Measuring and Testing a Modified Version of the South African Financial Cycle

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Abstract

This study reports on measuring and testing of a Composite Financial Cycle Index (CFCI) as a modified version of a South African Financial Cycle (FC). This is achieved through the adoption of thirteen monthly financial time series indicators observed over the period 2000M1 to 2018M12. In this context, a Two-Step Markov Switching Dynamic Factor in State-Space Form is utilised. The analyses are extended through the measurement of the SARB proxy index in order to facilitate comparison. The study provided evidence that the indicators of credit, house price and equity prices are the best indicators for measuring FCs in South Africa. However, there exist room for extension of the scope of financial time series variables used beyond these indicators. The added indicators proved to have more information content for financial crises forecasting. They have further proved to be better signals and to be better early warning indicators of financial crises in South Africa. Therefore, the addition of time series indicators beyond credit, house price and equity, increased the accuracy in measuring FCs, which could help prevent vulnerabilities from accumulating unnoticed.

Keywords and phrases: Composite Financial Cycle Index, Macroprudential Policy, State Space modelling, Dynamic Factor Model, Multinomial Logit Model, Markov Regime Switching.

1 INTRODUCTION

A key finding from the analyses of the 2007-2009 global financial crisis (GFC) from a systemic viewpoint is that problems originated as a result of inherent information asymmetry among interconnected market participants and propagated significantly via information uncertainty in financial markets (Oet, Bianco, Gramlich and Ong. 2012). This caused severe adverse selection and moral

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hazard problems. Financial markets became incapable of channelling funds efficiently from savers to households and firms with productive investment opportunities. Market observers did not know how to observe and consider signs of distress in the financial system and were not aware of the possible nature of the signs of distress (Mishkin (2007) and Oet et al. (2012)). As a result, the call for a Financial Cycle (FC) as an appropriate monitoring tool to support the ability to observe potential systemic risks and enable continuous assessment of the financial system conditions was strengthened.

The concept of FCs captures systemic patterns in the financial system that can have key macroeconomic implications and is associated with the concept of procyclicality of the financial system (Borio, Furfine and Lowe (2001) and Adrian and Shin (2010). A Financial Cycle is defined as "self-reinforcing inter-actions between the perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts" (Borio, 2014:2). The quoted definition has also been confirmed by other authors including Claessens, Kose and Terrones. (2011), Drehmann, Borio and Tsatsaronis (2012), Borio (2014), Ma and Zhang (2016), Cagliarini and Price (2017), Farrell and Kemp (2020) among others. FCs inhabit an essential role in the policy debate on how to enhance the resilience of the financial system. Understanding FCs is viewed as particularly relevant for informing the use of countercyclical Macroprudential policy (MaPP) (Galati, Hindrayanto, Koopman and Vlekke, 2016).

As is the case with other central banks around the world, there is a mandate for financial stability within the South African Reserve Bank (SARB). The SARB employs MaPP supervisory and monitoring tools, to protect and enhance financial stability in South Africa, as stipulated by the Financial Sector Regulations Act of 2017 (FSR Act 2017) (see Van Heerden and Van Niekerk (2017)). The definition of MaPP as adopted by the SARB, recognises the significance of systemic risk and the need to propose regulations that are aimed at addressing systemic risks and to build resilience in the financial system (Van Heerden and Van Niekerk, 2017). The definition of financial stability adopted by the SARB for purposes of the Financial Sector Regulations Bill posits more emphasis on the significance of resilience and confidence as suggested by Tucker (2011). Consequently, a reliable measure of the FC is also pertinent for South African policymakers, against the background of the responsibility and the renewed emphasis on financial stability regulatory and supervisory frameworks as provided by the FSR Act (Godwin, Howse and Ramsey, 2017).

During the recent past, increasing research efforts have been devoted towards accurately measuring and characterising FCs (see Borio et al. (2001), Claessens et al. (2011), Claessens et al. (2012), Drehmann et al. (2012), Borio (2014), Ma and Zhang (2016), Kota and Goxha (2019)). These researchers have identified a FC that is best characterised by the co-movement of medium-term cycles in equity prices, credit-to-GDP ratios, and house prices. While these studies are an evidence of a growing number of studies measuring and characterising FCs, these studies have mainly been concentrated on developed or a group of developed countries. Developing and underdeveloped countries have to date seen limited efforts devoted towards studying FCs.

In South Africa as in other developing countries, there has been limited amounts of effort being dedicated towards studying FCs. Noteworthy, the studies by Boshoff (2005), Bosch and Koch (2020) and Farrell and Kemp (2020) are an exception. These authors utilised three financial time series variables namely: credit-to-GDP, property prices and equity prices in measuring and characterising the South African FC. Results obtained aligned with those of other studies in the FCs literature (see for example Drehmann et al. (2012)). The SARB also considers similar information in determining the official South African Financial cycle.

Notwithstanding these efforts, some authors (see Cagliarini and Price (2017) & Kota and Goxha (2019)) have argued that, the world is still far from thoroughly understanding FCs, especially in developing and underdeveloped countries. Mainly due to the fact that the concept of FCs is still in its infant stages of development and its knowledge is by far limited. Others (see Chorafas (2015) & Kota and Goxha (2019)) have argued that the financial system of a country is too broad to be represented by a group of only three variables *viz:* equity prices, credit to GDP and house prices. Additionally, these variables only represent a small set of variables needed, which can be expanded to include indicators such as, credit spreads, risk premia, defaults rates *inter alia*. The analysis of these added variables facilitated the measuring of risks and provided a perception of exposure (Hatzius et al. (2010), Ng (2011) and Chorafas (2015) and Kota and Goxha (2019)).

Against the background of the above discussion, this study argues that, the option of central banks to measure and characterise FCs utilizing three financial time series variables, is substantiated. Nonetheless, given the broad and dynamic nature of the financial system, this option may still fall short as some markets and market participants are not captured by the current measure. Therefore, the current FC may not be representative of the true dynamics of a country's financial system. This led us to ask; should the scope of financial time series variables used to measure the South African FC be expanded? Further, is the current South African FC measure representative of the true dynamics of the South African financial system?

To respond to the above questions, this study measured and tested a Composite Financial Cycle Index (CFCI) as a modified version of the current South African FC. Due to the current South African FC being publicly unavailable, we extended this analysis by measuring the current South African FC following the SARBs' procedure but using a different method. We then compared these two indices, in order to determine the most appropriate measure of the South African FC. The measurement part was achieved through the incorporation of thirteen- and three-monthly financial time series variables observed over the period January 2000 - December 2018, into a Two-Step Markov Switching Dynamic Factor Model in State Space Form (TS-MS-DFM-SSF). The testing part was achieved through the confirmation of stylised features of FCs as laid out in Borio (2014). To facilitate comparison, a Logistic Model was adopted to evaluate the relationship between these indices and periods of financial crisis, focusing both on how they coincide in time and whether or not these indices can be used as early warning indicators.

The study provided evidence that the indicators of credit, house prices and equity prices are the best indicators for measuring FCs in South Africa. However, there exist room for extension of the scope of financial time series variables used beyond these indicators. The added indicators proved to have more information content for financial crises forecasting. They have further proved to be better signals and better early warning indicators of financial crises in South Africa.

The rest of the study is organised as follows: section two illuminates a review of theoretical and empirical literature relevant to the topic of FCs and highlights indicators that should be used to measure FCs. Section three presents different methodologies used to achieve the objectives of this study. Section four entails a description of the results and subsequent analysis, while section five presents conclusions and policy recommendations.

2 REVIEW OF RELATED LITERATURE

Should the scope of financial time series variables used to measure FCs be expanded? Are the current FC measures representative of the true dynamics of a country's financial system? These are some of the defining questions that shape the literature on FCs at least since Hatzius et al. (2010) and Drehmann et al. (2012). While these remain important in ensuring the accuracy of the FCs of different countries, little or no effort has been devoted towards addressing them. This section gives an overview of the existing theoretical and empirical literature on measuring and characterising Financial Cycles (FCs) and the extent to which the abovementioned questions are addressed.

2.1 Conceptual and Empirical Literature

Conceptually, financial crises may occur due to an increase in asymmetric information from a disruption in the financial system. This causes a rise in adverse selection and moral hazard problems, which leads to financial markets being incapable of channelling funds efficiently from savers to households and firms with productive investment opportunities (Mishkin, 2007). Market participants do not recognize this susceptibility to information uncertainty as a systemic dimension sufficiently in advance. As a result, financial markets fail to function efficiently; this results in a marked contraction of the economy. This was found to have led to the global financial crisis (GFC) and the subprime financial collapse of 2007-2009 (Mishkin, 2007).

The abovementioned finding highlights an important problem of the lack of lucidity about the system's conditions and their causes, and the inability to detect risks well in advance. This is crucial for risk managers as guardians of organisational stability, as well as financial supervisors, as guardians of financial system stability (Mishkin, 2007). For all observers, this lack of lucidity prevents the monitoring of build-ups in the financial system, and if an event has occurred or is imminent, it prevents restoration and maintenance of stability. As for any guardians of stability, it hinders the design of effective and efficient crisis management strategies, and impedes the ability to prevent future systemic crises (Hollander and Van Lill, 2019).

As a result, an appropriate monitoring tool may support the ability to observe potential systemic risks in the financial system and enable continuous assessment of the financial system conditions. In addition, it would enable supervisors to observe causes of stress in the system, and by providing alerts, it would assist in dispersing the information uncertainty and allow risk managers time to counteract. Such a tool for monitoring and supervising the proliferation of relevant aspects in the financial system may be constructed as a Financial Cycle (FC) (Drehmann et al. (2012) and Oet et al. (2012)).

Empirical work on FCs remains relatively infantile. It has its roots in the literature on systemic boom busts patterns in the financial system that interact with the real economy. This could be traced back to 1933, (see Fisher (1933)), 1978 (see Kindleberger and Aliber (1978)), 1986 (see Minsky (1986)) and 1992 (see (Minsky, 1992)). Presently, two literature strands remain relevant. The first strand of literature consists of empirical work on early warning indicators of financial stress (Kaminsky et al. (1998) and Demirgüç-Kunt and Detragiache (2005)). This work has been declared comprehensive in Shin (2013), as it amalgamates a variety of financial, real, institutional and political factors. It focused rather on the goodness of fit than on the provision of theoretical explanations of empirical facts (Shin, 2013).

The second and most recent strand of literature has documented how the dynamics of credit and asset markets are associated with financial distress and macroeconomic activity (Borio and Lowe (2002), Detken and Smets (2004), Schularick and Taylor (2012) and Taylor (2015)). This strand of literature revealed that financial instability is an endogenous phenomenon that follows cyclical patterns. Additionally, the perception exists that excessively strong growth in credit and asset prices reflects increases of financial imbalances that can potentially unwind disruptively with negative macroeconomic consequences (Galati, Hindrayanto, Koopman and Vlekke, 2016). Within this context, the concept of a FC is central and a number of key aspects with regard to its measurement and development, have been highlighted (Claessens et al., 2011).

Following from the above paragraph, these key aspects include the absence of a widely agreed upon definition for FCs. While Borio, Furfine and Lowe (2001), Borio and Lowe (2002) and Borio (2014), defined FCs as "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financial constraints, which translate into booms followed by busts". Drehmann et al. (2012) have proposed defining FCs as a distance between two financial crises, recommending credit-to-GDP as a starting point. Others (Krznar and Matheson, 2017:4). defined FCs as "an average of a cyclical component of the financial variables such as real credit, credit-to-GDP or property prices, extracted using a univariate, statistical filter targeting a specific frequency". The first definition remained dominant, as is evident in most recent papers on

FCs (see Claessens et al. (2010), Claessens et al. (2011), Borio (2014), Ma and Zhang (2016), Cagliarini and Price (2017) and Farrell and Kemp (2020)).

The relevant literature has also highlighted the lack of consensus on the financial variables/indicators that should be used to measure FCs or be included in constructing Composite Financial Cycle Indices (CFCIs) (Krznar and Matheson, 2017). This is mainly due to the fact that risk perceptions and attitudes towards risks are not easily measured directly. As a result, the selection of appropriate variables for measuring FCs relies upon literature justifications (Krznar and Matheson, 2017). For example, Claessens et al. (2010), Drehmann et al. (2012) and Borio (2014), explained that the most parsimoniously method of measuring FCs is in terms of credit and property prices. These scholars have found credit and property prices to be closely interlinked more especially at low frequencies. Accordingly, this confirmed the significance of credit in financing building and purchase of real estate property.

Several other studies (see Krznar and Matheson (2017), Shen, Ren, Huang, Shi and Wang (2017), Farrell and Kemp (2020) and Bosch and Koch (2020)) have followed on the footsteps of the abovementioned studies to measure FCs. Their findings, have led to similar conclusions. For instance, Krznar and Matheson (2017) measured a Brazilian FC using real credit cycles and the credit-to-GDP ratio. They found credit to be more important in shaping the Brazilian FC. Further, Shen et al. (2017) measured a Chinese FC following on the footsteps of Drehmann et al. (2012). These authors utilised three financial time series variables namely; credit-to-GDP, house prices and equity prices. Results revealed that, these variables best represent the Chinese FC.

Notwithstanding the abovementioned studies, research sourced from the Bank for International Settlements (BIS) and the Bank of Albania has revealed that these variables (credit and house prices) represent the smallest set of variables needed. They are used to depict the mutually reinforcing interactions between positive and negative forces, financing constraints, perceptions of value and assumed risk that could cause economic disruptions. This small group of key variables can be expanded to include factors such as credit spreads, risk premia, default rates *inter alia*. The analysis of these added variables facilitate measuring risk and providing a perception of exposure (Chorafas, 2015).

To date, recent studies (see Aikman et al. (2015), Ma and Zhang (2016), Schüler et al. (2016) and Billio and Petronevich (2017)) have shown that excluding other relevant variables might lead to inconclusive results. Accordingly, the most prudent way of characterising FCs is to statistically combine a variety of financial variables and extract their common factor. This has allowed for the incorporation of numerous financial variables capturing a wide variety of financial markets, deemed necessary for FCs. This has further evoked the interest of different scholars in studying the appropriate statistical methods for measuring FCs. While, empirical work is still evolving on this avenue of research, recent studies have relied on three approaches to measure FCs, *viz:* turning point analysis, frequency-based filters and unobserved component time series models.

The turning point analysis approach refers to the traditional method of measuring Business Cycles (BCs) through dating their peaks and troughs, as introduced by Burns and Mitchell (1946). To date, this method remains relevant, as organisations such as the National Bureau of Economic Research (NBER) and the Euro Area Business Cycle Dating Committees (EABCDC) still rely on it to measure Business Cycles (BCs) (Venter, 2017). It has also been applied on the FCs literature as seen in the works of Claessens et al. (2010), Claessens et al. (2011) and Claessens et al. (2012). These authors characterised FCs by means of dating the peaks and troughs in credit-to-GDP, property prices and equity prices; and found that the cycles in these individual financial variables tended to be more stretched out in time and ampler than the BC. Notwithstanding its wide application, this method is not without its shortcomings. In particular, there is little theory available to explain the findings, further, these findings can be sensitive to censoring assumptions (Cagliarini and Price, 2017).

The second approach relies on frequency-based filters, statistical filters and band-pass filters such as, the Hodrick Prescott filter, the band-pass filters of Baxter and King (1999) and Christiano and Fitzgerald (2003). These have been applied in a number of studies on FCs (see Aikman, Haldane and Nelson (2015), Cagliarini and Price (2017), Bosch and Koch (2020) and Farrell and Kemp (2020)). For example, in Aikman et al. (2015) the band-pass filter of Christiano and Fitzgerald (2003) was applied to examine the interactions between business and credit cycles. Part of the empirical evidence obtained pointed to the existence of credit cycles with similar features as those identified by turning point analysis. However, these filters may introduce spurious cycles into the results, due to the assumptions made about the length of BCs (Cagliarini and Price, 2017).

The third and most recent approach involved the application of unobserved component time series models (UCTM) or model-based filters such as the Kalman filter. This entailed a joint decomposition of an amalgamation of variables into long-term trends and a combination of short-and-medium term cycles (Galati et al., 2016). While this approach is more popular on the BCs literature (Valle e Azevedo et al. (2006)), it has been rarely applied on the FCs literature. Considering Koopman and Lucas (2005) as an example, they extracted cycles from credit spreads, business failure rates, and real GDP in the Unites States and found evidence of comparable medium-term cycles. In contrast to the non-parametric filters mentioned above, this approach possesses a number of advantages (Galati et al., 2016).

Firstly, rather than imposing ad-hoc parameters on the Kalman filter, these parameters are model-based and they are derived from estimating an unobserved component model by the Maximum Likelihood method. Secondly, as the filter is model-based, it allows for ease of using diagnostic tests of fit and validity of the model and the accuracy of the estimates thereafter. Thirdly, unlike non-parametric filters which rely on predetermined frequencies in order to extract cycles, model-based filters estimate frequencies. Lastly, model-based filters have the ability to handle both normal and non-normal data, which is beneficial for research on FCs as financial data usually have long memory (Galati et al., 2016).

Despite the several methodological and non-methodological issues abovementioned, the second strand of literature has also cited several unique features of FCs. These includes; a close association between FC peaks and periods of financial distress; financial crises and bank crises, a much lower frequency than the traditional business cycle; the ability to detect financial distress with a good lead in real time, and a length and amplitude that's not constant in nature. These features have been confirmed by a number of studies in the FCs literature, including among others; Boshoff (2005), Claessens et al. (2011), Drehmann et al. (2012), Borio (2014), Krznar and Matheson (2017), Shen et al. (2017). Accordingly, it is fitting to state; to be regarded as a suitable supervisory and monitoring tool for financial stability, any measured Composite Financial Cycle Index should possess most if not all the above-mentioned features.

South African studies (see Boshoff (2005), Bosch and Koch (2020) and Farrell and Kemp (2020)) have also devoted efforts towards measuring and characterising FCs. These have trailed on the footsteps of Drehmann et al. (2012), and utilised three financial time series variables namely credit, house prices and equity price to measure the South African FC. For example, Farrell and Kemp (2020) found that real credit and house prices are key indicators to measure FCs in South Africa. They also found a FC that is longer and has a larger amplitude than the BC, whose peaks are closely associated with periods of distress. Bosch and Koch (2020) utilised similar information to measure the South African FC and confirmed the results above.

Accordingly, the present study differs from the abovementioned studies in three aspects, firstly the study considered the extension of the scope of time series variables used to measure the South African FC. Secondly, the study used the CFCI measured here and confirmed all the 5 stylised features of FCs as found in the literature. Lastly, this study compared the CFCI of this analysis to the FC which proxy the SARB FC, in order to determine the most appropriate measure of the South African FC. According to authors knowledge, few if any studies have devoted effort towards the analyses of this kind, especially in the South African context. The following section provides the statistical methods utilised to achieve the objectives of this study.

3 DATABASE AND METHODOLOGY

3.1 Database and Data Modifications

We constructed an extensive dataset using monthly series of financial variables for South Africa penning the period 2000M01 to 2018M12. For ease of interpretation and the understanding of how cycles evolve over time, the sample is divided into three sub periods namely: pre-crises, crises and post crises periods. This is mainly to ensure that we cover both the pre and post 2007-2009 Global Financial Crises (GFC). While the current South African FC followed on the footsteps of .Drehmann et al. (2012), which considered the financial system as a collection of three financial market segments and selected three financial variables in the measurement of the FC Index. The modified version of this analysis deviated from this, through the selection of thirteen monthly financial time series variables that frugally describe FCs in South Africa and capture six financial markets including; equity market, foreign exchange market, financing market, credit market, real estate market, and the securitisation market.

These variables include; the real broad effective exchange rate (RBEER), which is a measure of value of the currency against a weighted average of several foreign currencies divided by a price deflator or index of cost (Pineda et al., 2009). House prices (HP), which are measured by the Residential Property Price Index showing indices of residential property prices over time. All Share Price Index (ASP) which is the total share prices for all shares for South Africa. Long Term Government Bonds Yields (LTGBY), represents long-term interest rates exceeding 10 years. 10-year Government Bond Yields (GB10Y) and 5-year Government Bond Yields (GB5Y), representing long-term and short-term interest rates less than or equal to 10 years.

Total credit to the Private Non-Financial Sector (TCPFS), which is pro-vided by domestic banks, all other sectors of the economy and non-residents. Nominal Effective Exchange Rate (NEER) calculated as geometric weighted av-erages of bilateral exchange rates. Treasury Bill Rates (TBILL) "is a short-term debt obligation of the central government" (De Angelis, Aziakpono and Faure, 2005).. The three measures of money in South Africa: M1, M2 and M3. Lastly, Interbank Lending Rate (ILR), which is the rate charged on short-term loans between South African banks (Labuschagne, Louw and Ndanga, 2010).

Data for these variables was gathered from the Reserve Bank of South Africa, OECD database, World Bank database, International Monetary Fund's interna-tional financial statistics, Federal Reserve Bank of St Louis and the Bank for In-ternational Settlements (in the year 2019). These variables were first converted into a single unit of measure through the adoption of a min-max normalisation method, given as follows:

$$\mathbf{V'_{it}}=\frac{\mathbf{V_{it}}-\mathbf{Min(V_i)}}{\mathbf{Max\,(V_i)}-\mathbf{Min(V_i)}} \tag{1}$$

where V_{it} is the value of variable i during period t; $Min(V_i)$ and $Max\,(V_i)$ denotes minimum and maximum respectively. This is shown by variable i in the sample period t. V'_{it} on the other hand, shows the normalised value of the variables. Once all the variables were in a single unit of measure, the methodology discussed below was adopted to measure both the FC and the modified version (the CFCI).

3.2 Composite Financial Cycle Index Measurement Approach

Contrary to the methodological approaches mainly adopted to measure the FC in the South African literature (see Bosch and Koch (2020) and Farrell and Kemp (2020)). This study showed that a Markov Switching Dynamic Factor Model, could be a suitable method for FC analyses in South Africa. Following on the footsteps of Kim and Yoo (1995), it was assumed that the growth rate cycle has two stages, for example, downturn and upturn. Financial Sector activity in this case was characterised by an unobservable factor extracted from an amalgamation of several observable variables. The switch between regimes was assumed to occur instantaneously with no transition periods. Motivation for this assumption came from the fact that the transition period before deep crises is usually short enough to be omitted (Doz and Petronevich, 2016).

The model is divided into two equations; one defining a factor model, and the other defining a Markov Switching model, which was assumed for the common factor. The first equation showed each series of the information set decomposed into the sum of a common component and an idiosyncratic component as follows:

$$\mathbf{y_t}{=}\gamma\mathbf{f_t}{+}\mathbf{z_t} \tag{2}$$

where y_t is a $N \times 1$ vector of financial indicators, f_t is a univariate common factor, z_t is a $N \times 1$ vector of idiosyncratic components, which is uncorrelated with f_t at all leads and lags, and γ is an $N \times 1$ vector. One requirement from this equation is for all variables to be stationary i.e. some variables will appear as first differences of non-stationary financial indicators (Doz and Petronevich, 2016).

The second equation defined a Markov Switching model of Hamilton (1989). This model has the ability to mark time. In terms of this method, a latent random variable s_t governs the state or regime with, $s_t = 0$ indicating low or negative growth, and $s_t^* = 1$ indicating high or positive growth. Two states, signifying positive and negative average growth rates are adequate to mark turning points since $\Delta y_t < 0$ indicates a downturn and $\Delta y_t > 0$ indicates an upturn (Bosch and Ruch, 2013).

Consider the development of a series y_t, where $t = 1, 2, ..., T$ which is characterised by two states as follows:

$$\textbf{State 1}: \ \mathbf{y_t}{=}\boldsymbol{\mu_1}{+}\boldsymbol{\varepsilon}_\mathbf{t} \tag{3}$$

$$\textbf{State 2}: \ \mathbf{y_t}{=}\boldsymbol{\mu_2}{+}\boldsymbol{\varepsilon}_\mathbf{t} \tag{4}$$

where μ_1 and μ_2 are the intercept terms in state 1 and state 2, respectively. ε_t is a white noise error with variance σ^2. The two states model shifts in the intercept term and it is not known in which state the process is at, therefore, the state variable is unobserved. Markov-switching regression models allow the parameters to vary over the unobserved states. In the simplest case, this model can be expressed as a Markov Switching Dynamic Regression model (MSDR) with a state-dependent intercept term. MSDR models allow a rapid adjustment after the process changes state. These models are often used to model monthly to higher-frequency data. When the process is in state s at time t, a general specification of the MSDR model is written as:

$$\mathbf{y_t}{=}\boldsymbol{\mu}_{\mathbf{s_t}}{+}\mathbf{x_t}\boldsymbol{\alpha}{+}\mathbf{z_t}\mathbf{B}_{\mathbf{s_t}}{+}\boldsymbol{\varepsilon}_\mathbf{s} \tag{5}$$

where y_t is the dependent variable, μ_s is the state-dependent intercept, x_t is a vector of exogenous variables with state-invariant coefficients α, z_t is a vector of exogenous variables with state-dependent coefficients B_s, and ε_s is an independent and identically distributed (i.i.d.) normal error with mean *0* and state-dependent variance ε_s^2, x_t and z_t may contain lags of y_t. MSDR models allow states to switch according to a Markov process. In this study, a two state Markov Regime Switching Dynamic Regression model was adopted to conform to the growth rate cycle downturns and upturns of the FC. Consequently, equation 5 above is rewritten as follows:

$$\mathbf{CFCI_t} = \boldsymbol{\mu}_{\mathbf{s_t}} + \mathbf{L1.CFCI_t}\boldsymbol{\alpha} + \mathbf{L2.CFCI_t B_{s_t}} + \boldsymbol{\varepsilon}_\mathbf{s} \tag{6}$$

The transition probabilities of a change in state from state i to state j are summarised with the use of a transition matrix namely P, for a two state Markov chain as follows:

$$\mathbf{p} = \begin{bmatrix} \frac{p_{11}}{1-p_{11}} & \frac{1-p_{22}}{p_{22}} \end{bmatrix} \tag{7}$$

where, $p_{ij} = (s_t = j|s_{t-1} = i)$, meaning that the probability that the current state is j given that the previous state was i. In order to be able to estimate the coefficients of the above equation, one has to maximise the log-likelihood of the unconditional density function of y_t. For the purposes of identifying the FC turning points from the model above, filtered probabilities were calculated. The calculated filtered probabilities were based on information available until period $t-1$ (Doz and Petronevich, 2016).

The model proceeds in two-steps as follows:

1. The initial step involved the extraction of a common factor f_t from an amalgamation of a large set of financial variables as suggested by recent literature (see Chorafas (2015) and Kota and Goxha (2019)). In this context, a Dynamic Factor Model in State Space Form was adopted. A dynamic factor illustration of the data with unobserved factors, loadings and idiosyncratic components can be written as follows:

$$\mathbf{x_t} = \mathbf{B_0 u_t} + \mathbf{B_1 u_{t-1}} + ... + \mathbf{B_p u_{t-p}} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{8}$$

where x_t is an $N-$dimensional vector of observed data at time $t, t = 1, ..., T$.This is determined by q dynamic factors u_t with loadings B_j up to lag p, i.e. $j = 1, ..., p$, and idiosyncratic components ε_t.

The above dynamic factor model is then written in *state-space* form with F_t as a state vector, as follows:

$$\mathbf{F_t} = \mathbf{AF_{t-1}} + \mathbf{Gw_t} \tag{9}$$

$$\mathbf{x_t} = \mathbf{BF_t} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{10}$$

where $A \equiv \begin{bmatrix} 0 & \cdots & 0 & 0 \\ I_q & \cdots & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \cdots & I_q & 0 \end{bmatrix}$, $A^{p+1} = 0$ (nilpotent), $G' = [I_q\, 0...0]$, $G \in R^{k\times q}$, $w_t \sim GWN(0, I_q)$ and $\varepsilon_t \sim GWN(0,\, V_\varepsilon)$.

Since the attainment of a *state space* form of the equation, the Kalman filter can be used to write the likelihood function in prediction/ error form, assuming normally distributed errors. The initial estimate of the state vector is $\hat{F}_0 = 0$ with variance given by $V_{\hat{F}_0} = I_k$, and one step ahead predication given by $\hat{F}_{t+1|t} = AF_t$. The priori variance is equal to $V_{\hat{F}_{t+1|t}} = V_{\hat{F}_t} A^{'} + GG^{'} = I_k$. The Kalman filter algorithm produces $\hat{F}_{t+1} = \hat{F}_{t+1|t} + K_{t+1}pe_{t+1}$, with prediction-error $pe_{t+1} = x_t - \hat{x}_{t+1|t}$, where $\hat{x}_{t+1|t} = B\hat{F}_{t+1}$. The gain algorithm yields $K_{t+1} = V_{\hat{F}_{t+1}} B^{'} [BV_{\hat{F}_{t+1}} B^{'} + V_\varepsilon]^{-1}$ and the posterior variance obtained is $V_{\hat{F}_{t+1}} = (I - K_{t+1}B)V_{\hat{F}_{t+1}}$.

The steady state filter converges to $V_{\hat{F}_{t+1}} \rightarrow V_{\hat{F}}$ where $\hat{F}_{t+1|t} = A\hat{F}_{t|t-1} + AK(x_t - \hat{x}_{t|t-1})$ with gain: $K = V_{\bar{F}} B^{'} [BV_{\bar{F}} B^{'} + V_\varepsilon]^{-1}$ and variance: $V_{\bar{F}} = A\left[V_{\bar{F}} - KBV_{\bar{F}}\right] A^{'} + GG^{'}$. In this context, the study estimated the following equation to measure the Composite Financial Cycle Index for South Africa:

$$\left(\frac{\mathbf{f_t}}{\mathbf{f_{t-1}}}\right) = \begin{pmatrix} \theta_1 & \theta_2 \\ 1 & 0 \end{pmatrix} \left(\frac{\mathbf{f_{t-1}}}{\mathbf{f_{t-2}}}\right) + \left(\frac{\mathbf{V_t}}{\mathbf{0}}\right) \tag{11}$$

$$\begin{pmatrix} \mathbf{\Delta RBEER_t} \\ \mathbf{\Delta HP_t} \\ \mathbf{\Delta ASP_t} \\ \mathbf{\Delta GB10Y_t} \\ \mathbf{\Delta GB5Y_t} \\ \mathbf{\Delta TCPFS_t} \\ \mathbf{\Delta LTGBY_t} \\ \mathbf{\Delta NEER_t} \\ \mathbf{\Delta M1_t} \\ \mathbf{\Delta M2_t} \\ \mathbf{\Delta M3_t} \\ \mathbf{\Delta TBILL_t} \\ \mathbf{\Delta ILR_t} \end{pmatrix} = \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \\ \gamma_5 \\ \gamma_6 \\ \gamma_7 \\ \gamma_8 \\ \gamma_9 \\ \gamma_{10} \\ \gamma_{11} \\ \gamma_{12} \\ \gamma_{13} \end{pmatrix} f_t + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \\ \varepsilon_{8t} \\ \varepsilon_{9t} \\ \varepsilon_{10t} \\ \varepsilon_{11t} \\ \varepsilon_{12t} \\ \varepsilon_{13t} \end{pmatrix} \tag{12}$$

1. The second step estimates by Maximum Likelihood, the parameters of a Markov Switching Dynamic Regression Model. This was aimed at fitting a univariate model (as seen in Hamilton, 1989) to the estimated factor $\hat{f}_t$ which is taken as if it were an observed variable. In order to identify the CFCI peaks and troughs, the study followed the footsteps of Krznar (2011) and identified a peak of the CFCI in period t, if the financial sector activity was on an upturn in period *t-1* and filtered probability $Pr(s_{t+1} = 1|\Omega_{t-1}pq\mu_1\mu_2\sigma^2) \geq 0.5$, and a trough is defined in period t if the financial sector activity was on a downturn in period *t-1,* and filtered probability $Pr(s_{t+1} = 1|\Omega_{t-1}pq\mu_1\mu_2\sigma^2) \leq 0.5$.

3.3 Composite Financial Cycle Index Testing Approach

Once the FC and the modified CFCI are measured and their turning points identified according to section 3.2 above, in the present section, we proceeded to test and compare the two indices and their performances, through the confirmation of the stylised features as outlined in Drehmann et al. (2012) and Borio (2014). As an initial step, we would like to ensure that these cycles are meaningful and easily interpretable. Following on the footsteps of van den End (2006), Feridun (2008) and Al-Tarawneh (2012), a financial stability indicator is more meaningful and easily interpretable when it has boundaries. This is associated with the concept of financial stability as a continuum moving within the corridor.

The corridor is bounded by critical values within which the system is assumed to function well (van den End, 2006). Usually, these critical values are calculated as: the index mean ±1.5 standard deviations/index mean ±2 standard deviations. Therefore, financial instability is represented by larger movements of the financial stability index (Al-Tarawneh, 2012). The upper limit of the financial stability index (+1.5SD) is referred to as the *imbalances boundary*, and the lower limit of this index (-1.5SD) is referred to as the *instability boundary.* The area between the two boundaries is known as a *stability corridor* and this shows instances where the financial system appears to function well (van den End (2006) and Al-Tarawneh (2012)).

This enabled us to construct a binary crisis variable such that:

$$\mathbf{Y = CRISIS_t =} \begin{cases} \mathbf{1}, & \mathbf{CFC \geq AVG\,(CFCI) + 1.5SD(CFCI)} \\ \mathbf{-1}, & \mathbf{CFCI \leq AVG\,(CFCI) - 1.5SD(CFCI)} \\ \mathbf{0}, & \mathbf{otherwise} \end{cases} \tag{13}$$

where, *Crisis* has three outcomes: when FC / CFCI equals / exceeds its average plus 1.5 standard deviations, (*Y =1),* crisis have occurred due to increased imbalances. When FC / CFCI equals/less than its average minus 1.5 standard deviations, (*Y =-1)*, the crisis occurred due to increased instability. When FC / CFCI lies between the two boundaries, (*Y =0)*, this indicates that the financial system is not facing pressure to change, i.e. no possible financial crises (see van den End (2006) and Al-Tarawneh (2012).

Using the above information content and the financial distress periods identified through equation 13, the study confirmed the ability of the two indices to detect financial distress periods in South Africa. This is achieved through the comparison of these financial distress / crisis episodes with the known financial distress / crisis episodes found in the SA literature (see Bhundia and Ricci (2005) and Maredza and Ikhide (2013)). Further, the study compared the financial crisis episodes obtained above with the FC/ CFCI peaks obtained in section 3.2 above so as to confirm the close association of these as suggested in by Borio (2014).

Through the application of the BB algorithm, the study confirmed the turning points obtained in section 3.2 above and used the information from these turning points to describe the frequency, length and amplitude of the measured indices. Specifically, we produce measures of duration of expansions and contractions which are then used to examine the above features of the FC /CFCI. To facilitate comparison, a Multinomial Logit Model was adopted to evaluate the relationship between CFCI and FC and periods of financial crisis, focusing both on how they coincide in time and whether or not these indices can be used as early warning indicators. This is in view of the fact that the *crisis* variable is a binary variable with three outcomes; -1, 0 and 1 according to the definition of financial crises followed in this study, which considered financial crises that occur due to increased financial imbalances (rising CFCI) and increased instabilities (decreasing CFCI). The suggested models are as follows:

$$\mathbf{CRISES_t = C + CFCI_t + RBEER_t + TCPFS_t + M2_t} \tag{14}$$

$$\mathbf{CRISES_t = C + FC_t + RBEER_t + TCPFS_t + M2_t} \tag{15}$$

where the dependent variable $crises_t$ is constructed in equation 13 above, C is the constant term, $CFCI$ is the Composite Financial Cycle Index and FC is the South African FC proxy index. The other variables are deemed to be potential determinants of financial crisis in the literature (Al-Tarawneh, 2012) and their description is the same as in subsection 4.1. The following section provides the results and robustness analyses in accordance with the methods discussed above and Principal Component Analysis.

4 ESTIMATION RESULTS AND ANALYSIS

4.1 Two-step method

In the initial estimation process, we allowed the model to select final variables. According to the estimated output of the model, eleven out of the thirteen variables were retained. These are variables that can be considered essentially informative of the South African FC. These included the all-share price index, nominal effective exchange rate, interbank lending rate, 5-year government bond yield, 10-year government bond yield, long-term (exceeding 10 years) government bond yields, treasury bill rate, total credit to private non-financial sector, house price index, M1 and M3. The extent to which these individual variables explain the CFCI is shown in Table 1 below.

First step: Dynamic Factor Model in State space form

In the first step of this procedure, a common factor was extracted from the eleven financial time series variables. Applying a Dynamic Factor Model in State Space Form (DFM-SSF) and Principal Component Analysis (PCA) for validity purposes, we considered that the first principal component/ factor provides a good approximation of the common factor. This common factor is here referred to as a Composite Financial Cycle Index, and is illustrated in figure 1 below.

To give meaning and ease of interpretation to the CFCI, Figure 1 below shows the CFCI for South Africa relative to the ±1.5 standard deviation boundaries. The CFCI points to increasing stability (rising CFCI) close to the financial imbalances boundary (+1.5SD) during the Rand crisis of 2001-2003 (Bhundia and Ricci, 2005). The appreciating CFCI during 2001-2003 was accounted for by the depreciated Rand by 26% against the US Dollar. The increased in long-term bond yields by less than 100 basis points. The rise in share prices by 28% and increased real GDP. This is followed by an accelerated increase in financial instability (declining CFCI), which surpasses the instability boundary (between 2005 and 2006).

The CFCI also pointed to a rapid recovery (rising CFCI) from below the instabilities boundary to above the imbalances boundary during the GFC of 2007-2009. This is followed by a rapid increase in instability (declining CFCI) close to the instabilities boundary (between 2009 and 2010). It is noteworthy that the periods of declining CFCI (2003-2006 and 2008-2010) are preceded by rapid increases in the CFCI. During the latter, imbalances grow to such an extent that the imbalances boundary is reached. The sharp rising of the CFCI in 2006-2008 and the sharp fall in 2008-2010, showed that when favourable developments (such as strong growth in credit, rising asset prices and falling interest rates) become excessive, they may become a source of instability. This means that both upward (potential build-up of imbalances) and downwards (manifestation of instability) outliers of the CFCI are meaningful signals about financial stability.

Second Step: Markov Switching Dynamic Regression Model

Figure 2 below illustrates the CFCI level (black line) together with the calculated filtered probabilities of the Markov Switching DR model (grey line). Following Krznar (2011), a peak of the CFCI is defined in period t, if financial sector activity was on an upturn in period *t-1* and filtered probability $Pr(s_{t+1} = 1|\Omega_{t-1}pq\mu_1\mu_2\sigma^2) \geq 0.5$. Further, a trough is defined in period t if financial sector activity was on a downturn in period *t-1,* and filtered probability $Pr(s_{t+1} = 1|\Omega_{t-1}pq\mu_1\mu_2\sigma^2) \leq 0.5$.

On the basis of the aforementioned rule for turning points identification in view of filtered probabilities two peaks of the CFCI (blue bars) were identified, one in May 2003 another in September 2008 (see Table 2 below)

These are the highest points that marks the end of expansion in financial activity and the beginning of contraction in financial activity. In cases where peaks occur at or above the +1.5 standard deviation boundary, these marks the end of financial imbalances within the financial system (see also Bhundia and Ricci (2005)). Also identified, are two troughs (see Table 2 above) of the CFCI shown in Figure 2 by the red bars, one in January 2006, another in July 2011. Again, these points mark the end of deteriorating financial activity and the transition to expansion. In cases where these points occur at or below the -1.5 standard deviation boundary, these marks the end of instabilities in the financial system. These peaks and troughs closely align with those found in others studies in the South African literature (see Bosch and Koch (2020) and Farrell and Kemp (2020)).

4.2 Testing the Composite Financial Cycle Index

This subsection involved testing the CFCI through the confirmation of the stylised features of FCs, as laid down in Borio (2014). As an initial step, the study assessed the ability of the CFCI to detect financial crises episodes in South Africa. To this end, through the adoption of equation 13 above which construct a crises variable such that, there are reference boundaries and when the CFCI surpasses these boundaries, that signifies the occurrence of financial crises. Figure 3 below shows the outcome of this analysis, with the red bars indicative of financial crisis. Accordingly, two periods of financial crisis are identified: August 2005 – April 2006, where the CFCI surpasses the instabilities boundary and crisis lasting about 9 months and January 2008 – March 2009, where the CFCI surpasses the imbalances boundary, with crisis lasting about 15 months.

The period August 2005 – April 2006 is considered here as signifying the events leading up to the subprime mortgage crisis/ the great recession which included a combination of vulnerabilities that developed in the financial system, along with a series of triggering events that began with the bursting of the United States housing bubble in 2005 – 2006. When house price declined and homeowner began to abandon their mortgages, it resulted to a decline in the value of mortgage backed securities held by investment banks. The combination of banks inability to provide credit to businesses and the homeowners paying down debt instead of borrowing and spending, resulted to the great recession of 2007 – 2009. Consequently, the South African economy started experiencing this effect in January 2008 – March 2009, lasting for about 15 months as compared to 19 months in the US.

As a second step, the study tested whether the CFCI peaks as identified in subsection 4.1 are closely associated with the financial crisis periods detected above. This remains imperative as it helps explain the empirical regularity, where recessions that coincide with downturns of the FC are usually severe and deeper. Results from this analysis appear in Figure 4 below, with financial crises shown by the red bars, CFCI peaks by the blue bars and the grey shadings signifying recessionary periods. These results indicate that there is only one instance where financial crisis materialized at or close to the CFCI peak, this is the 2008-2009 GFC which occurred at or close to the September 2008 peak.

This was evident for only financial crisis that originated from domestic exposures in most industrialized economies (Borio, 2014). In South Africa however, this was evident from financial crises that originated from external exposures (GFC). This result points to new evidence on the occurrence of financial crises in developing countries as opposed to developed countries.

As a third step, we produce measures of duration of expansions and contractions which are then used to examine the frequency, length and amplitude of the CFCI. Results from this are shown in Table 3 above. Through the application of the Bry and Boschan algorithm with the criterion of .Drehmann et al. (2012) for phase and cycle durations, we found that there has been one financial cycle in South Africa during the period under consideration. The cycle deviates from its' potential level thus reaching a peak in May 2003 and September 2008.

These results indicate that the trough of the current FC was reached in June 2011 and the FC is currently on an upturn Phase. This is closely associated with the conclusion of Farrell and Kemp (2020) whose FC reached a trough around 2013, it is also different from Bosch and Koch (2020) whose current FC has not reached a lower turning point.

Following on the footsteps of .Hiebert et al. (2018) tables 3 and 4 shows the average length of upturns and downturns and compares this with the average length of the business cycles obtained from Bosch and Koch (2020). Results indicate that FC upturns in South Africa last longer than downturns. Further, the overall length of the FC is 7,2 years and exceeds that of the BC which is 5,8 years. This is consistent with .Drehmann et al. (2012) who found that the FC lasts between 5 to 20 years and it is usually longer than the BC.

Table 5 reports the average amplitude between the FC turning points, results indicate that FC upturns are more intense than FC downturns. Further, this intensity does not remain constant over time, however, varies with the different phases. This result points to biasedness between amplitude and length of the FC phases. Overall, we found our CFCI to possess all the features of FCs as laid out in the literature. This result also points to new evidence on the occurrence of financial crises in developing countries as opposed to developed countries.

4.3 Does the Composite Financial Cycle Index differ from the South African Financial cycle?

In this subsection we compared the CFCI measured by a common factor extracted from an amalgamation of thirteen monthly financial time series variables, with the current South African FC measure. Due to the South African FC being publicly unavailable, we have taken the liberty and measured this index through the application of the method used for our CFCI. Therefore, the South African FC in this analysis represents a common factor extracted from an amalgamation of total credit, house prices and equity prices. Such a comparison remains imperative so as to answer the questions of; whether or not should the scope of FC variables be extended and whether the current FC best captures the dynamics of the South African financial system. Figure 5 below illustrates this comparison.

Figure 5 below shows the CFCI of this analysis (black line), together with FC which proxy the SARB FC (red line), relative to their ± 1.5SD boundaries. The figure shows that the two indices are having the same pattern and follow the same path. Through statistical evidence, the two indices share the same turning points and identifies the same periods as periods of financial imbalances and financial instabilities. Further, there exists a simple correlation of 100% between the two indices. The SARB FC also shows larger variations compared to the CFCI of this analysis, this is especially during periods of financial instabilities and or imbalances. This is confirmed by larger amplitudes between the different turning points as compared to those of our CFCI.

To determine the quality of these FC measures, we evaluate the relationship between each index and the periods of financial crisis, focusing on their interactions in time. The main aim is to determine the potential of each index measure in explaining periods of financial crisis. To this end, a multinomial logit model is applied and results are shown in Table 6 below.

It is worth noting that, the coefficient estimates of the multinomial logit model can be difficult to interpret because they are relative to the base outcome. Therefore, another way to evaluate the effect of covariates is to examine the marginal effects. Table 6 shows the marginal effects of the two indices on both financial instabilities and imbalances periods (columns 3 and 5). Accordingly, the CFCI has the highest potential of explaining both financial instabilities and financial imbalances. This is shown by the higher marginal effects compared to those of the FC proxy; being -0.4% in the period of financial instabilities and 0.9% in the period of financial imbalances.

Extending the above multinomial logit results and focussing this time on early warning indicator analysis and financial crises determinants. The study included other variables which are deemed to be potential early warning indicators in the South African literature and tested whether the two indices are potential early warning indicators for imminent financial crises. The included variables are; real broad effective exchange rate, M2 money stock and total credit. Results from this are shown in Table 7 in the appendix section of this study. From this it is evident that, both the CFCI and the FC proxy are strong determinants of financial crises in South Africa, with the effect of the CFCI being greater than that of the FC proxy, looking at marginal effects. Results also indicate that, among all else, an excessive appreciation of the CFCI is alarming. On the other variables, both M2 and total credit are not significant determinant of financial crises in south Africa, while there is important information content to be learnt through excessive appreciation of the RBEER.

Additionally, we followed on the footsteps of Drehmann and Juselius (2014) and use the statistical method of the AUROC curve in order to evaluate the suitability of the each of the above indices. We measured the signalling ability of each of the indices through plotting the AUROC curve (area under the receiver operator characteristic curve) which here evaluates the accuracy of forecasting financial crises for each of the indices. The statistics of the AUROC is displayed below, with a value of 0.5 indicating that the index does not provide enough information to forecast financial crises, and a value of 1 indicating that the index provides perfect information for forecasting financial crises. Values between 0.5 and 1 serve to measure an index with best performance, since a perfect index does not exist (see Drehmann and Juselius (2014), Doz and Petronevich (2016) and Kota and Goxha (2019)).

After fitting a logit model for each of the two indices, we then used the AUROC statistic in order to evaluate the performance of these indices in terms of providing information for forecasting financial crises in South Africa. Results from this are shown in Table 8 above, and these show that the performance of the two indices for crises forecasting is equal, given by an AUROC statistic of 0.6250. According to the general classification on forecasting accuracy of the AUROC indicators, it can be concluded that, the two indices do provide some important information content in terms of forecasting imminent financial crises in South Africa.

Through the comparison of the above indices and the cyclical components of total credit, house prices and equity prices (see figures 6 and 7 in appendix), it is clear that these two indices follow the same path as that of the cyclical components of these variables. Further, the analysis indicated that the FC index which is used here to proxy for the SARB FC, is largely influenced by the indicator of total credit. However, through statistical analysis, total credit is not a significant determinant of financial crises in South Africa. This analysis has also indicated that there is greater information content for financial crises forecasting on the CFCI than on the FC proxy, though not a substantial difference. This analysis further revealed that, the CFCI is a better early warning indicator of financial crises in South Africa compared to the FC proxy, so much so that, an excessive appreciation of this index is alarming. The following section provides conclusions and policy recommendations in line with the results obtained above.

5 CONCLUSIONS AND RECOMMENDATIONS

This study has measured and tested a Composite Financial Cycle Index (CFCI) as a modified version of the current South African FC. Due to unavailability of the current South African FC, this analysis was extended by measuring a FC index following the procedure of the SARB but using a different method, hence this was referred to here as a SARB FC proxy index. We then compared these two indices, in order to determine the most appropriate measure of the South African FC. The measurement part was achieved through the incorporation of thirteen- and three-monthly financial time series variables observed over the period January 2000 - December 2018, into a Two-Step Markov Switching Dynamic Factor Model in State Space Form (TS-MS-DFM-SSF). The testing part, was achieved through the confirmation of stylised features of FCs as laid out in Borio (2014). To facilitate comparison, a Logistic Model was adopted to evaluate the relationship between these indices and periods of financial crisis, focusing both on how they coincide in time and whether or not these indices can be used as early warning indicators.

The measured CFCI was found to possess all the stylised features of FCs as found in the literature. Further, through comparison of the SARB FC proxy and the CFCI of this analysis we added new evidence into the FCs literature, specifically the South African FCs literature. Firstly, this analysis has indicated that the FC index which is used here to proxy for the SARB FC, is largely influenced by the indicator of total credit. Secondly, through statistical analysis, total credit was found to be an insignificant determinant of financial crises in South Africa. Thirdly, this analysis has also indicated that there is greater information content for financial crises forecasting on the CFCI than on the FC proxy. Fourthly, this analysis further revealed that, the CFCI is a better early warning indicator of financial crises in South Africa compared to the FC proxy, so much so that, an excessive appreciation of this index is alarming.

Therefore, considering the graphical illustrations, statistical evidence and expert judgement, we conclude that the indicators of total credit, house prices and equity prices are the best choice of indicators for measuring FCs in South Africa, hence the option of the SARB is substantiated. However, there exist room for extending the scope of financial time series variables used to measure FCs in South Africa.

An important issue here is the length of time series used in measuring these FC indices. Such that, the period which includes a larger scope of time series indicators is usually shorter compared to the period which includes a fewer number of time series indicators, and this due to data unavailability on most of the financial time series indicators. Therefore, for longer periods of time the three variables can be used and for shorter periods of time, the scope may be extended as these results suggested that there is improved forecasting accuracy and measurement accuracy through extension of the scope of time series variables and this ensures that the FC is truly representative of the dynamics of the country's financial system.

One implication of these results is that, the inaccuracy in measuring FCs has the potential to allow for vulnerabilities to accumulate unattended, which poses threats to the financial system and increase risk of exposure. As a result, it is recommended that the SARB consider extending the scope of financial time series variables included in measuring FCs, especially for shorter periods of time, as the added variables have proved to possess greater information content for forecasting of financial crises periods in South Africa. It is also recommended that model-based methodologies for measuring FCs be considered, as they offer a number of advantages compared to statistical filters. Among others, rather than imposing an ad-hoc parameter on the filter, these parameters are model driven. Further, since this is a model-based filter, it provides researchers with the opportunity to use diagnostics to test for validity and fit of the model. Furthermore, model-based filters can handle non-normal data with ease, which is important for modelling financial time series data as it usually has fat tails. This remains an active area of research which is currently the main focus of central banks across the globe. While a number of issues are being explored, future studies can also explore the interactions of Business and Financial cycles, provide evidence of the possibility and extent of coordination between Macroprudential and Monetary Policies. In addition, a model-based approach on the role of Financial cycles in Business cycle models and optimal policy mix analyses warranted.

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Table 1: Proportion of Variation of the CFCI Explained by Individual Variable

	CFCI	ASP	NEER	ILR	GB5Y	GB10Y	LTGBY	TB	TC	HP	M1	M3
f	**1.000**	**0.210**	**(0.787)**	**0.795**	**(0.298)**	**(0.295)**	**0.118**	**0.146**	**1.000**	**0.171**	**(0.081)**	**0.156**

Source: Authors' own estimates.
NB: Negative numbers in parenthesis.

Table 2: Composite Financial Cycle Index Dates at Peaks and Troughs

Peaks	**Troughs**
MAY 2003	January 2006
SEPTEMBER 2008	June 2011

Source: Authors' own estimates.

Table 3: Dates and Length of the Composite Financial Cycle

Financial Cycle Turning Points			
Upward Phase	**Duration**	**Downwards Phase**	**Duration**
Jan 2000 – May 2003	40	June 2003 – Jan 2006	32
Feb 2006 – Sep 2008	32	Oct 2008 – June 2011	33
July 2011 - Current	91		
Average duration in years	4.5		2.7

Source: Authors' own estimates

Table 4: Average Length of CFCI compared with the Business Cycle.

Composite Financial Cycle Index			Business Cycle		
Peak to Trough	Trough to peak	**Overall**	Peak to Trough	Trough to Peak	**Overall**
2.7	4.5	**7.2**	2.4	3.4	**5.8**

Source: Bosch and Koch (2020) & Authors' own estimates

Table 5: Average Amplitude Between CFCI Turning Points

Peak – Trough 2003M5 – 2006M1	Trough – Peak 2006M1 – 2008M9	Peak – Trough 2008M9 – 2011M6
-0,5298	0,7840	-0,7043
-52,98%	78,40%	-70,43%

Source: Authors' own estimates

Table 6: Relationship between CFCI, FC and Financial Crisis

VARIABLES	(Y=-1)	ME(Y=-1)	(Y=1)	ME(Y=1)
CFCI	0.088*** (0.023)	-0.004*** (0.001)	0.137*** (0.024)	0.009*** (0.002)
FC	**0.054*** (0.014)**	**-0.002*** (0.001)**	**0.083*** (0.014)**	**0.005*** (0.001)**

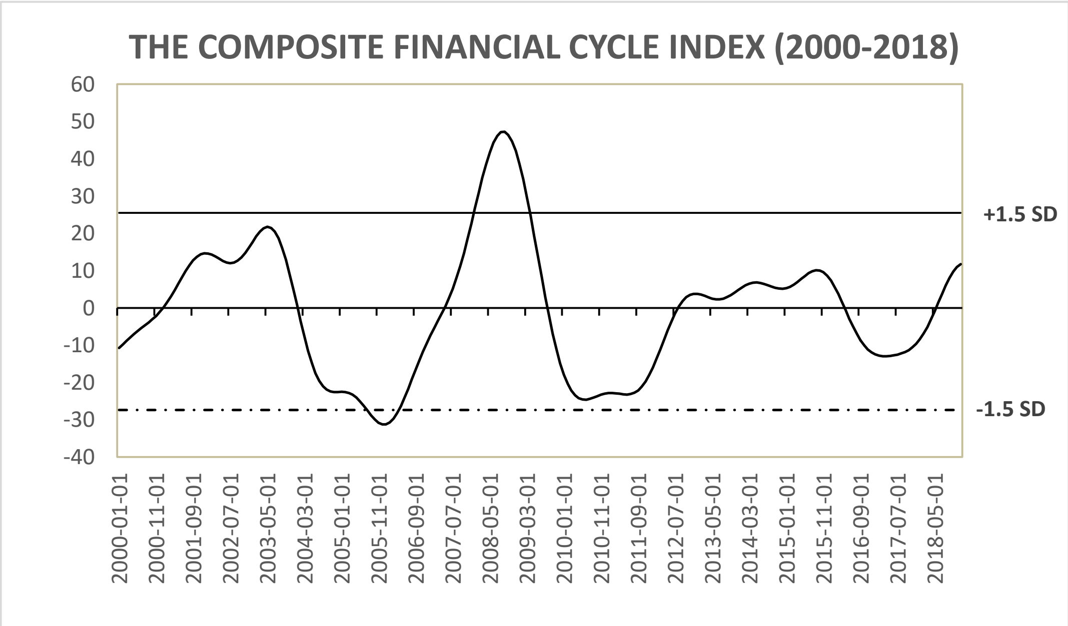
Source: Authors' own estimates. Note: Standard errors in parenthesis.
**** Implies significance at a 1% level, ** Implies significance at a 5% level,*
** Implies significance at a 10% level.*

Table 8: AUROC Output

	AUROC STATISTIC
CFCI	0.6250
FC	0.6250

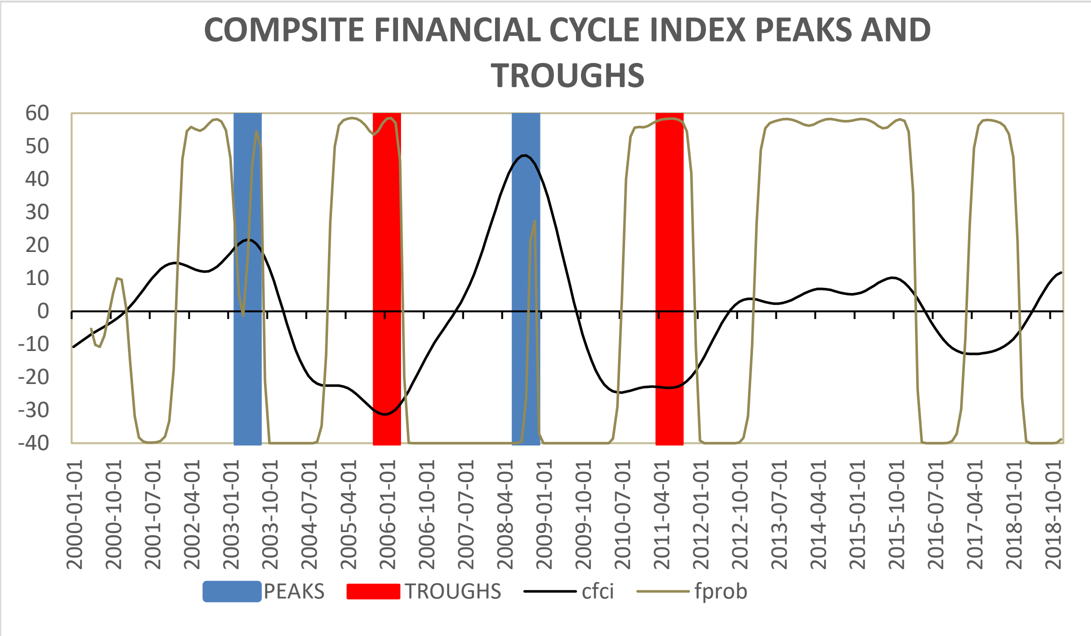
Source: Authors own estimates

Figure 1: DFM-SSF Composite Financial Cycle Index



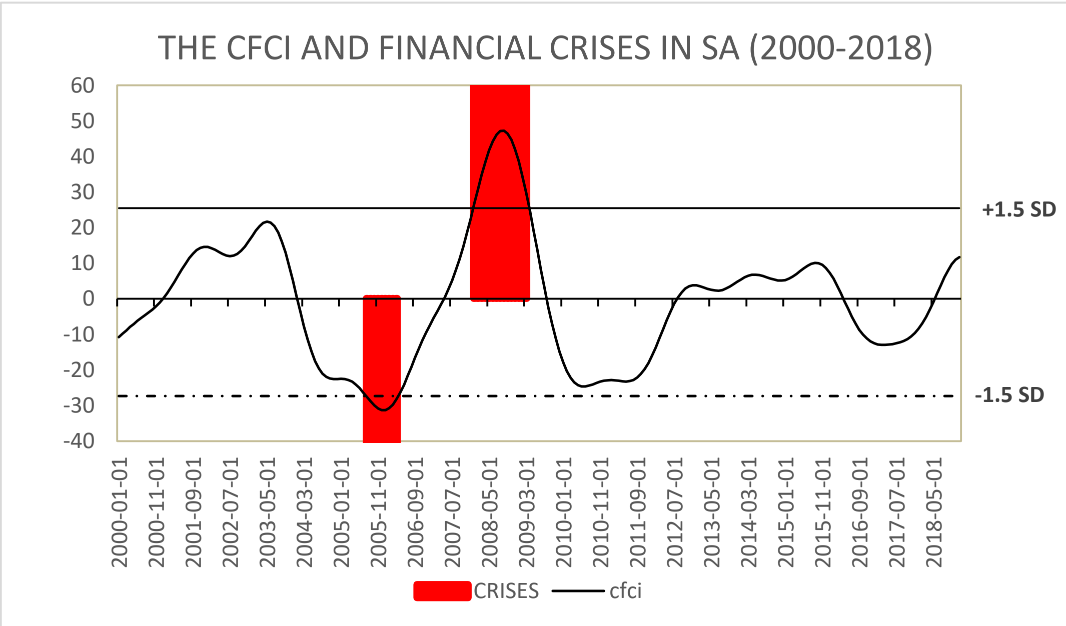
Source: Authors own estimates.

Figure 2: CFCI and Filtered Probability, the Two-step estimation



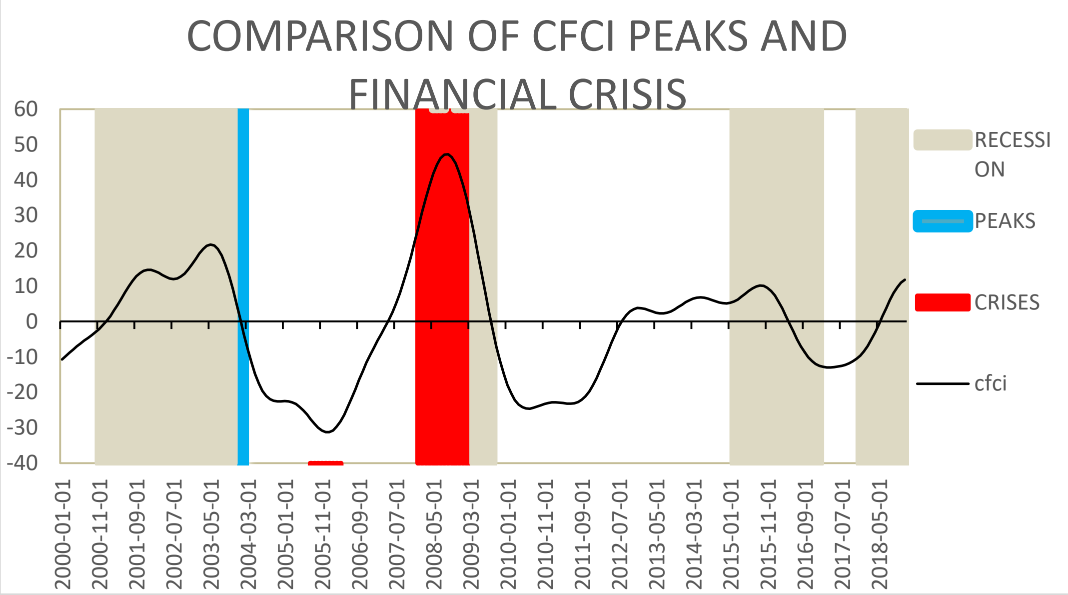
Source: Authors' own estimates.

Figure 3: Financial Crises in South Africa



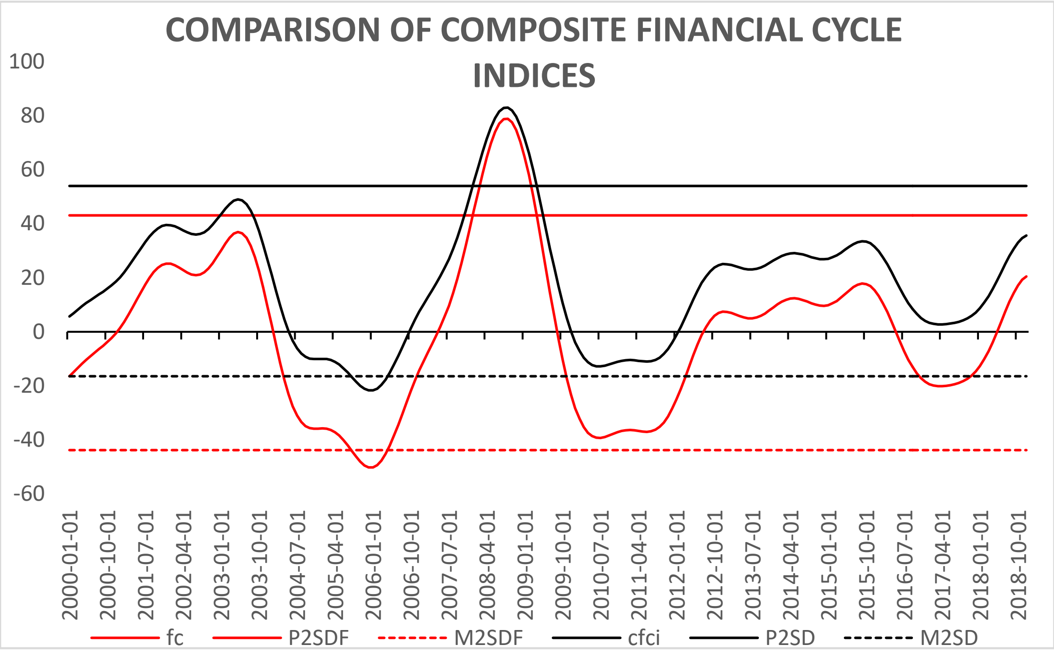
Source: Authors' own estimates.

Figure 4: Comparing CFCI Peaks with Financial Crisis



Source: Authors' own estimates

Figure 5: Comparison of Composite Financial Cycle Indices



Source: authors' own estimates.

APPENDICES

A.1. Screen plot of the eigenvalues Multinomial Logit Results for FC and CFCI

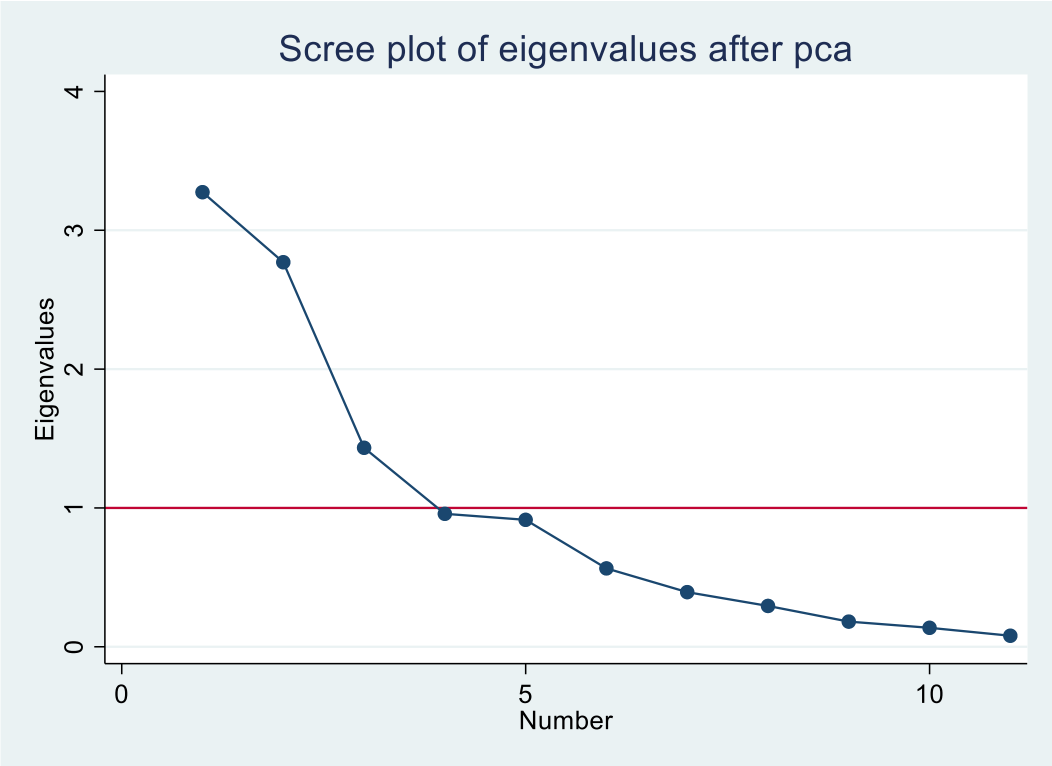
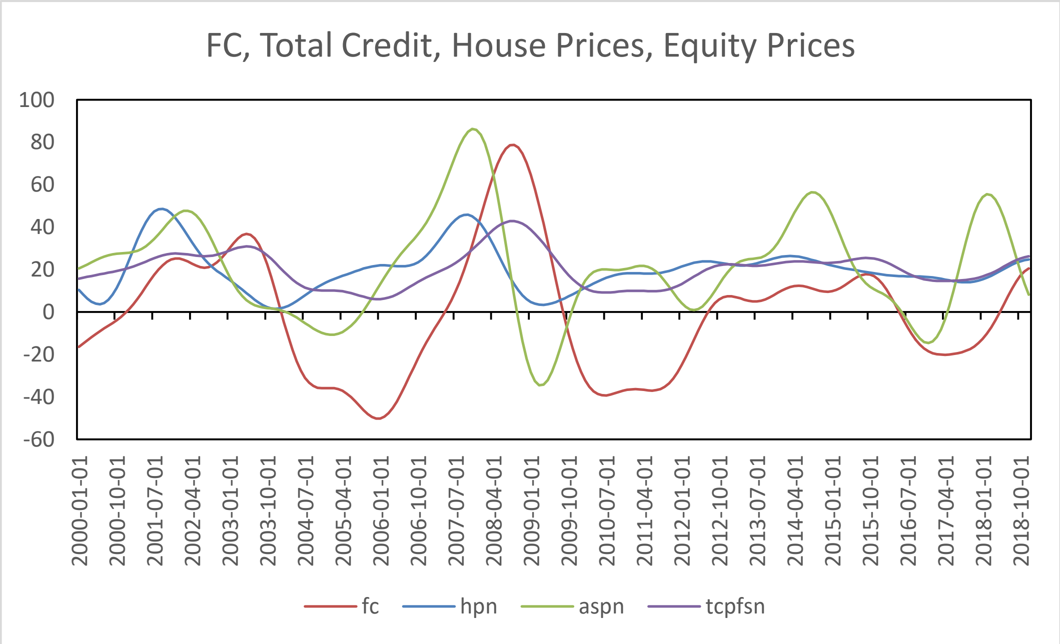


Table 7: Coefficient Estimates of the Multinomial Logit Model.

VARIABLES	(Y=-1)	ME(Y=-1)	(Y=1)	ME(Y=1)	(Y=-1)	ME(Y=-1)	(Y=1)	ME(Y=1)
CFCI &FC	-0.065* (0.037)	-0.003** (0.001)	0.191*** (0.032)	0.012*** (0.003)	-0.40* (0.023)	- 0.002** (0.001)	0.116*** (0.019)	0.007*** (0.002)
RBEER	2.779 (2.628)	0.088 (0.105)	6.759*** (1.911)	0.408** (0.160)	2.779 (2.628)	0.088 (0.105)	6.759*** (1.911)	0.408** (0.160)
M2	-0.020 (2.041)	-0.004 (0.077)	1.062 (1.116)	0.065 (0.069)	-0.020 (0.041)	-0.004 (0.077)	1.062 (1.116)	0.065 (0.069)
TCPFS	-1.866 (1.853)	-0.074 (0.071)	1.288 (1.177)	0.084 (0.072)	-1.866 (1.853)	-0.074 (0.071)	1.288 (1.177)	0.084 (0.072)
CONSTANT	-3.906** (1.728)	-	-7.302*** (1.560)	-	-3.859** (1.744)	-	-7.442*** (1.575)	
LR Statistic (DF=8) Probability	41.77 0.000				41.77 0.000			
Log Likelihood	-71.713							

Source: Authors' own estimates. Note: Standard errors in parenthesis.
**** Implies significance at a 1% level, ** Implies significance at a 5% level,*
** Implies significance at a 10% level.*

A.3. Comparison of SARB FC and its Constituencies



Source: Authors' own estimates