
q_2	1	1	8	8	8	8	8	9	8
Wald (p-value)	0.358 (0.798)	0.049 (0.920)	4.377 (0.342)	5.175 (0.314)	4.457 (0.386)	4.448 (0.370)	4.858 (0.412)	6.640 (0.286)	4.889 (0.438)
Recursive FCI as independent variable									
y_t: Industrial production growth									
q_1	4	3	12	5	8	11	11	8	5
q_2	6	3	1	3	11	11	9	5	5
Wald (p-value)	33.415 (0.000)***	5.746 (0.228)	0.426 (0.782)	9.704 (0.188)	29.051 (0.002)***	44.404 (0.002)***	33.002 (0.004)***	26.108 (0.012)**	35.797 (0.002)***
y_t: Treasury bill									
q_1	12	12	12	12	12	12	12	12	12
q_2	2	2	3	3	5	5	5	6	6
Wald (p-value)	12.393 (0.066)**	20.439 (0.004)***	22.639 (0.004)***	22.430 (0.020)**	25.146 (0.006)***	22.168 (0.010)**	20.789 (0.028)**	22.136 (0.020)**	21.192 (0.030)**
y_t: Inflation									
q_1	4	6	6	12	12	12	12	12	12
q_2	1	2	1	1	1	1	1	1	12
Wald (p-value)	0.434 (0.804)	12.949 (0.126)	4.831 (0.414)	3.988 (0.450)	4.970 (0.438)	6.009 (0.386)	7.108 (0.322)	7.379 (0.298)	33.089 (0.012)**

Notes: Wald is the in-sample F-statistic used to test the null hypothesis of no Granger-causality (bootstrapped p-values in parenthesis). ***/**/* indicates rejection of the null hypothesis (i.e. there is evidence of Granger causality) at the 1/5/10% level of significance

7. References

Borio, C. & Lowe, P., 2002. Asset Prices, Financial and Monetary Stability: Exploring the Nexus. *Bank for International Settlements Papers,* Volume 114.

Brave, S. & Butters, R., 2011. Monitoring Financial Stability: A Financial Conditions Index Approach. *Federal Reserve Bank of Chicago Economic Perspectives,* Volume 1Q/2011, pp. 22-43.

Castro, V., 2008. Are Central Banks Following a Linear or Nonlinear (Augmented) Taylor Rule?. *Warwick Economic Research Papers,* Volume 872.

Diclemente, R., Schoenholtz, K. & D'Antonio, P., 2008. A View of the U.S. Subprime Crisis. *Citi Global Economic and Market Analysis - Special Report*, 26 September.

English, W., Tsatsaronis, K. & Zoli, E., 2005. Assessing the Predictive Power of Measures of Financial Conditions for Macroeconomic Variables. *Bank for International Settlements Papers,* Volume 22, pp. 228-252.

Gauthier, C., Graham, C. & Liu, Y., 2004. Financial Conditions Indexes for Canada. *Bank of Canada Working Paper Series,* Volume 2004-22.

Goodhart, C. & Hofmann, B., 2001. *Asset Prices, Financial Conditions, and the Transmission of Monetary Policy.* Stanford University, Conference on Asset Prices, Exchange Rates and Monetary Policy.

Goodhart, C. & Hofmann, B., 2002. Asset Prices and the Conduct of Monetary Policy. *Mimeo, London School of Economics.*

Gumata, N., Klein, N. & Ndou, E., 2012. A Financial Conditions Index for South Africa. *IMF Working Paper,* Volume WP/12/196.

Hakkio, C. & Keeton, W., 2009. Financial Stress: What is it, How Can it be Measured, and Why Does it Matter?. *Federal Reserve Bank of Kansas City Economic Review.*

Hatzius, J. et al., 2010. Financial Conditions Indexes: A Fresh Look After the Financial Crisis. *National Bureau of Economic Research Working Paper,* Volume 16150.

Kasai, N. & Naraidoo, R., 2011. The Opportunistic Approach to Monetary Policy and Financial Markets. *University of Pretoria Department of Economics Working Paper Series,* Volume 2011-03.

Kilian, L., 1999. Exchange Rates and Monetary Fundamentals: What Do We Learn From Long-Horizon Regressions?. *Journal of Applied Econometrics,* 14(5), pp. 491-510.

Koop, G. & Korobilis, D., 2013. A New Index of Financial Conditions. *University of Glasgow Department of Economics Working Paper Series,* Volume 2013-06.

Lack, C., 2003. A Financial Conditions Index for Switzerland. *Bank for International Settlements Papers,* Volume 19, pp. 398-413.

Ludvigson, S. & Ng, S., 2009. Macro Factors in Bond Risk Premia. *The Review of Financial Studies,* Volume 22(12), pp. 5027-5067.

Ludvigson, S. & Ng, S., 2010. A Factor Analysis of Bond Risk Premia. In: A. Uhla & D. Giles, eds. *Handbook of Empirical Economics and Finance.* Boca Raton: Chapman and Hall, pp. 313-372.

Mayes, D. & Viren, M., 2001. Financial Conditions Indexes. *Bank of Finland Discussion Papers,* Volume 17/2001.

Montaglioni, A. & Napolitano, O., 2004. Financial Conditions Index and Interest Rate Settings: A Comparative Analysis. *Istituto di Studi Economici Working Paper Series,* Volume 8.2005.

Ng, S. & Perron, P., 2001. Lag length selection and the construction of unit root tests with good size and power. *Econometrica,* Volume 69(6), pp. 1519-54.

Oet, M., Bianco, T., Gramlich, D. & Ong, S., 2012. Financial Stress Index: A Lens for Supervising the Financial System. *Federal Reserve Bank of Cleveland Working Paper Series,* Volume 12-37.

Quantec, 2007. A Financial Conditions Index for South Africa. *Economic Research Note,* Issue 1/2007.

Rapach, D. & Strauss, J., 2011. *Financial Sector Shocks and G-7 Business-Cycle Fluctuations.* St. Louis, Midwest Economics Association Meetings.

Rapach, D. & Weber, C., 2004. Financial Variables and the Simulated Out-of-Sample Forecastability of U.S. Output Growth Since 1985: An Encompassing Approach. *Economic Enquiry,* 42(4), pp. 717-738.

Rosenberg, M., 2009. Global Financial Market Trends & Policy. *Bloomberg Financial Conditions Watch*, 3 December.

Swiston, A., 2008. A U.S. Financial Conditions Index: Putting Credit Where Credit is Due. *IMF Working Paper Series,* Volume WP/08/161.

8. Appendix – Principal Components Methodology

The indices estimated in this study are compiled using PCA. PCA has the useful objective of combing many variables into a few linear combinations or principal components (factors), and is thus widely used in index number generation. The principal components are obtained by computing the eigenvalue decomposition of the observed variance matrix, and the first principal component accounts for the maximum variance. p Principal components can be created for p variables, however it is hoped that a minimum number of components can be used to account for maximum variance. The system of linear combinations generating the principal components (PC_i) from the original variables (X_i) with weights a_{pp} is as follows:

$$
\begin{aligned}
PC_1 &= \boldsymbol{a}_1'\boldsymbol{X} = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1p}X_p \\
PC_2 &= \boldsymbol{a}_2'\boldsymbol{X} = a_{21}X_1 + a_{22}X_2 + \cdots + a_{2p}X_p \\
&\vdots \\
PC_p &= \boldsymbol{a}_p'\boldsymbol{X} = a_{p1}X_1 + a_{p2}X_2 + \cdots + a_{pp}X_p
\end{aligned}
\tag{4}
$$

For the p variables in this system, the covariance matrix, Σ, and correlation matrix, $\boldsymbol{\rho}$, have a set of p eigenvalues $\{\lambda_1, \lambda_2, \ldots, \lambda_p\}$ and p eigenvectors $\{\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_p\}$. The eigenvectors determine the weights in the linear combinations of the principal components, and if each eigenvector has elements e_{ik}:

$$
\mathbf{e}_1 = \begin{bmatrix} e_{11} \\ e_{21} \\ \vdots \\ e_{p1} \end{bmatrix}, \mathbf{e}_2 = \begin{bmatrix} e_{12} \\ e_{22} \\ \vdots \\ e_{p2} \end{bmatrix}, \ldots, \mathbf{e}_p = \begin{bmatrix} e_{1p} \\ e_{2p} \\ \vdots \\ e_{pp} \end{bmatrix}
\tag{5}
$$

Then the principal components are represented as:

$$
\begin{aligned}
PC_1 &= e_{11}X_1 + e_{21}X_2 + \cdots + e_{p1}X_p \\
PC_2 &= e_{12}X_1 + e_{22}X_2 + \cdots + e_{p2}X_p \\
&\vdots \\
PC_p &= e_{1p}X_1 + e_{2p}X_2 + \cdots + e_{pp}X_p
\end{aligned}
\tag{6}
$$

Each principal component's variance is equal to the corresponding eigenvalue, $\mathbf{Var}(\mathbf{PC_p}) = \boldsymbol{\lambda}_\mathbf{p}$. For the purposes of this study, we choose the first PC_1 as our factor or FCI, which accounts for 17 per cent of the total variance.