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Article

Macroprudential and Monetary Policies in South Africa, Complements or Substitutes?

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Abstract: The article reports on the complementarity and substitutability of Macroprudential and Monetary policies in South Africa, based on the interactions of both Business and Financial cycles. To this end, a Dynamic Conditional Correlations and the Asymmetric Dynamic Conditional Correlations MGARCH models together with the Artificial Neural Network VAR model, both linear and nonlinear causality specifications, and the Structural VAR model were adopted for synchronization, causality analysis and the analysis of shocks to cycles, respectively. Empirical evidence obtained is such that, under conditions of financial and real economic stress in South Africa, there exists high synchronicity and bidirectional causality between CBCI and CFCI. Hence, Macroprudential and Monetary policies become complements, there exists interdependence between the two policies and actions of one policy contributes to the improvement of the other. However, under normal times there exist no synchronicity and a unidirectional causality relationship running from CBCI to CFCI, was observed. Under such conditions, Macroprudential and Monetary policies become substitutes, therefore independent of each other, hence, only one policy can achieve the desired outcome. Overall, a shock to one cycle is a major determinant of the fluctuations of the other cycle.

Keywords: Financial Cycles; Business Cycles; Macroprudential Policy; Monetary Policy; Policy Coordination; Artificial Neural Network VAR

1. Introduction

This article aims to disentangle with certainty when are macroprudential (MaPP) and monetary (MP) policies complements or substitutes at different stages of business and financial cycles (BCs and FCs) interactions in South Africa. Now, what do we know? Well, we know that in the aftermath of the 2007-2009 Global Financial Crises (GFCs), it became lucid to central bankers, policymakers and academic scholars that price stability alone is not sufficient to stabilize both the financial system and the entire economy. As a result of this realization; it further became clear that policymaker require a somewhat broader approach to safeguard the financial system (Frait, Malovaná, and Tomšík, 2014; Malovana and Frait, 2017). This led to the emergence of the regulatory framework which is macro-systemic risk dedicated known as Macroprudential policy (MaPP). According to present literature (see Malovana and Frait, 2017: 2) MaPP is best defined as "the tools utilized to target sources of risk of disruptions to the provision of key financial services that is caused by the impairment of all or parts of the financial system".

Currently, both MaPP and MP areas form a fundamental segment of the Central Banks' policy framework worldwide. Specifically, in South Africa, the Financial Sector Regulations Bill (FSR Bill), has made it apparent that, apart from the objective of price stability, the South African Reserve Bank (SARB) is also responsible for monitoring and regulating the South African financial system for potential systemic risks (Bank, 2016). Accordingly, the SARB must ensure that it takes all the necessary actions to prevent systemic risks events and to alleviate the effects of these events on financial stability through the application of appropriate MaPP toolkits of instruments. This indicates that, the SARB is now an amalgamated monetary and supervisory authority, responsible for both the objectives of price and financial stability.

It is this incorporation of MaPP within the functioning of Central banks that has sparked interest among scholars in understanding the interactions of both MaPP and MP. To date is it apparent that the two policy areas are not independent of each other. For instance, in pursuit of their independent and different objectives (price and financial stability) MaPP may have implications for MP, similarly, MP may have implications for MaPP (Dunstan, 2014). As a result, there exists near consensus in the literature (see Dunstan, 2014; Frait et al., 2014 among others) that both these policies affect the functioning of the financial system as well as the entire economy. Therefore, it remains essential that, when designing and implementing the objectives of these two polices, central banks consider the nature of their interactions. This is in line with the strand of literature which places emphasis on the coordination of these policies.

It is further agreed that at times conflict may arise between these two policy areas due to the necessity for them to operate in differing directions. For instance, conflict may arise as a result of time inconsistency associated with the conduct of both policies, as well as in situations where the economy is at different stages of business cycles (BCs) and financial cycles (FCs) (Malovana and Frait, 2017; Malovaná et al., 2023). This, therefore, means that it is possible that the interactions between these policy areas differs with the different stages of business and financial cycle interactions. This was proven in Dunstan, (2014), Frait et al. (2014), Malovana and Frait (2017), Malovaná et al. (2023), and Spencer (2014), where it was concluded that the right policy mix between the two policy areas will partly depend on the different stages of BCs and FCs. It was further proven in Nyati, Muzindutsi and Tipoy (2023) that the interactions of these policies are highly influenced by the synchronicity and the de-synchronicity of the two cycles (BCs and FCs).

What remains unknown is which policy option is to be implemented in normal times and at times when there exists conflict. Some have advocated for MaPP to be temporarily adopted; while others have advocate for MP to be always adopted (Dunstan, 2014; Frait et al., 2014; Malovana and Frait, 2017; Malovaná et al., 2023; Spencer, 2014). In Nyati et al. (2023) it was concluded that in the events of crises management both macroprudential and monetary policies needs to be implemented with no need for coordination. However, when there is crises prevention only one policy needs to be applied and a greater need for coordination arises. The present article is an extension of the analysis by Nyati et al. (2023) and also builds on other studies which have demonstrated effort to study the interactions between the two cycles with the aim of enhancing the understanding of the interactions between the two policy areas (Akar, 2016; Frait et al., 2014; Gökalp, 2018; Malovana and Frait, 2017; Sala-Rios, Torres-Solé, and Farré-Perdiguer, 2016; Spencer, 2014; Tsiakas and Zhang, 2018). While many of the abovementioned studies have established a strong relationship between the two cycles. They have however, failed to use the interactions between these two cycles and the subsequent theoretical literature to inform complementarity or substitutability of these two policies, for purposes of implementing the appropriate policies during appropriate events.

In this context and in line with the cyclical component of systemic risks, the present article set out to examine at what stages of BCs and FCs interactions are MaPP and MP policies complements or substitutes. Our contribution is twofold, firstly, through the adoption of a time varying Dynamic Conditional Correlations Multivariate GARCH (DCC MGARCH) model, an Asymmetric Generalized DCC MGARCH model, the article examines the synchronicity and the extent of synchronization between the two cycles (these results are adopted from Nyati et al. (2023)). Secondly, the above results are extended through the adoption of the Granger causality test and the Artificial Neural Network Vector Autoregressive Model (ANN-VAR) for the examination of the linear and nonlinear Causality relations at different phases of cyclical interactions, respectively;. Lastly, through the adoption of a structural vector autoregression model (SVAR) and impulse response analysis, the article examines the impact of a shock from one cycle to another vis-à-vis. It is apparent that the results from all three models must be aligned and tell the same story for them to be valid. The

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previous results adopted from the literature play a crucial role here as a first step to the present analyses.

2. Theoretical and Empirical Literature

As the aftermath of the 2007-2009 global financial crises hit various nations by surprise, it then led to a sparked interest in understanding the dynamics and interactions between Macroprudential and Monetary policies worldwide. Presently, it is widely agreed that the two policies greatly affect the functioning of both the economy and the financial system, hence, they are interdependent (Agénor, Alper, and da Silva, 2013; Malovana and Frait, 2017; Smets, 2014). However, there still exists divergence of views on the analytical and policy approach that needs to be taken to manage such interactions. This has led to the emergence of three currently dominant strands of literature on the analyses of interactions between MaPP and MP. The first strand builds on the idea that there must be a clear separation of policy objectives also referred to as the modified Jackson Hole consensus. Explicitly, supporters of this view are of the idea that, the focus of the central banks should only be on price stability while an external stakeholder could be assigned to manage MaPP and ensure financial stability in the economy. Basically, these are of the view that there exists independence between the two policy areas hence, their objectives are also independent (Malovaná et al., 2023).

The second strand is of the view that the two policy areas hence, their objectives are highly interdependent and inseparable. The supporters of this strand advocate for continuous communication and some degree of coordination between these two policies. This basically means, in an event where there is a desire to implement a policy, the two areas need to be in continuous consultation so that a desired outcome, favorable to all, be achieved. Macro-financial linkages, creating feedback loops between the real economy and the financial system, are at the core of this view (Dunstan, 2014; Frait et al., 2014; Hollander and Van Lill, 2019; Malovana and Frait, 2017). The final strand is of the view that Central banks must be willing and able to take risks of financial stability into account in MP conduct even if current forecast indicated no risk to price stability; this is referred to as the "lean against the wind consensus". Believers and promoters of this view acknowledge that MaPP cannot fully tackle the existing or potential systemic risks while MP can be effective in this pursuit (Malovaná et al., 2023).

In line with the abovementioned theoretical beliefs, present empirical work (see Dunstan, 2014; Frait et al., 2014; Hollander and Van Lill, 2019; Malovana and Frait, 2017; Nyati et al., 2023 among others) has made it lucid that indeed there exists a great deal of interactions between Macroprudential and Monetary policies. As a result, in their configuration, authorities need to consider the nature of their interactions, ensure the right policy mix is attained through proper policy coordination (Spencer, 2014). The fundamental idea is to attain the right policy mix and to ensure that the main aims of the two policies are not unfavorably affected by too heavily diverting attention of the policies towards secondary objectives. Further, to avoid costs associated with consequences of policy action where non is required, or policy inaction where some is desired (Hollander and Van Lill, 2019). This inclines heavily on the beliefs of the strand of literature which advocates for policy coordination between MaPP and MP.

Even though the attainment of the right policy mix remains crucial for every central bank across the globe. Empirically, it has been shown that, the practicalities of the attainment of this policy mix remains a difficult task for almost all central banks (Hollander and Van Lill, 2019). According to Malovana and Frait (2017), the main contributing factors to this coordination difficulty, has been our limited understanding of the nature of the interactions between MaPP and MP policies. This has strengthened the likelihood of failure to achieve the main policy objectives. Consequently, it has also posed threats to the credibility of the institutions and hindered proper decision making about policy actions. Accordingly, this makes it necessary to study the interactions between MaPP and MP. This is in line with the cyclical component of systemic risks as opposed to the structural component of systemic risks (Hodula, Janků, and Pfeifer, 2023).

In accordance with Hodula et al. (2023), the concept of systemic risk has two important branches, a cyclical branch and a structural branch. The cyclical branch basically deals with the evolution of the financial cycle, its measurement and characteristics and its relationship with the real economy. While the structural branch is focused on the distribution of risks within the financial sector. Presently, within the second strand of literature and in line with the cyclical branch of systemic risk, two literature components remain relevant. The first component of literature comprises of empirical work on the analysis of coordination and optimal policy mix between MaPP and MP, mainly through the adoption of Dynamic Stochastic General Equilibrium Models (DSGE) (Agur, 2019; Claessens, 2013; Kokores, 2015; Liu and Molise, 2020; Pan and Zhang, 2020; PAOLI and Paustian, 2017; Smets, 2018). However, these models usually fail to fully capture the dynamics of monetary and financial conditions (Frait et al., 2014). Hence, they are more useful when the focus is on the structural branch of systemic risk.

The second literature component places more emphasis on the interactions between MaPP and MP as being highly influenced by the different stages of BCs and FCs. As a result, it postulates that, for authorities to attain the right policy mix between these two policies, attention should be paid to the interactions of these cycles as the right policy mix is partly influenced by these cyclical interactions (Adrian and Liang, 2016; Frait and Komárková, 2010; Frait et al., 2014; Malovana and Frait, 2017; Spencer, 2014; Nyati et al., 2023). Due to this, a surge in interest on measuring and diagnosing the stylized features of the interactions between BCs and FCs, was seen in the literature (Borio, 2014; Borio et al., 2001; Claessens, Kose, and Terrones, 2011; Claessens et al., 2012; Farrell and Kemp, 2020;Nyati et al., 2021; Nyati et al., 2023). Yet, limited amount of effort is still seen devoted towards studying the interactions between BCs and FCs to enhance the understanding of the interactions between MaPP and MP, this is the aim of this study.

Within this limited number of studies as mentioned above, two prevalent approaches exist in the analyses of interactions between MaPP and MP based on BCs and FCs interactions. This includes the analyses of synchronization and the extent of synchronization between the two cycles. In accordance with Dunstan (2014) and Spencer (2014), a rule for analyzing the interactions between MaPP and MP through the synchronization of BCs and FCs, was provided. This postulates that, when BCs and FCs are *synchronized*, MaPP and MP decisions will be complementary. According to our present analysis this means that when BCs and FCs are synchronized, MaPP and MP become complements. Hence, actions of one policy will improve actions of another thus, leading to improved overall outcome in terms of policy actions. However, when there exists *desynchronization* between BCs and FCs, MaPP and MP decisions are noncomplementary. In our present analysis, this means that MaPP and MP will be substitutes. This means that only one policy is relevant to achieve the best outcome, hence, a careful balancing approach is necessary in this case to avoid issues of policy mismatches (see Dunstan (2014) and Spencer (2014)). It remains imperative to note that, several rules with regards to these analyses might be available due to the complexities with regards to the interactions of cycles and policies. It is our belief that these analyses are still at their infant stages hence, any developments are adequate.

While the analyses of cyclical synchronicity and de-synchronicity have appeared in the literature before (Ahmed, Chaudhry, and Straetmans, 2018; Artis, Krolzig, and Toro, 2004; Comrey and Lee, 2013; Gächter, Riedl, and Ritzberger-Grünwald, 2012; Gogas and Kothroulas, 2009; Kose, Otrok, and Prasad, 2008; Mink, Jacobs, and De Haan, 2007; Nzimande and Ngalawa, 2016; Savva, Neanidis, and Osborn, 2010). These were biased towards the analyses of BCs alone or FCs alone, there exist only a few studies which are dedicated to the analysis of synchronization and desynchronization of BCs and FCs simultaneously. Among the fewer studies, results often remained diverse. While some found BCs and FCs to be highly synchronized, others have found these cycles to be highly desynchronized (Akar, 2016; Billio and Petronevich, 2017; Choudhry, Papadimitriou, and Shabi, 2016; Gökalp, 2018; Oman, 2019; Sala-Rios et al., 2016). For example, in Billio and Petronevich (2017) it was found that synchronization differs with the differing regimes of interaction between the two cycles. Further, in Oman (2019) it was found that, FCs are less synchronized compared to BCs.

Conversely, in Claessens et al. (2012) the study of synchronicity between BCs and FCs was conducted. Evidence was obtained showing that, there exists strong synchronicity between different phases of BCs and FCs. Similar sentiments were found in Akar (2016), where the relationship and synchronicity between BCs and FCs in Turkey, was examined. Evidence of strong synchronization between BCs and FCs was found. These results were confirmed in Gökalp (2018) who also showed that the two cycles are immensely synchronized in the Turkish economy. Most importantly, in Nyati et al. (2023), trailing on the footsteps of Dunstan (2014), Spencer (2014) and Billio and Petronevich, 2017, the authors utilised South African data to analyse the interactions of MaPP and MP through BCs and FCs synchronisation. It was concluded that under economic and financial stress conditions, BCs and FCs are highly synchronised therefore, MaPP and MP decisions are complementry. While under normal times BCs and FCs are desynchronised, hence, MaPP and MP decisions are noncomplementary. The present article is an extension of these analysis and it aims to validate these results and extend them through the analyses of linear and non linear causality at different phases of interactions and the analysis of cyclical shocks.

The above empirical evidence, clearly illustrate that the synchronicity of BCs and FCs is indeed regime or phase dependent. This makes it certain to policymakers that different policy actions will be relevant depending on which regime or phase the financial system and the economy is at. However, these stylized facts points only to the correlation but not to the causal relationship between BCs and FCs (Tsiakas and Zhang, 2018). As a result, the question of the extent, significance, and direction of causality between BCs and FCs is another significant avenue of research in understanding the interactions of MaPP and MP based on the interactions of BCs and FCs. This is one of the contributions of this present article. A growing number of studies (Gómez-González, Ojeda-Joya, Zárate, and Tenjo-Galarza, 2014; Gomez-Gonzalez, Villamizar-Villegas, Zarate, Amador, and Gaitan-Maldonado, 2015) has been dedicated to this avenue of research.

Accordingly, a rule for analyzing the interactions between the real economy and the financial system *viz:* MaPP and MP, based on the causal relationship between BCs and FCs was developed. Based on this rule, if the FC is found to be causing the BC, it holds that; financial system dynamics must be considered in MP decisions aiming at stabilizing the economy; this is called the *positive view*. This is in line with cyclical synchronization as above discussed, which leads to MaPP and MP being complements/ interdependent. However, if the FC does not cause the BC, it holds that, financial system dynamics should not enter in MP decisions aiming to stabilize the economy; this is referred to as the *negative view* (Gómez-González et al., 2014). This is in accordance with cyclical desynchronization view, where MaPP and MP become substitutes. Again, as done above, it remains imperative to note that, several rules with regards to these analyses might be available due to the complexities with regards to the interactions of cycles and policies. It is our belief that these analyses are still at their infant stages hence, any developments are adequate. In support of the positive view, Gomez-Gonzalez et al. (2015) performed a frequency domain Granger type causality tests for three Latin American economies. The authors found evidence of causality running from credit cycles to GDP cycles in all three economies. Further, Shen, Shi, and Wu (2019) added that the FC runs ahead of the BC but not vice versa. Which means that the FC causes the BC, and causality runs in one direction; this was for all 31 Chinese provincial areas.

Furthermore, Aravalath (2020) adopted a Toda-Yamamoto causality test in an attempt to understand the causal links between BCs and FCs in India. Results showed evidence of causality in India running from the FC to the BC. Such findings pointed to a need to carefully design macroeconomic policies with macroprudential orientation, to achieve financial and macroeconomic stability. Moreover, in Si, Liu, and Kong (2019), the causal relationship and co-movement between stock market cycles and BCs was investigated. Adopting Chinese data penning the period 1992Q1-2018Q1, results showed evidence of causality between the stock market cycles and BCs in China. Specifically, stock market cycles tended to lead BCs in expansion periods, whereas BCs tended to lead stock market cycles in recession periods. In support of the negative view, Sala-Rios et al. (2016) investigated a causality relationship between Business and Credit cycles (CCs) in Spain over the

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period 1970-2014. Results obtained showed that fluctuations of the BC were leading those of credit. Further, the causality direction analyses between economic and bank credit growth in South Africa, was investigated in Chakanyuka (2016). Through the adoption of Granger causality method and South African data penning the period 1980Q1-2013Q4, results provided evidence of the existence of unidirectional causality, running from the forma to the latter.

While the above studies clearly supported either the positive or the negative view. Other studies have obtained mixed results pointing to the existence of bidirectional causality between the real economy and financial sector indicators. For example, in Choudhry et al. (2016), the relationship between stock market volatility and the BC in four major economies *viz:* the US, Canada, Japan and the UK, was investigated. The authors utilized both linear and non-linear bivariate causality tests to carry out the analysis. Results showed evidence of a bivariate causal relationship between the two variables. Further, a direction of causality between BCs and FCs was investigated in Tsiakas and Zhang (2018). Utilizing a vector autoregressive model and mixed frequency data for five industrialized countries, results showed evidence of strong bidirectional causality between the two cycles. Lastly, Azizi and Moradi (2019) surveyed the relationship between stock market volatility and BCs in the Iranian economy during the period 2000-2016. Results showed evidence of one-sided linear and two-sided nonlinear causality between BCs and stock market volatility.

Holistically, the extensive ground of literature as analyzed above points to different conclusions with regards to the synchronicity and the direction of causality between BCs, FCs, and real and financial sector indicators. This is expected as the concepts of cyclical interactions and policy interactions are still at their infant stages of development. And given their complex dynamics, it is still not known with certainty how these interrelate. Further, while several empirical papers have been written on these important avenues of research, the theoretical and empirical literature has rather remained scant for the South African economy. Noteworthy, the work of Chakanyuka (2016) is an exception. As a result, the present article delves into the analyses of synchronization and causation between BCs and FCs, with a sole purpose of providing new evidence about the complementarity and substitutability of MaPP and MP policies in South Africa. Specifically, the article extends the works of Nyati et al. (2023) through the analyses of the complementarity and substitutability of MaPP and MP based on the synchronization and causal links between BCs and FCs. Differently from all the abovementioned studies, the present study examines synchronicity and causality at different phases of BCs and FCs interactions. These results are further validated through the analysis of cyclical shocks, via SVAR impulses. According to authors knowledge, this article is the first of its kind to examine the complementarity and substitutability of MaPP and MP, at different stages of interactions between BCs and FCs. It is also the first to examine the impact of shocks from one cycle to another, this is a major innovation of this article.

3. Database and Methodology

3.1. Database and Data Modifications

To carry out the objectives of this article, we borrowed data on the composite indices as developed by Nyati et al. (2023) and Nyati et al. (2021). This includes the Composite Business Cycle Index and the Composite Financial Cycle Index as developed by the abovementioned authors. According to Nyati et al. (2023) the indices were constructed from an extensive database using monthly time series of financial and economic variables for South Africa, penning the period 2000M01 to 2018M12. Due to the lack of consensus in the literature on the number and specific indicators to be used in the construction of these indices. The authors trailed on the on the footsteps of Krznar and Matheson (2017), Chorafas (2015), Ma and Zhang (2016), among others, to measure the CFCI. The authors also trailed on the footsteps of Doz and Petronevich (2016), Venter (2017) and Vermeulen, Bosch, Rossouw, and Joubert (2017), among others, to measure the CBCI. Accordingly, thirteen (13) and eighty (80) monthly financial and economic time series variables were adopted to

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measure the CFCI and the CBCI, respectively. The graphical illustration and description of these indices is shown on the appendix section of this article.

3.2. Model Specification for the Interactions of MaPP and MP

3.2.1. Synchronization Between BCs and FCs

The present article does not run the synchronization tests between BCs and FCs as something that is new in the literature. However, these tests are borrowed from the analyses of Nyati et al. (2023) and the results obtained are used here as an initial step and extended via the different methods detailed below. According to Nyati et al. (2024) both a Dynamic Conditional Correlations MGARCH model of Engle (2002) and Tse and Tsui (2002) and an Asymmetric Generalized DCC (AGDCC) MGARCH model as proposed by Cappiello et al. (2006) were adopted to carry out the analyses of cyclical synchronicity. Specifically, the DCC MGARCH was adopted as it is capable of adequately assessing continuous variations in correlations between variables. Also, as it can account for the dynamic evolution of the relationship between variables at each point in time. The Asymmetric Generalized DCC (AGDCC) was adopted to account for asymmetric effects. Explicitly, to differentiate between the effects of a positive and negative shock. The models are estimated as detailed below.

Models Estimation Process

Trailing on the footpaths of Engle's (2002) methodology, we estimate the DCC model by maximizing the log-likelihood function as follows:

$$L(\theta,\phi)^2 = -\frac{1}{2}\sum_{t=1}^{T}(\ln(2\pi) + \ln(|D_tR_tD_t|) + \varepsilon_t'(D_tR_tD_t)^{-1}\varepsilon_t) \tag{1}$$

Utilizing the fact that: $H_t = D_tR_tD_t$, equation 1 above is simplified as follows:

$$L(\theta,\phi) = -\frac{T}{2}ln(2\pi) - \frac{1}{2}.\sum_{t=1}^{T}(2.ln|D_t| + \varepsilon_t'(D_tD_t)^{-1}\varepsilon_t)\frac{1}{2}\sum_{t=1}^{T}(ln|R_t|\varepsilon_t'(R_t{}^{-1})^{-1}\varepsilon_t) \tag{2}$$

The second step involves the utilization of the maximized value in equation 2 above to maximize the correlation part as follows:

$$L_c(\theta,\phi) = -\frac{1}{2}\sum_{t=1}^{T}(\ln|R_t| + \varepsilon_t'(R_t{}^{-1})^{-1}\varepsilon_t) \tag{3}$$

The parameter estimates of the two-step DCC estimation procedure, as outlined above, are both consistent and asymptotically normal (Engle, 2002). Due to the limitations of the DCC model in accounting for asymmetry, the ADCC MGARCH model of Cappiello et al. (2006) was adopted mainly for this purpose. All necessary tests were carried out before the estimation of the above models, including the stationarity tests, the multivariate normality test, test for dynamic correlations and the Ljung-Box Q statistics tests.

3.2.2. Bivariate Linear Granger Causality Test

To detect causal direction between two time series variables through the examination of correlation between the contemporary value of one variable and the historical values of the other variable, the Granger causality test is adopted (Choudhry et al., 2016; Granger, 1969). In line with Granger's definition of causality, consider two variables, *viz:* x_t and y_t: y_t is strictly Granger causing x_t if the conditional distribution of x_t, given historical values of $x_{t-1}, x_{t-2}, \ldots$ and $y_{t-1}, y_{t-2}, \ldots$, differs from the conditional distribution of x_t, given the historical observations

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$x_{t-1}, x_{t-2}, \ldots$ only. Intuitively, y_t is a Granger cause of x_t if adding historical values of y_t to the information set, increases the knowledge on the distribution of current values of x_t. More precisely, the linear Granger causality test is conducted based on the following two equation model:

$$x_t = \varphi_1 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_{1t} \tag{4}$$

$$y_t = \varphi_2 + \sum_{i=1}^{n} \gamma_i x_{t-i} + \sum_{i=1}^{n} \delta_i y_{t-i} + \varepsilon_{2t} \tag{5}$$

where: in this case x_t is the Composite Financial Cycle Index (CFCI), y_t is the Composite Business Cycle Index (CBCI), n is the optimal lag length based on the Akaike information criteria (AIC), the Schwarz information criteria (SIC) and the Bayesian information criteria (BIC). ε_{1t} and ε_{2t} are the residuals, φ_1 and φ_2 are constants while α_i, β_i, γ_i and δ_i, where $i = 1, \ldots, n$, represents the relationship between the variables of interest. To test for Granger causality, the interest is on the null hypothesis that variable y_t does not Granger cause variable x_t, which is rejected if the coefficients β_i are jointly significantly different from zero. Therefore, if y_t Granger causes x_t it is posited that the past values of y_t can provide information about x_t (Choudhry et al., 2016). Correspondingly, the null hypothesis that x_t does not Granger cause y_t is rejected if and only if the estimated coefficients γ_i are significantly different from zero. Lastly, there exists bidirectional causality if causality is found to be running in both directions (Choudhry et al., 2016).

In summary, one could test for linear Granger causality between x_t and y_t through testing the following null and alternative hypotheses separately:

$$H_0^1: \beta_1 = \cdots = \beta_p = 0 \text{ and } H_0^2: \gamma_1 = \cdots = \gamma_p = 0$$

In accordance with these, four testing results are possible:

1. If both the hypotheses are accepted, there is no linear causal relationship between x_t and y_t.
2. If hypothesis H_0^1 is accepted but H_0^2 rejected, there is unidirectional linear causality from x_t to y_t.
3. If hypothesis H_0^1 is rejected but H_0^2 accepted, there is unidirectional linear causality from y_t to x_t.
4. If both the hypotheses are rejected, then there exists feedback linear causality between x_t and y_t.

3.2.3. Bivariate Nonlinear Granger Causality Test

The Granger causality test, as developed in Granger (1969), is based on the supposition of linear relationships between time series indicators. As a result, it is unable of exploring nonlinear causal associations between these indicators (Choudhry et al., 2016). For this purpose, the present article proposes an implementation of an extended version of the Granger causality test utilising the Vector Autoregressive Artificial Neural Network (ANN-VAR) model, as found in Hmamouche (2020).

The ANN-VAR(p) model is a multi-layer perceptron neural network model that considers the p previous values of the predictor indicators and the target indicator (Y) with the aim of predicting the future values of Y. Such a choice was made in order to permit for the possibility of forecasting each target indicator with a specific set of forecasters, since target indicators do not have the same forecasters (Hmamouche, 2020). First, the model reorganises the data in a form of a supervised learning, with respect to the lag operator. The optimisation algorithm utilised to update the weights of the network is based on the Stochastic Gradient Descent (SGD) algorithm.

The global function of the ANN-VAR(p) model can be written as follows:

$$Y_t = \Psi_{nn}\left(Y_{t-1}, \ldots, Y_{t-p}, \ldots, Y_{k(t-1)}, \ldots, Y_{k(t-p)}\right) + U_t \tag{6}$$

where Ψ_{nn} is the network function and U_t represents the error terms.

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A causality using the ANN-VAR(p) model- similarly to the well-known Granger causality test, to test causality between two indicators X and Y, two prediction models are considered. The first of these considers the past values of the target time series, while the second considers the past values of the target and the forecaster time series. These are shown below:

$$\text{Model}_1\text{: } Y_t = \Psi_{1nn}\left(Y_{t-1}, \dots, Y_{t-p}\right) + U_t \tag{7}$$

$$\text{Model}_2\text{: } Y_t = \Psi_{2nn}\left(Y_{t-1}, \dots, Y_{t-p}X_{t-1}, \dots, X_{t-p}\right) + U_t \tag{8}$$

where Ψ_{1nn} and Ψ_{2nn} are the network functions of Model_1 and Model_2, respectively using the ANN-VAR(p) model. The difference between these two models is evaluated through the comparison of the residual sum of squares of their errors, and the evaluation is carried out through the Fisher test to examine the null hypothesis that X does not Granger cause Y. The difference with this model, compared to the traditional Granger causality test, is that instead of utilising two VAR models (univariate and bivariate), two ANN-VAR(p) models are utilised. Therefore, one must alter the statistic of the Fisher test, because there are more parameters in the ANN-VAR(p) models than in the normal VAR model. Therefore, in this case, the statistic of the test is as follows:

$$F = \frac{(RSS_1 - RSS_2)/(d_2 - d_1)}{RSS_2/(n - d_2)}$$

where d_1 and d_2 are the numbers of parameters of the univariate and the bivariate models, respectively. These will depend on the chosen structure, *viz:* number of layers and neurons (Hmamouche, 2020).

3.2.4. Structural Vector Autoregression Model

Further from the estimation approaches detailed above, as a third objective of this study, the article examines the impact of a shock from one cycle to another. This is mainly to ascertain if each of these cycles contribute to each other's fluctuations and if so to what extent. To achieve this, a well-known model which seemingly remedy all the problems of simple VAR models is the Structural VAR model (Lutkepohl, 2017). To remedy one of the normal VAR issues where error terms become correlated, thus posing issues for impulse response analyses, we write the errors as a linear combination of structural shocks as follows:

$$e_t = Bu_t \tag{9}$$

Without generality losses, the following is imposed $E(u_t u_t') = I$

Since the task is to estimate parameters of a VAR model extended to include correlation among endogenous variables, and exclude correlation among error terms, equation 9 is combined with the standard VAR equation to produce a structural VAR model, given as follows:

$$Ay_t = C_1 y_{t-1} + \dots + C_k y_{t-k} + Bu_t \tag{10}$$

where the goal is to estimate A, B, and C_i. The identification problem is to move from population-level moments back to unique estimates of the parameters in the structural matrices. If it assumed that A is invertible, the structural VAR model can be written as:

$$Ay_t = A^{-1}C_1 y_{t-1} + \dots + A^{-1}C_k y_{t-k} + Bu_t \tag{11}$$

implying the following set of interactions:

$$A^{-1}C_i = A_i$$

for $i = 1,2, \dots, k$ and

$A^{-1}BB'A^{-1'} = \Sigma$

Through the estimation of A and B, recovering C_i could be straight forward, however, there exists many several A and B matrices that are consistent with the same observed Σ . As a result, it will be difficult to pin down A and B from Σ . A solution from this is to place $n^2 + n(n-1)/2$

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restriction on A and B to obtain unique estimates of A and B from $\sum$. The order conditions only ensure there are enough restrictions while the rank condition ensures there are enough linearly independent restrictions. The most common method of identification is to set $A = I$ and require B to be a lower triangular matrix, thus placing zeroes on all entries above the diagonal. The resulting mapping from structure to reduced form is:

$$BB' = \sum \tag{12}$$

along with the requirement that B be lower triangular. The reverse is true when A is lower triangular and $B = I$. Both these methods may be seen as imposing a causal ordering on the variables in the VAR, hence, the causal ordering represents beliefs of the researcher about the nature of the relationship between variables (Lutkepohl, 2017).

Using this method the article estimates the following equation and uses impulse response analyses to determine the effect of shocks from one cycle to another.

$$CFCI_t = \sigma_0 + \sigma_1 CBCI_t + \varepsilon_t$$

Once all the estimation procedures have been carried out and the results obtained, the following section then provides an interpretation of the results obtained through the application of the above-mentioned estimation procedures. This is the most crucial part of the article, as it aims to set out the key experimental results, which include, among others, the statistical analysis, and the significance and alignment of findings to the past literature.

4. Estimation Results and Analysis

4.1. Results on the Interactions Between MaPP and MP

4.1.1. Synchronization Between CFCI and CBCI

The synchronization results from both the two-step DCC and ADCC MGARCH models, are presented in this subsection. Trailing on the footsteps of Nyati et al. (2023) a GARCH (1,1) model was selected at the initial stage. Differently, form the above study, the present article estimated the DCC and the ADCC models under the multivariate student t (MVT) distribution only. The parameter estimates of these models are shown in Table 1, focusing only on the joint conditional correlations and the asymmetric components.

Table 1. Parameter Estimates of the DCC and the ADCC.

	DCC(MVT)	ADCC(MVT)
a	0.854***	0.855***
b	0.060*	0.060*
g	-	0
Shape	50.000***	50.000***
LL	766.01	767.34

NB: Significance levels: ***1%, ** 5%, *10%.

For specifics in the parameter descriptions and details, we refer the reader the initial part as found in Nyati et al. (2023). In accordance with the Table 1, the parameter estimates of a and b are statistically significant in both the models. This provides validity in the usage of a dynamic correlations model. Introducing the g parameter shows no significant positive or negative effect on the strength of the correlation since the parameters are zero and insignificant. Hence, it can be concluded that the asymmetric effect of shocks with the same signs does not seem to be important.

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In line with the estimates of the two models, Figures A3 and A4 plot the conditional correlations graphs for each model under the MVT distribution. Figure A3 shows the DCC MGARCH graphs, with the red graph showing the conditional correlations and Figure A4 shows the ADCC MGARCH graphs, with the red graph showing the conditional correlations. Noteworthy, in both the figures, the correlations between CFCI and CBCI are shown to vary with the varying dynamics in both the economic and financial sectors. Further, the two models have produced identical conditional correlations under the MVT distribution. This suggests that both the ADCC and the DCC models are adequate in measuring the time-varying conditional correlations.

This sub-section applies the conditional correlations obtained above to study the interactions between MaPP and MP. Figure 1 shows these conditional correlations, together with the recession periods for South Africa as obtained from the OECD database, and the periods of financial crises as determined by the CFCI.

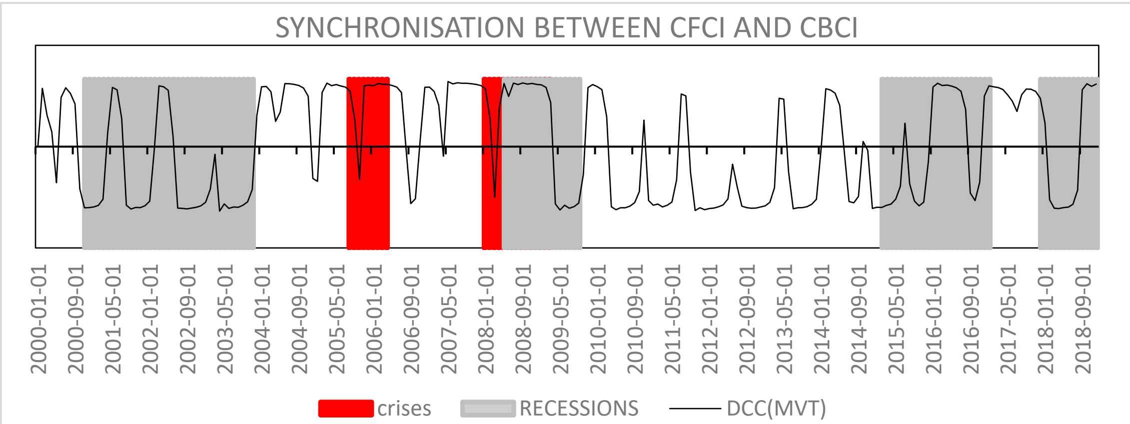

Figure 1. Synchronization between CFCI and CBCI.

Again, for ease of interpretation the period under examination was broken down into three sub periods as outlined above. The article also compares the co-movement at times when the financial system is under stress, the real economy is at a recession, and when both the financial system and the real economy are facing no stress.

In accordance with the analyses of Nyati et al. (2023), these results indicate that, when the real economy is faced with considerable stress and the economy is at a recession, there is higher volatility in the co-movement between BCs and FCs in South Africa. However, when the financial system is under stress so much so that there are financial crises/ imbalances in the country, the cycles tend to highly co-move with fewer instances of divergent. As a result, in can be concluded that, under normal times, where neither the financial system nor the real economy is under considerable stress, the two cycles tend to move in opposite direction, which is shown by negative co-movement in the post GFC sub-period.

4.1.2. Analyses of Linear and Nonlinear Granger Causality Between CFCI and CBCI

As a first objective of this article, the present sub-section provides empirical evidence on the analysis of interactions between MaPP and MP in South Africa, based on the causal relationships between BCs and FCs. This is achieved through testing for both linear and nonlinear causality relationships between CBCI and CFCI. For this purpose, the article considered the usual Granger causality test and an Artificial Neural Network VAR (Vector Auto-Regressive) model using a Multi-Layer Perceptron, specification and the corresponding linear and nonlinear Granger causality tests, respectively. Results from these methods are shown and discussed in the following sub-sections.

Bivariate Linear Causality Results

Table 2 reports the full-sample results of the bivariate linear causality relationship between CFCI and CBCI. According to the results in Table 2, the null hypothesis that CFCI does not Granger cause CBCI is rejected at all significance levels, and it is concluded that CFCI Granger causes CBCI. Further, the null hypothesis of no Granger causality from the CBCI to CFCI is rejected at all significance levels, and it is concluded that CBCI Granger causes CFCI.

Table 2. Bivariate Linear Causality between CFCI and CBCI.

	CFCI→CBCI	CBCI→CFCI
Lags	5	5
GCI	1.195	0.760
F-test	9.774***	4.825***
Critical Value	2.305	2.305

Thus, there exists evidence of a strong bidirectional linear causality relationship between CBCI and CFCI, such that, CBCI distresses CFCI vis-à-vis. These analyses are extended through the examination of the causal relationship between CBCI and CFCI within the three sub-periods, *viz:* pre GFC, GFC, and post GFC. Results from this are shown in Table 3.

Table 3. Bivariate Linear Causality in the three sub-periods.

	PRE-GFC *p*-value	GFC *p*-value	POST-GFC *p*-value
Null-Hypothesis			
No Causality CFCI to CBCI	0.000	0.000	0.063
No Causality CBCI to CFCI	0.000	0.000	0.000

Consequently, the results point to strong bidirectional causality between CBCI and CFCI in both the pre- GF crises and the GF crises sub-periods. Nevertheless, the post crises results are seemingly different, even though there exists evidence of causality between the two cycles. However, the relationship is only strongly significant from CBCI to CFCI, and relatively weakly significant from CFCI to CBCI, as shown by a *p*-value of 0.063.

These results demonstrate the existence of a strong bidirectional linear causality relationship between Business and Financial cycles in South Africa. Consistent with the correlation results above, it is found that a linear causality relationship between the two cycles is stronger in both directions during tight financial and economic conditions, while during normal times it is found to be stronger in one direction (CBCI to CFCI). These analyses are further extended through the consideration of nonlinear causality as shown below.

Bivariate Nonlinear Causality Results

This sub-section extends the previous linear causality analyses through the discussion of results under the nonlinear causality framework based on the ANN-VAR model, as discussed in section 3 above.

Table 4 reports the full sample results of the bivariate nonlinear causality test between CFCI and CBCI. In accordance with the table, the F-test statistics are both insignificant, pointing to no evidence of nonlinear causality relationship between CBCI and CFCI, which runs in either direction.

Table 4. Bivariate Nonlinear Causality between CFCI and CBCI.

	CFCI→CBCI	CBCI→CFCI

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Lags	5	5
GCI	0.001	0.009
F-test	0.006	0.046
Critical Value	1.676	1.676

Hence, it is concluded with certainty that business and financial cycles in South Africa exhibit a linear causal relationship, as opposed to a nonlinear causal relationship which runs in either direction. These results also suggest that there exist no nonlinear features, and these are not important is capturing the dynamics of business and financial cycles in South Africa.

4.1.3. Analyses of Impulse Responses Between CFCI and CBCI

As a second objective of this article, we present the analyses of shocks from one cycle to the other and we observe the responses of these cycles after the shock. Figure 2 presents the graphical illustration of these, the top panel shows the effect of a CBCI shock to itself, and the effect of a CBCI shock to CFCI. The bottom panel represents the effect of a CFCI shock to itself and the effect of CFCI shock to CBCI.

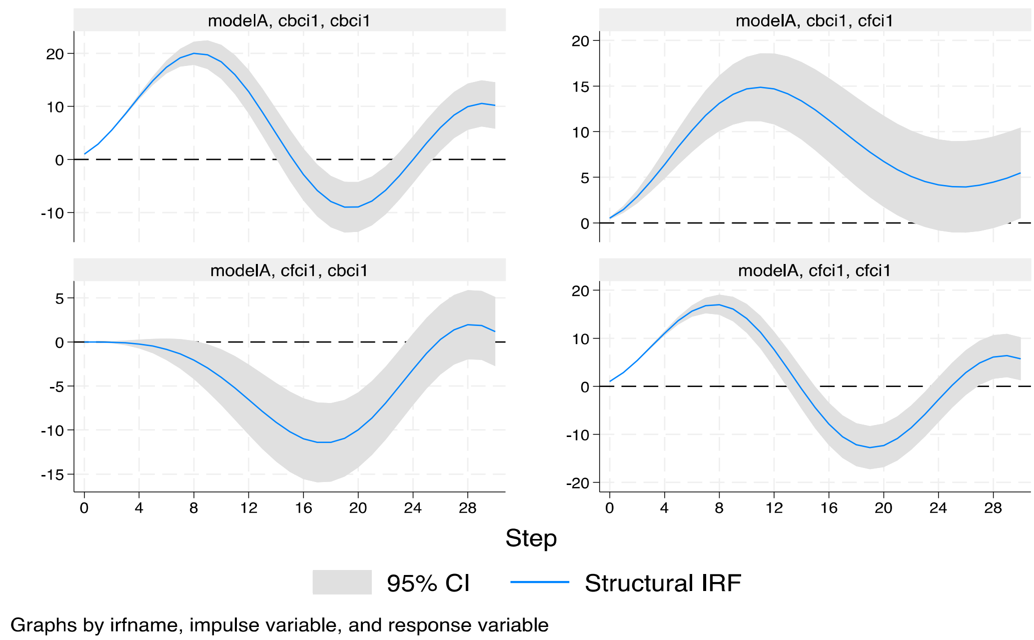

Figure 2. Structural impulse response analysis.

According to the top panel of figure 2, a CBCI shock leads to an increase in CBCI, with the CBCI returning and not staying at a state of equilibrium after 16 months. As CBCI does not remain at equilibrium, larger fluctuations in CBCI around equilibrium are observed, with no clear evidence of remaining in equilibrium afterwards. A CBCI shock also leads to larger fluctuations in CFCI above equilibrium, with no evidence of CFCI reverting to equilibrium over time. Further, a CBCI shock seems to have immediate effects on CFCI.

The bottom panel of figure 2 also shows that a CFCI shock leads to a decrease in CBCI with CBCI reverting to equilibrium about 25 months later. Interesting to note, a CFCI shock does not have immediate effects on CBCI, the effect starts to be seen about 3 months after the shock. Further, priori results have shown that the fluctuations in the CFCI are contributed by a shock to itself (Ma and Zhang, 2016). The analysis of this article finds conjecture of these results, where the CFCI shock leads to a larger fluctuation in CFCI around equilibrium, with no clear evidence of remaining in equilibrium.

4.2. Discussion of Findings

In line with the analyses of Nyati et al. (2023), it is clear that, BCs and FCs are mostly synchronized than desynchronized in South Africa. This is especially when the real economy is under considerable stress, thus, faced with recessions, and more especially when there are financial crises/ imbalances. While under normal times when both the financial system and the real economy are not facing any pressure from stress, the two cycles are desynchronized. Therefore, trailing on the conclusions of the above study, and other literature (see Dunstan, 2024 and Spencer, 2014), it can be said that, under conditions of financial and real economic stress in South Africa, when there is crises management than crises prevention, MaPP and MP become complements. Hence, the two policies become interdependent, such that, actions of one policy will improve the actions of another thus, leading to improved overall outcome in terms of policy actions.

However, under normal conditions when there is crises prevention than crises management, MaPP and MP decisions are noncomplementary, this means that MaPP and MP are substitutes, hence, there is policy independent. This means that only one policy is relevant to achieve the best outcome, hence, a careful balancing approach is necessary in this case to avoid issues of policy mismatches. These results are consistent with those found in Nyati et al. (2023) and Billio and Petronevich (2017) which found that synchronization of BCs and FCs will depend largely on which phase of the cycles the economy is at. Further, these are consistent with the conclusions of Constâncio et al. (2019) which revealed that, the two cycles are not always synchronized, hence, policies that target the FC powerfully complement policies that target the BC.

Noteworthy, the findings in this article also find major support on the findings of Svensson (2018), which suggested that, under normal times when there is crises prevention, the two policies are better conducted separately, and in crises times when there is crises management, the two policies are better conducted co-ordinately. These findings, therefore, add new empirical evidence in developing as opposed to developed or a group of developed countries, about the complementarity and substitutability of MaPP and MP based on the interactions between BCs and FCs.

The causality results shows support of both the positive and the negative views, as suggested by Gomez-Gonzalez et al. (2015) and Shen, Shi, and Wu 2017) and such support depends on which state of the BCs and FCs the economy is at. Specifically, these results point to the existence of strong bidirectional causality between BCs and FCs in South Africa, this is especially under conditions when the financial system and the real economy are under considerable stress. This is in support of the positive view and it means that, during crises periods in South Africa, in making MP decisions about the stability of the economy, MP authorities need to include FC dynamics in the process. Therefore, in such cases, there exists policy interdependence and the two policies become complements.

Under normal times the CFCI is found not to be causing CBCI. This is in support of the negative view and it holds that, in making decisions about the stability of the economy, MP authorities need not to include FC dynamics in the process as there is no significance value it would add. As a result, there is policy independence and the two policies are said to be substitutes. These results also correspond and validate the synchronisation results by Nyati et al. (2023). Further, these results are consistent with those found in Choudhry et al. (2016) & Tsiakas and Zhang (2018) where the authors found evidence of strong bidirectional causality between BCs and FCs in the countries examined.

These are also consistent with basic economic theory based on the financial accelerator literature, which asserts that; the relationship between financing indicators and economic growth is not unidirectional but rather bidirectional (see Sala-Rios et al. (2016)). In this context, developments in economic activity affects financial activity, and gyrations in financial activity affects economic activity (Svensson, 2018). For example, on the one hand, deteriorations in credit may be a result of an external shock which slows or contract economic activity, or because of worsened business prospects. On the other hand, via different channels of transmission, the deteriorated credit might lead to decreased investment capacity, decreased consumptions and sharp economic downturns (Sala-Rios et al., 2016).

These interactions between financial and economic activities are controlled by the conduct of both MaPP and MP. Therefore, these are representative of the interactions between MaPP and MP. For instance, via the balance sheet channel, an increase in the policy rate would lead to a decrease in the prices of assets that can be used as collateral when applying for credit. This thus, increases the mark-up that borrowers must pay for external financing, which then results in decreased demand for credit. This gives rise to deteriorating credit growth and subsequently consumer and investment demand, which may contract or slows economic activity vis-à-vis (Frait et al., 2014).

Overall, to further support the results above, the impulse response analysis reveal that a shocks from one cycle leads to considerable fluctuations in the other, and the CBCI shock has immediate impact as opposed to the CFCI shock. Most importantly, these results are in line with the procyclical nature of the financial system in relation to the real economy. They suggest that there exists a mutually reinforcing mechanism through which the financial system can amplify macroeconomic fluctuations and possibly lead or exacerbate financial imbalances. Hence, it can be posited that in an attempt to stabilise the financial system, the SARB need to consider developments in the BC (see Nyati et al. (2023)). This is further evidence that the CBCI leads the CFCI, MP gets into all the cracks of all policies and a CBCI has more information content in terms of the financial system management.

5. Conclusion and Policy Recommendations

The present article contributes to the relatively scant literature on macroeconomic policy interactions in South Africa, through the examination of the complementarity and the substitutability of MaPP and MP at different stages of interaction between BCs and FCs. Our empirical evidence validates the analyses of Nyati et al. (2023) and are in line with the analyses of the literature such as Billio and Petronevich (2017), Constâncio et al. (2019) and Svensson (2018) among others. Explicitly, we conclude that under conditions of financial and real economic stress in South Africa, when there is crises management than crises prevention, BCs and FCs are highly synchronized and there exists strong bidirectional causality between the two cycles. Therefore, MaPP and MP become complements hence, the two policies are interdependent, meaning that actions of one policy will improve the actions of the other hence, leading to improved overall outcome in terms of policy actions. However, under normal conditions when there is crises prevention than crises management, BCs and FCs become desynchronized and there is unidirectional causality (From BC to FC). As a result, MaPP and MP are noncomplementary, this means that MaPP and MP are substitutes, hence, there is policy independent. This means that only one policy action is required to achieve the desired outcome and the inclusion of both might lead to severe conflict and policy mismatches.

Overall, the analyses of this article put emphasis and policy lessons that the management of the two cycles remains of vital importance in informing the interactions of the two policy areas. Therefore, the analysis of the interactions of these cycles remains an initial step towards the understanding of the interaction between the two policy areas and their coordination. It is therefore, recommended that central banks consider with caution the interactions of the two cycles in configuring the two policies, as this has proven to give a clear indication of when there is interdependence and when there is independence. Further, the analyses have proven that policies that target the FC powerfully complement policies that target the BC, as a result, Monetary authorities need to carefully design macroeconomic policies with macroprudential orientation to achieve both financial and economic stability. Failure to do this may lead to complicated policy decisions, undermine transparency, and potentially be damaging to the credibility of both MaPP and MP. Further, policy decision mismatches may lead to overall welfare loses.

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preparation, M.C.N.; writing—review and editing, S.M.; visualization, M.C.N.; supervision, M.C.N.; project administration, M.C.N.; funding acquisition; M.C.N.

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Data Availability Statement: The data used in this study was achieved from various public sources such as: the South African Reserve Bank Database, the Federal Reserve Bank of St Louis, the Bank for International Settlements, and the Organization for Economic Co-operation and Development.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Graphical Illustration of the Interactions Between CBCI and CFCI

The results of the interactions between MaPP and MP based on the interactions of BCs and FCs, are presented here. The section begins with graphical analysis then move on to the statistical analyses, in accordance with the set objectives. For ease of interpretation the period of study is divided into three sub periods; *viz:* pre GFCs (2000M01-2006M12), GFCs (2007M01-2010M12) and post-GFCs (2011M01-2018M12) periods. The figure shows that the two indices follow the same path, with CBCI leading CFCI. While noting a few instances of divergence (in 2002/07 and in 2015/11), the two indices are almost moving together as one during the periods 2007/08 and 2008/05, which marks the GFCs period.

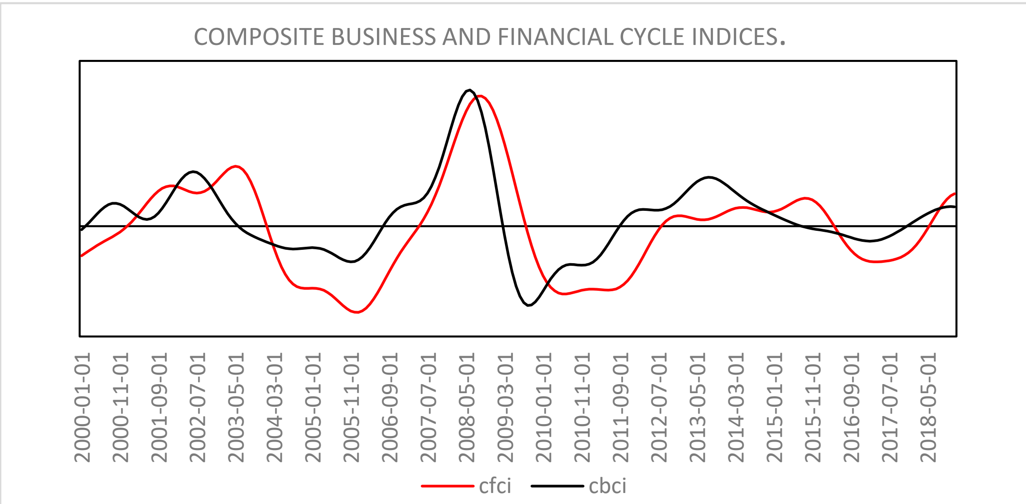

Figure A1. Interactions between CBCIs and CFCIs.

A measure of simple correlation between the two indices equals to 0.7147, for the whole sample. This implies that, about 71.46 percent of the time, these indices are moving together, thus proving high rate of correlation between the two indices. Correlation in the sub-periods is given as; 72,93% (2000M01-2006M12), 73,02% (2007M01-2010M12), and 72,68% (2011M01-2018M12), respectively. This is proof of the close association of BC and FC, as found in the literature. It is further proof that the two cycles tend to be highly interrelated during periods of financial distress.

First Step: DFM and PCA

In the first step of this procedure, common factors were extracted from an amalgamation of eleven and eighty economic and financial time series variables, respectively. Applying a Dynamic Factor Model in State Space Form (DFM-SSF) and Principal Component Analysis (PCA), it was considered that the first factor and the first principal component provides good approximation of the

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common factors. These common factors are here referred to as the Composite Business Cycle Index and the Composite Financial Cycle Index and are illustrated in Figure 1 below.

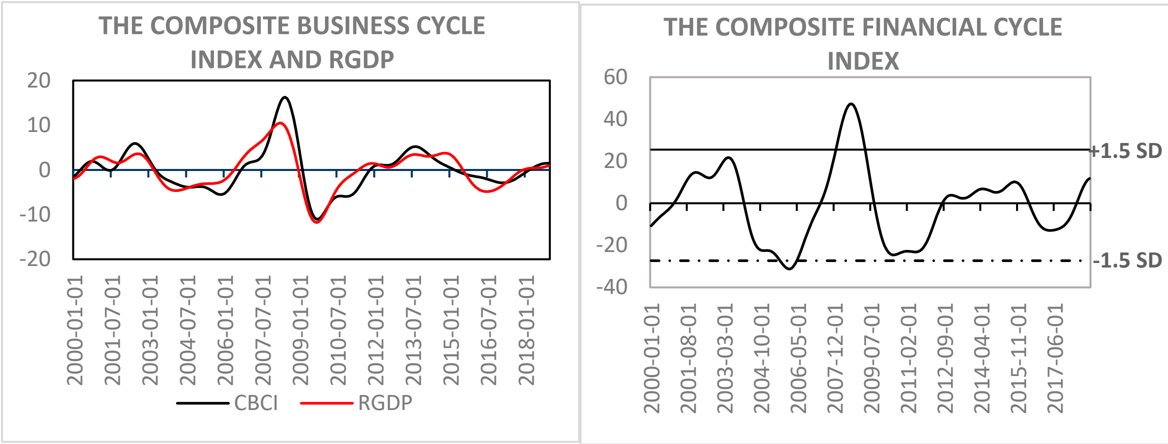

Figure A2. DFM-SSF AND PCA Composite Business and Financial Cycle Indices.

Panel A of Figure 1 shows the CBCI together with the cyclical component of the South African Real Gross Domestic Product (RGDP), for validity purposes. Accordingly, the dynamics of the CBCI are closely related to the dynamics of RGDP. This is confirmed by a simple correlation stat of 0.8803 for the whole sample. This is reasonable strong thus, indicative that the factor is relevant and is a valid measure of the South African CBCI. Panel B of the figure shows the CFCI relative to the ±1.5 standard deviation boundaries. The CFCI captures with accuracy both the periods of instabilities and imbalances. Further, main events such as the 2001-rand crises and the 2007-2009 GFC seem to be captured well by the index. Furthermore, the index indicates that both upwards (potential build-up of imbalances) and downwards (manifestation of instabilities) phases, are meaningful signals about financial instabilities.

Second step: Markov Switching Dynamic Regression Model

Table 3 shows results of the turning points of both the CBCI and the CFCI, as obtained from the filtered probabilities of the MSDR model. Based on the rule (see subsection 3.2) for turning points identification in view of filtered probabilities we identified two peaks of the CBCI, one in March 2003 and another in August 2008; also identified are two peaks of the CFCI one in May 2003 another in September 2008 (see Table 3 below). These are the highest points that marks the end of expansion and the beginning of contraction/ recession periods in financial and/ real activity.

Table A1. CBCI and CFCI Dates at Peaks and Troughs.

CBCI		CFCI	
Peaks	**Troughs**	**Peaks**	**Troughs**
March 2003	March 2004	May 2003	January 2006
August 2008	July 2010	September 2008	June 2011

We further identified two troughs of the CBCI, one in March 2004 and the other in July 2010; and two troughs of the CFCI one in January 2006, another in June 2011. Again, these points mark the end of recession in real activity/ deteriorating financial activity and the transition to expansion. Accordingly, the average length of the upturn phases exceeds the average length of the downturn phases in both the indices. Further, the overall length of the CFCI (7.2 years) exceeds the overall length of the CBCI (7.0 years), and the CBCI length of this analysis is comparable to that of Bosch and Koch (2020). These results are in line with those of Drehmann, Borio, and Tsatsaronis (2012) which posited that the FC lasts between 5-20 years and is usually longer than the BC.

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Appendix B

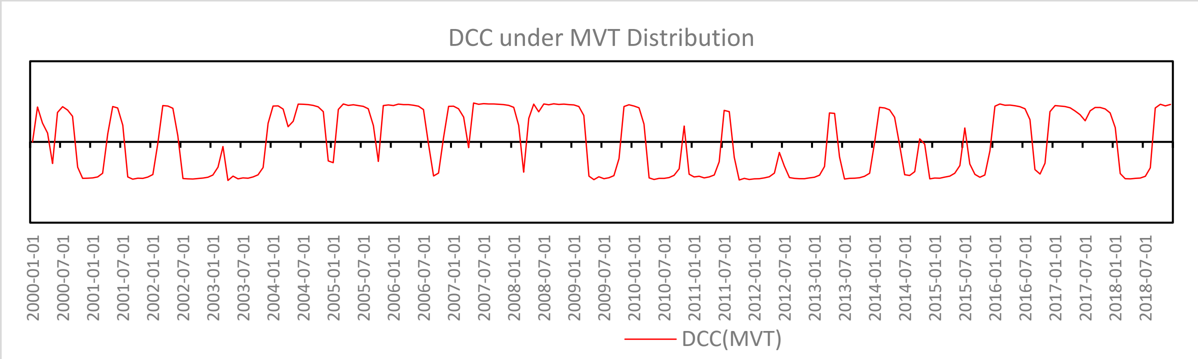

Figure A3. DCC-MGARCH Graphs.

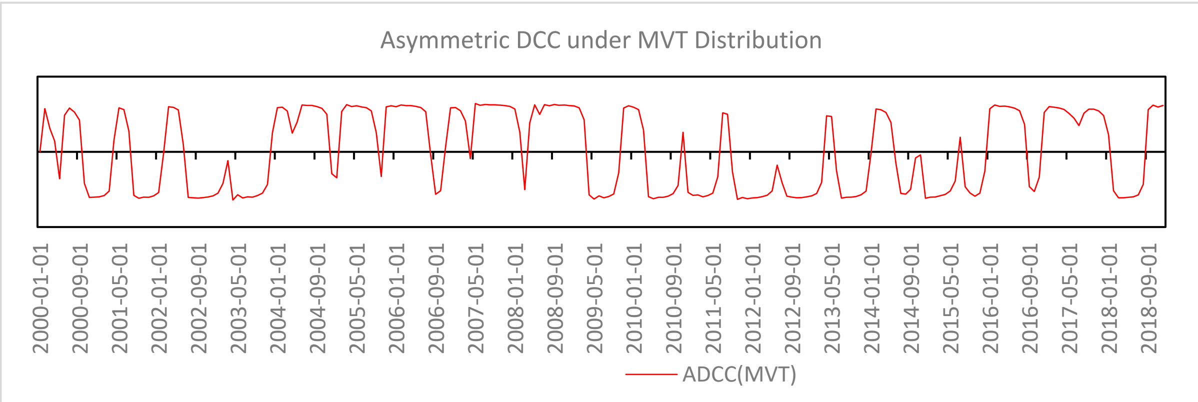

Figure A4. ADCC-MGARCH Graphs.

Appendix C

Table A2. CFCI Variables, Description and Sources.

VARIABLE	ABREVIATION	DESCRIPTION	SOURCE
Real Broad effective exchange rate	**RBEER**	RBEER 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, Cashin, and Sun, 2009).	**South African Reserve Bank**
House Prices	**HP**	HP is measured by the Residential Property Price Index showing indices of residential property prices over time.	**Bank for International Settlements**
All Share Price Index	**ASP**	ASP is the total share price for all share on the JSE.	**South African Reserve Bank**
Long-term Government bond yields	**LTGBY**	LTGBY represents long-term interest rates exceeding 10 years	**South African Reserve Bank**
10-year Government bond yields	**GB10Y**	GB10Y represents long-term interest rates equal to 10 years	**South African Reserve Bank**
5-year Government bond yields	**GB5Y**	GB5Y represents short-term interests rates less than 10 years	**South African Reserve Bank**

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Total credit to the private non-financial sector	**TCPFS**	TCPFS is provided by domestic banks, all other sectors of the economy and non-residents.	**OECD, Reserve Bank of St Louis**
Nominal effective exchange rate	**NEER**	NEER is calculated as geometric weighted averages of bilateral exchange rates.	**OECD, Reserve Bank of St Louis**
Treasury Bill Rate	**TBILL**	TBILL "is a short-term debt obligation of the central government".	**South African Reserve Bank**
The three measures of money in South Africa	**M1, M2 and M3**	Narrow Measure, Intermediate measure, Broad measure	**South African Reserve Bank**
Interbank Lending rate	**ILR**	ILR is the rate charged on short-term loans between South African banks**.**	**OECD, Reserve Bank of St Louis**

Table A3. CBCI Variables, Description and Sources.

List of indicators used to describe Composite Business Cycle Index	
SARB Selected Monthly release	WHOLESALE SALES
SARB Selected Monthly release	RETAIL SALES
SARB Selected Monthly release	NEW PASS VEHICLE
SARB Selected Monthly release	Real estate loans
SARB Selected Monthly release	IP-Total M
SARB Selected Monthly release	IP-food and beverages
SARB Selected Monthly release	IP-Raw Material
SARB Selected Monthly release	IP-textiles, Leather,
SARB Selected Monthly release	IP-wood and paper
SARB Selected Monthly release	IP-Equipment
SARB Selected Monthly release	IP-Durable Material
SARB Selected Monthly release	IP-Fuels
SARB Selected Monthly release	Building Plans Pd
SARB Selected Monthly release	Real Eff EX
SARB Selected Monthly release	M0
SARB Selected Monthly release	M1
SARB Selected Monthly release	M2
SARB Selected Monthly release	SA/ US dollar
SARB Selected Monthly release	SA /British pound
SARB Selected Monthly release	SA /Euro
SARB Selected Monthly release	SA /Japanese yen
SARB Selected Monthly release	Reserves of commercial Banks
SARB Selected Monthly release	Total Loans
SARB Selected Monthly release	Total Credit Ext
SARB Selected Monthly release	PPI-ALL GROUPS
SARB Selected Monthly release	PPI-INTERMEDIATE
SARB Selected Monthly release	PPI-CRUDE OILS
SARB Selected Monthly release	PPI-MANUFACTURING
SARB Selected Monthly release	PPI-METAL PRODS

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SARB Selected Monthly release	PPI-METALS PPI-FOOD
SARB Selected Monthly release	CPI-ALL ITEMS
SARB Selected Monthly release	CPI-APPAREL
SARB Selected Monthly release	CPI-TRANSPORT
SARB Selected Monthly release	CPI-MEDICAL C
SARB Selected Monthly release	CPI-COMMODITY
SARB Selected Monthly release	CPI-DURABLES
SARB Selected Monthly release	CPI-SERVICES
SARB Selected Monthly release	CPI-ALL ITEMS LF
SARB Selected Monthly release	CPI-ALL ITEMS LS
SARB Selected Monthly release	CPI-ALL ITEMS LMC
SARB Selected Monthly release	Treasury Bills
SARB Selected Monthly release	5 Year Gvnt Bonds
SARB Selected Monthly release	10-year Gvnt Bonds
SARB Selected Monthly release	All Share Prices
SARB Selected Monthly release	Gvnt Debt
SARB Selected Monthly release	Gold Reserves
SARB Selected Monthly release	Total Exports
SARB Selected Monthly release	Total Imports
SARB Selected Monthly release	Budget Balance
SARB Selected Monthly release	Liquidation of Co
SARB Selected Monthly release	Total Credit to PS
SARB Selected Monthly release	Prime lending rate
SARB Selected Monthly release	investments
SARB Selected Monthly release	Gvnt Exp
SARB Selected Monthly release	Total Mining
SARB Selected Monthly release	Manufacturing
SARB Selected Monthly release	Comp Leading
SARB Selected Monthly release	Comp Coincident
SARB Selected Monthly release	Comp Lagging
SARB Selected Monthly release	Interest rates
SARB Selected Monthly release	total reserves
SARB Selected Monthly release	OECD Indicator for SA
SARB Selected Monthly release	Employment-Manu
SARB Selected Monthly release	Employment-Cons
SARB Selected Monthly release	Employment-Service
SARB Selected Monthly release	unemp-15-24
SARB Selected Monthly release	Gvnt Final consumption
SARB Selected Monthly release	unemp 25-54
SARB Selected Monthly release	unemp 55-64
SARB Selected Monthly release	employment-industry
SARB Selected Monthly release	employment-Agriculture
SARB Selected Monthly release	GDP Growth

SARB Selected Monthly release	Household Debt
SARB Selected Monthly release	Real GDP
SARB Selected Monthly release	Gross Domestic EXP
SARB Selected Monthly release	Final Cons HH
SARB Selected Monthly release	Final Cons GVNT
SARB Selected Monthly release	Gross Fixed CF
SARB Selected Monthly release	Foreign Direct Inv

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