Asian Journal of Economic Modelling
ISSN(e): 2312-3656
ISSN(p): 2313-2884
DOI: 10.55493/5009.v13i3.5605
Vol. 13, No. 3, 470-489.

URL: www.aessweb.com

The synchronization of business cycles and financial cycles in Saudi economy: New evidences from wavelet decomposition

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Article History
Received: 11 June 2025
Revised: 26 August 2025
Accepted: 5 September 2025
Published: 19 September 2025

Keywords
Business cycles
Financial cycles
Saudi Arabia
Synchronization
Wavelet.

JEL Classification:
C49; E58; E32; E44.

ABSTRACT

This paper aims to study the connectedness and potential synchronization between financial and business cycles in the Saudi economy during the period 1970-2022. To surpass univariate filters such as HP and CF, which allow the extraction of cycles only when frequencies are predetermined, we opt for three novel techniques: the continuous wavelet coherence, the wavelet quantile correlation, and the maximum overlap discrete wavelet transform with turning point analysis. These methods assume that the characteristics of cycles are not fixed over time and allow the dominant frequencies to change from one period to another. Moreover, the adopted methodology enables the determination of the existence of common cycles between variables and the evaluation of their intensity over time. To understand real business cycles, movements in non-oil per capita real GDP are used, while financial cycles are captured through the credit-to-GDP ratio. Our results reveal that, in Saudi Arabia during 1970-2022, financial cycles are longer and more extensive than real business cycles, and the two cycles are synchronized approximately 55% of the time. Wavelet coherence and phase difference indicate that the synchronization between financial cycles and business cycles fluctuates significantly across frequencies and over time. Wavelet quantile correlations demonstrate that the relationship between business and financial cycles varies across different quantile frequencies and time horizons. These findings are of primary importance for authorities to design appropriate macroprudential policies.

Contribution/ Originality: The primary contribution of this study is the application of innovative techniques, such as wavelet decomposition and the Wavelet Quantile Correlation Transform, to analyze the synchronization between financial and real business cycles in Saudi Arabia. Our findings suggest a lack of synchronization or episodic divergence between the two cycles, which has significant implications for the policies and objectives of monetary authorities.

1. INTRODUCTION

Recognizing the differences between business and financial cycles is essential for policymakers to design effective policies that promote both economic growth and financial stability. The conduct of monetary policy and macroprudential policy is complementary if business and financial cycles are synchronized; however, the two policies conflict when the cycles are out of sync. Although there is no consensus on the definition of financial cycles, analysis of cyclical fluctuations in financial systems has become a central topic for economists and regulators since the 2008 subprime crisis. The global financial crisis (GFC) 2007-2009 prompted an increased focus on the role of financial factors in driving real economic fluctuations. Prior to the GFC, the main instrument used by central banks to achieve both monetary and financial stability was the interest rate. Nevertheless, this policy has led to excessive credit growth and over-indebtedness of the private sector. Consequently, understanding the relationship between business and financial cycles is becoming a priority for researchers and policymakers.

Since the pioneering work of Burns and Mitchell (1946), Economists have been interested in analyzing business cycles, especially in developed countries. In contrast, work on the financial cycle and its relationship with the business cycle has become extensive only after the GFC. Empirical literature (see, among others, (Borio, 2014; Borio, Drehmann, & Xia, 2018) states that financial cycles are dominated by medium and long-term cyclical components (8-30 years), while real business cycles are short-term components (less than 8 years). Therefore, if the characteristics of financial cycles differ from those of business cycles, then monetary and fiscal policy are imperfect tools for addressing them, and macroprudential policy will be the appropriate stabilizing strategy. The macroprudential policy framework is designed to address the risks and vulnerabilities that arise in the financial system, including those associated with the financial cycle. Thus, the specific measures employed within the macroprudential framework take into account the characteristics of the financial cycle. Macroprudential policies are typically countercyclical; they are designed to dampen excessive exuberance during the expansion phase of the financial cycle and mitigate the severity of downturns during the contraction phase. In the standard approach, the calibration of the countercyclical buffer is based on the magnitude of deviation of the credit-to-GDP ratio from its trend, which is a financial cycle indicator. Then, the efficacy of macroprudential policy depends on the position of the economy relative to the financial cycle. According to Cerutti, Claessens, and Laeven (2017), macroprudential policy would be more effective in economies where the financial cycle is broader and when this cycle is in the boom phase rather than in the bust phase. According to Borio (2014), using univariate filters such as the Hodrick-Prescott (HP) filter, Christiano-Fitzgerald (CF) filter, or Pass-Band filter could not allow reflecting the evolution of real and financial cycles. This type of filter only allows the extraction of cycles when frequencies are predetermined. Consequently, specifying an ex-ante interval that is too short can exclude important cyclical components. Additionally, the dominant components of the cycle can change from one period to another and deviate from the interval initially specified by the univariate filter. Therefore, the use of univariate filters may lead to the conclusion that the cycle has lost power or even disappeared, when in reality, its length has changed. Conversely, specifying too wide an interval could result in information loss. In summary, detecting common cycles using univariate filters is inappropriate, especially when focusing on a fraction of possible frequencies. Other works, Hiebert, Jaccard, and Schüler (2018) use spectral analysis to estimate the dominant frequency of cycles, but these approaches do not allow the dominant frequencies to change over time. Consequently, the comparison of real and financial cycles by these methods assumes that these cycles evolve in different frequency intervals. To overcome the limitations of frequency and spectral methods, which specify a priori a frequency interval, it seems more prudent to deduce this interval directly from the data. The wavelet method makes it possible to determine the most likely frequencies of business and financial cycles. This method assumes that the characteristics of cycles are not fixed over time and allows the dominant frequencies to change from one period to another. Moreover, wavelet methodology allows the determination of the existence of common cycles between variables and to evaluate their intensity over time.

In this vein, this study seeks to fill this research gap and is the first attempt to characterize the financial cycles in Saudi Arabia and understand their linkages with the business cycles using continuous and discrete wavelet methods during the period 1970-2022 for yearly data. This study differs from others in that it jointly uses discrete wavelet decomposition and the continuous wavelet coherence and phase difference to investigate the time-varying co-movement between real business cycles and financial cycles. Moreover, our study uses the novel quantile wavelet correlation transform and combines the maximum overlap discrete wavelet transform and turning point method to identify expansion (upturn) and contraction (downturn) phases of the cycles and determine their duration and amplitude.

The main contributions of this paper are:

- The characterization of the stylized facts of real and financial cycles in the Saudi Arabian economy.
- Identifying business and financial cycles in the Saudi economy and studying their general features.
- Determining and analyzing linkages and synchronization between real business cycles and financial cycles in the time-frequency domain.

The paper is organized as follows. Section 2 reviews the literature. Section 3 presents the wavelet methodology, briefly outlining the theoretical foundations of the Continuous Wavelet Transform (CWT), Wavelet Coherence (WC), Wavelet Phase Difference (WPD), the Maximum Overlap Discrete Wavelet Transform (MODWT), and the Wavelet Quantile Correlation Transform (WQCT). Section 4 examines the data properties and their cyclical movements using a univariate filter. Section 5 analyzes the co-movements and synchronization of real business and financial cycles using wavelet methods. Finally, Section 6 concludes and offers policy recommendations.

2. LITERATURE REVIEW

Interactions between the financial sector and the real economy have always been a central topic for economists. Since the seminal work of Minsky (1977) and Minsky (1986) and the well-known financial instability hypothesis (FIH), many strands of literature have been developed. The basic idea of the FIH is that during an economic expansion period, companies adopt an overleveraged behavior due to the easy access to credit. This could lead to payment defaults, causing a credit crunch followed by contraction in real economic activities. At the end of the 90s, new-Keynesian economists (Bernanke, Gertler, & Gilchrist, 1999; Kiyotaki & Moore, 1997) proposed the Financial Accelerator Model (FAM) to demonstrate how a small shock in the financial sector could lead to the development of a financial business cycle. More recently, Claessens, Kose, and Terrones (2011) pointed out that out of 84 crises experienced by 24 emerging economies during the 1978–2011 period, 42 were associated with credit crunch, asset price bust, or financial crises. All these crises, including the GFC (2007-2009), have shown that a country with stable macroeconomic conditions can experience instability in the financial sector, which in turn could destabilize macroeconomic performance (Creel, Hubert, & Labondance, 2015). This was the major reason why, since the 2008 GFC, the study of the properties of real and financial cycles and their synchronization has seen a resurgence of interest. A large body of this literature has focused on the synchronization of real business cycles and/or financial cycles between developed countries. Studying the credit cycles in sixteen euro-area countries over 1990-2013, Samarina, Zhang, and Bezemer (2017) find that credit cycles diverged between and within countries following the introduction of the Euro, while De Grauwe and Ji (2016) find a high degree of business cycle synchronization over 1995-2014. Looking beyond Europe, Jordá, Schularick, and Taylor (2016) find that advanced economies have become more synchronized. Stremmel and Zśamboki (2015) find that financial cycles are less synchronized in tranquil periods and more synchronized in periods of common financial stress.

Concerning business and financial cycles synchronization, prior empirical studies focus on the dynamic links between credit and output, but studies on the interactions between different phases of business cycles (recessions and recoveries) and financial cycles (downturns and upturns) remain scarce and limited. One of the main studies post-GFC is that of Stijn Claessens, Kose, and Terrones (2012), who find links between financial cycles (credit, house prices, and equity prices) and business cycles (GDP). Assessing their study on quarterly data of 44 countries over the period 1960.1-2010.4, they notice that different phases of the financial cycle and business cycle are strongly linked. They also argue that recessions associated with financial disruptions tend to be longer and deeper than other recessions, and that recoveries associated with rapid growth in credit and house prices are often stronger. Galati, Hindrayanto, Koopman, and Vlekke (2016) find that financial cycles are longer and more ample than business cycles. Similarly, Gerdrup, Kvinlog, and Schaanning (2013) and Detken et al. (2014) find that the average length of the financial cycle is around four times that of the business cycle. In the case of Turkey, Akar (2016) used total credit volume and asset prices as proxies for financial cycles and GDP and household consumption to measure business cycles. He found evidence of high synchronization among the financial and business cycles. Ma and Zhang (2016) found evidence for a significant influence of financial cycles on business cycles in the US, UK, Japan, and China economies, and observed that the financial cycle leads the fluctuations in macroeconomic variables, especially during periods of financial instability.

More recently, applying multivariate unobserved-component models to six OECD countries (France, Germany, Italy, Spain, the United Kingdom, and the United States), Rünstler and Vlekke (2018) found that financial cycles are longer than business cycles, ranging from thirteen to eighteen years. In the case of G-7 countries, using a spectral approach, Schüler, Hiebert, and Peltonen (2017) found that financial cycles exhibit higher amplitude and persistence than business cycles, with financial cycles lasting an average of 15 years, compared to 6-7 years for business cycles.

The reviewed literature studies only the time aspect of business and financial cycles synchronization. Consequently, it neglects the frequency characteristics of time series. Very few studies associate the two dimensions using novel techniques such as wavelets. For example, in the case of India, Lagesh (2022) adopts a methodology in two steps. In the first step, he uses the maximum overlap discrete wavelet transform (MODWT) to decompose the time-scale of the series. In the second step, the turning point analysis proposed by Harding and Pagan (2002) and Harding and Pagan (2003) is adopted to generate the basic characteristics of financial and business cycles. To derive the aggregate measure of financial cycles, Lagesh (2022) retains two financial variables, real credit flow and equity prices, and uses the Index of Industrial Production to decompose the business cycles. Empirical results indicate the presence of a well-defined financial cycle and reveal that the financial cycles in India have, on average, an amplitude of 12 years (6 years expansion and 6 years contraction). The amplitude of the financial cycle is found to be significantly greater than that of the business cycle.

Reviewing the literature in this field, we depict that the only study treating the case of Saudi Arabia has been conducted by El-Baz (2018). He investigated financial and business cycles synchronization using the Quarterly cycle dating algorithm of Bry and Boschan (1971) over the period 1970Q1-2016Q4[1]. The degree of synchronization between business and financial cycles was assessed using the concordance index developed by Harding and Pagan (2003). The results showed that financial upturns and downturns last longer than economic expansions and contractions. El-Baz (2018) also found that the amplitude and slope of financial upturns and downturns are higher than those of economic cycles. In addition, financial cycle episodes occur more frequently than business cycle episodes. Output and credit tend to move together about 60 percent of the time, but the study concluded that they are not perfectly synchronized.

El-Baz (2018) further used a vector autoregression (VAR) model to examine the effects of financial (credit) cycles on Saudi Arabia's real economy through monetary transmission mechanisms. The model included endogenous variables such as real GDP, consumer prices, domestic credit, short-term interest rates, and the real effective exchange rate. Findings indicated that a positive domestic credit gap shock can boost real GDP, meaning that financial upturns (downturns) have a positive (negative) impact on the real economy.

The synchronization of real and financial cycles has also been studied using wavelet methods. The main difference between the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT) is how they handle the scale parameter; the CWT discretizes the scale more finely. Njegić, Živkov, and Damnjanović (2017) applied wavelet coherence and phase-difference analysis to study business cycle synchronization among Central and Eastern European Countries (CEEC) and the EU-15. They used seasonally adjusted real GDP for the period 1995Q2 to 2016Q3 and followed a two-step method. First, they extracted the cyclical component of deseasonalized real GDP growth using two non-parametric filters: the Hodrick–Prescott (HP) filter and the band-pass (BP) filter. Second, they used the cyclical component generated by these filters with the wavelet-based co-movement measure of Croux, Forni, and Reichlin (2001) to analyze synchronization. Their results showed that CEEC business cycles are generally

[1] The interpolation method is used to derive quarterly series for both real GDP and real bank credit to the private sector.

synchronized with EU-15 cycles, but the strength of synchronization varies across frequencies and over time. Finally, they found that the HP and BP cycles produce relatively similar results for most countries.

This work is part of the continuity of this literature. In this paper, we aim to follow the methodology adopted by Njegić et al. (2017) and go beyond by considering the WQCT and the MODWT-turning point in the case of Saudi Arabia over 1970-2022. Our purpose is to identify business and financial cycles in the Saudi economy and to study their general features and their synchronization through the time-frequency scale. To the best of our knowledge, no previous work has associated CWT, MODWT, and WQCT to apprehend business and financial cycles synchronization. We deem that our results will be of main concern for decision-makers when conducting fiscal and monetary policy.

3. EMPIRICAL METHODOLOGY

In the literature, four types of empirical approaches are used to measure business and financial cycle characteristics: (i) the turning point method (Stijn Claessens et al., 2012), (ii) filtration methods (Drehmann, Borio, & Tsatsaronis, 2012), (iii) frequency methods based on the Fourier transform (Strohsal, Proaño, & Wolters, 2019) (iv) the Wavelet method (Lagesh, 2022; Njegić et al., 2017). However, each method has its limitations. The turning-point method calculates the local minima and maxima of a series based on a predetermined rule. Frequency methods require a pre-specification of the cycles' frequency range. The advantage of the spectral method over filtration methods is that it does not require an a priori assumption about the frequency interval within which the cycle is supposed to operate.

In sum, the first three methods quantify the contribution of each cyclical component to the dynamics of the series, on average, over the observed duration, and they can only identify frequency changes over time by dividing the sample into short durations (Strohsal et al., 2019). The Wavelet method addresses the limitations of the frequency method by allowing analysis of both the temporal and frequency dimensions. Moreover, macroeconomic series are usually characterized by non-stationarity, volatility, seasonality, and structural discontinuities. The wavelet technique is suitable for analyzing these phenomena without imposing simplifying assumptions such as stationarity.

To study the synchronization between business and financial cycles in Saudi Arabia, we employ three advanced techniques: continuous wavelet transform (CWT), maximum overlap discrete wavelet transform (MODWT) associated with turning point analysis, and wavelet quantile correlation transform (WQCT). In the literature, CWT and MODWT are typically used separately. In this study, we utilize them in conjunction. This approach is motivated by the fact that CWT does not always have higher power in indicating synchronization, while MODWT is more robust in decomposing cycles at different frequencies to analyze synchronization. Additionally, we perform the novel WQCT as an extension of the quantile correlation procedure. The WQCT can identify information across different quantile frequencies and time horizons, enabling us to reveal the dynamic dependence structure over varying time scales.

3.1. Wavelet Methodology

Wavelet analysis decomposes a time series into simpler functions that capture information. Wavelets are derived from a single function, called the mother wavelet ψ_(u,s) (t), defined by its time position (u) and scale (s). Following previous studies (Aloui, Hamida, & Hathroubi, 2024; Rua & Nunes, 2009; Torrence & Compo, 1998) Our method uses wavelets for feature extraction and multi-resolution analysis, whereby wavelets are defined as:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \quad (1)$$

Wavelets are assumed to be square-integrable functions, i.e., $\psi(.) \in L^2(\mathbb{R})$. In Equation 1, $1/\sqrt{s}$ refers to the normalization factor ensuring the unit variance of the wavelet, $\|\psi_{u,s}\|^2 = 1$. u is the location parameter providing the exact position of the wavelet and s is the scale dilatation parameter of the wavelet and defines how the wavelet is stretched. Accordingly, the higher scale implies a more stretched wavelet, which is appropriate for the detection of lower frequencies.

It is worth noting that many types of wavelets have been developed in the literature. Each type has specific characteristics and is generally applied to different research problems. In this study, we jointly employ discrete wavelet decomposition and continuous wavelet coherence, along with phase difference, to examine the time-varying co-movement between real business cycles and financial cycles in the Saudi economy. In the literature, the Morlet wavelet is most commonly used as the mother wavelet. It is a complex wavelet defined within a Gaussian envelope, offering good time–frequency localization. Formally, the Morlet wavelet is expressed as:

$$\psi^{M}(t) = \frac{1}{\pi^{1/4}} e^{i\omega_0 t} e^{-t^2/2} \qquad (2)$$

Where ω_0 is the central frequency of the wavelet. Following Rua and Nunes (2009)., we also set $\omega_0 = 6$. This choice of value for ω_0 enables a good balance between time and frequency localizations. The Morlet wavelet is centered at the point $(0, w_0/2\pi)$ in the time-frequency domain (Luís Aguiar-Conraria, Azevedo, & Soares, 2008).

3.1.1. Continuous Wavelets

According to Rua and Nunes (2009) the continuous wavelet transform is given by.

$$W_x(u,s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overline{\psi\left(\frac{t-u}{s}\right)} dt \qquad (3)$$

Specifically, $W_x(u,s)$ is obtained by projecting the specific wavelet $\psi(.)$ on the selected time series. The major merit of the continuous wavelet transform is the ability to decompose and then, consequently, reconstruct the function $x(t) \in L^2(\mathbb{R})$ such as:

$$x(t) = \frac{1}{C_\psi} \int_0^{\infty} \left[\int_{-\infty}^{\infty} W_x(u,s) \psi_{u,s}(t) du \right] \frac{ds}{s^2}, \quad s > 0 \qquad (4)$$

It is worth noting that the main feature of the wavelet transform is the energy preservation of the selected time series.

3.1.2. Wavelet Coherence and Phase Differences

The wavelet coherence of two time series $x = \{x_n\}$ and $y = \{y_n\}$is defined as the localized correlation coefficient between these series in the time-frequency space (Torrence & Compo, 1998). Researchers usually use this tool to detect co-movements in two time series. Following Torrence and Webster (1999) the wavelet coherence is computed as the squared absolute value of the smoothed cross-wavelet spectra normalized by the product of the smoothed individual wavelet power spectra of each time series.

$$R^2(u,s) = \frac{\left|S(s^{-1}W_{xy}(u,s))\right|^2}{S(s^{-1}|W_x(u,s)|^2) S(s^{-1}\left|W_y(u,s)\right|^2)} \qquad (5)$$

Where s denotes the smoothing parameter and u is the location parameter. $W_x(u,s)$, and $W_y(u,s)$ represent the wavelet power spectrum of the series x (y) respectively. The cross-wavelet power spectrum, $W_{xy}(u,s)$, illustrates the area in the time-scale space where the series exhibits high common power, while also measuring the local covariance of two variables at each scale. Wavelet coherence equals one in the absence of smoothing. Additionally, the squared wavelet coherence coefficient satisfies $0 \leq R^2(u,s) \leq 1$. A value close to zero indicates weak correlation, whereas a value near one signifies strong correlation. Thus, wavelet coherence provides a suitable tool for examining the joint dynamics of real business cycles through non-oil GDP and financial cycles through credit to the private sector across both time and frequency.

We also calculate the phase difference, which reflects the lateness of the oscillations between two variables as a function of frequency. The phase difference of two time series, denoted as $\phi_{x,y}$, characterizes their phase relationships.

This measure provides insight into the positioning of the time series within the pseudo-cycle. The phase difference is given as:

$$\phi_{x,y}(u,s) = \tan^{-1}\left(\frac{\mathfrak{I}\{S(s^{-1}W_{xy}(u,s))\}}{\mathcal{R}\{S(s^{-1}W_{xy}(u,s))\}}\right) \text{ with } \phi_{x,y} \in [-\pi,\pi] \qquad (6)$$

Where $\mathfrak{I}$ and $\mathcal{R}$ are the imaginary and real parts of the smooth power spectrum, respectively. For two time series, phase difference informs about their oscillation (cycles) in different time-horizons, indicates how the direction of their correlation evolves over time, and shows the lead-lag relationship between them. We interpret the phase difference in terms of the arrow's direction or in terms of $\phi_{x,y}$ interval. Arrows pointed to the right or $\phi_{x,y} \in [0,\pi/2]$ (left or $\phi_{x,y} \in [\pi/2,\pi]$) indicate that variables are in phase (out of phase). If arrows move to the right and up or $\phi_{x,y} \in [-\pi/2,0]$ (down or $\phi_{x,y} \in [-\pi,-\pi/2]$), the first variable x is leading (lagging). By contrast, if arrows move to the left and up (down), the variable x is lagging (leading).

3.1.3. Maximum Overlap Discrete Wavelet Transform

As mentioned before, in this paper, we use the discrete wavelet method in conjunction with the continuous one because the latter does not always have higher power in indicating synchronization, while the former is more robust in decomposing cycles at different frequencies to study synchronization. Moreover, we use the MODWT because it overcomes the limitation of DWT. This choice is motivated at least by two considerations. First, contrary to DWT, MODWT does not require a dyadic length of the series and avoids the drop of some observations. Second, using MODWT allows for avoiding the down-sampling problem, specific to DWT, because MODWT has the same resolution as the original time series at each stage of the wavelet filtering.

Using a MODWT wavelet filter, a time series $Y(t)$ can be decomposed as:

$$Y(t) = Y_0(t) + \sum_{j-0}^{n} X_j(t) \qquad (7)$$

Where $Y_0(t)$ represents the trend component of the series and $X_j(t)$ represents fluctuations around cycle components. j stands for the depth of the decomposition, which needs to be fixed based on satisfying the requirement that $j \leq \log_2(\text{lenght}[Y])$. In order to estimate $Y_0(t)$ and $X_j(t)$ we use the pyramid algorithm procedure (Mallat, 1989), which uses transfer functions of high-pass and low-pass filters. Moreover, in order to rapidly perform wavelet decomposition, we use the multiresolution analysis (MRA) proposed by Mallat (1989).

Once the cyclical components of the series are identified, we apply the Bry and Boschan (1971) algorithm[2] to determine turning points.

3.1.4. Wavelet Quantile Correlation Transform

The WQCT is a novel econometric procedure proposed by Kumar and Padakandla (2022) as an extension of the traditional quantile correlation estimator developed by Percival and Walden (2000) and by Li, Li, and Tsai (2015). Because this technique has many benefits, such as the identification of information over different quantile frequencies as well as different time horizons, it has recently attracted the interest of many researchers in different fields (see, among others, Chishti, Azeem, and Khan (2023). To define the WQCT of two time series X_t and Y_t we have to decompose these series using MODWT, then we apply the quantile correlation to the pair of wavelet details $d_j[X]$ and $d_j[Y]$ for all $j = 1,2, \ldots$ J. For a level of decomposition j and the τ^{th} quantile, we can write the WQCT as follows:

$$WQCT_\tau(d_j[X, d_j[Y]) = \frac{qcov_\tau(d_j[X], d_j[Y])}{\sqrt{var\left(\phi_\tau\left(d_j[Y] - Q_{\tau,d_j[Y]}\right)\right) var(d_j[X])}} \qquad (8)$$

[2] The algorithm was initially developed for monthly data but was extended to quarterly frequency by Harding and Pagan (2002). and by Inklaar (2003) to annual series.

Where $qcov_{\tau}(d_j[X], d_j[Y])$ is the quantile covariance between details $d_j[X]$ and $d_j[Y]$. $Q_{\tau,d_j[Y]}$ is the τ^{th} quantile of detail $d_j[Y]$ and ϕ_{τ} is an information function. Results from WQCT are interpreted in terms of color codes. Deep black color boxes denote negative wavelet quantile correlation between pairs of variables, while the extreme yellow color represents a strong positive association.

4. DATA: SOURCES, FREQUENCIES, AND SERIES' PROPERTIES

New econometric methods, and particularly the wavelet method, are eager for data. Empirical results depend on the length of the series and their frequencies. To study real business and financial cycles and the interactions between them, researchers usually use quarterly data. This kind of data is usually available in developed countries, while developing countries, in general, suffer from a lack of high-frequency data. Saudi Arabia began to publish quarterly data for some indicators only since 1993, but most of the macroeconomic variables exist in annual frequency since 1970. While the credit to GDP ratio series exists in quarterly frequency over 1993-2022, the quarterly non-oil GDP series is available only for the period 2010-2022. In addition, there are no quarterly proxy series, as required by the quadratic loss function methodology, allowing the generation of quarterly non-oil GDP series. These reasons lead us to use annual data for the period 1970-2022. The adoption of a relatively long period is motivated by the integration of different episodes of business and financial cycles of the Saudi economy. We have combined and confronted two sources, the Saudi General Authority of Statistics (GASTAT) and the World Bank (WB), to construct our series. In the literature, real business cycles are usually apprehended through total per capita real GDP. The use of per capita real Non-oil GDP is preferable for assessing the economic performance of oil-rich countries due to several reasons: Firstly, the fact that the oil sector is an enclave with little forward or backward linkages to the rest of the economy. Historically, oil exports have accounted for a substantial majority of Saudi Arabia's total exports. While oil exports in Saudi Arabia represented an average of 77% of total exports throughout the last decade, the contribution of the oil sector to employment represented approximately 4.7% only. Secondly, the oil industry is managed by the public sector, and its output is highly affected by the decisions taken in OPEC. In the literature, financial cycles are represented through a myriad of variables. In the case of India, Lagesh (2022) uses credit and equity prices, while in the case of the USA, Yan and Huang (2020) use credit, credit-to-GDP ratio, house prices, and equity prices. Stijn Claessens et al. (2012) choose credit, housing, and equity markets to analyze financial cycles. In our case, financial cycles will be understood mainly through domestic credit to the private sector as a percentage of GDP, as it constitutes the single most important link between savings and investment. All variables are adjusted for seasonality using X13.

Table 1 presents the variables used in the study, their sources, and frequency.

Table 1. Variables, sources, and frequency.

Indicator	Frequency	Period	Source
Domestic credit to the private sector as % of GDP (CGDP)	Annual	1970-2022	WB (Global Financial Development Database)
Per capita real Non-oil GDP (NOGDP)	Annual	1970-2022	GASTAT

4.1. Graphs and Statistical Properties of the Series

Table 2 presents a summary of descriptive statistics of the credit to GDP ratio (CGDP) and per capita non-oil real GDP (NOGDP) and their cycle components using the Christiano-Fitzgerald filter (CF), and Table 3 presents their correlations. From the results reported in Table 2, it is evident that all time series exhibit positive skewness, implying that the distributions have longer right tails. Moreover, the cyclical component of NOGDP records the highest kurtosis value, suggesting that most conditional variances are concentrated in the tails of the distribution rather than around the mean. The Jarque–Bera test statistics further confirm that these deviations are statistically significant, thereby strongly rejecting the null hypothesis of normality under the Gaussian distribution.

Table 2. Descriptive statistics.

Statistic	CGDP	NOGDP	CGDP_CF	NOGDP_CF
Mean	25.115	32229.75	-0.207	85.604
Maximum	56.800	45081.10	6.674	3532.664
Minimum	2.750	21583.36	-7.511	-2221.493
S.D.	14.757	6661.481	2.620	814.119
Skewness	0.371	0.570185	0.256	1.261
Kurtosis	2.262	2.200808	4.390	9.128
Jarque-Bera	2.147	3.797501	4.302	86.034
Observations	47	47	47	47

Figure 1 presents the evolution of the CGDP and NOGDP during the study period. It shows a lack of co-movement between the two variables.

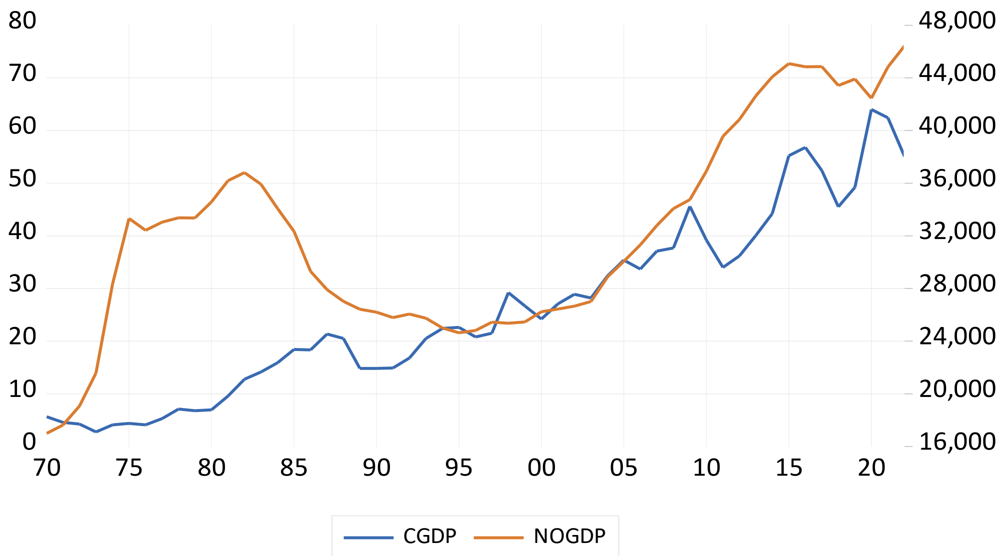

Figure 1. Credit-to-GDP ratio and non-oil GDP.

Note: On the left axis CGDP in percentage and on the right axis NOGDP in Saudi Riyals.

Table 3. Correlation matrix.

Variable	CGDP	NOGDP	CGDP_CF	NOGDP_CF
CGDP	1.000	0.582	0.118	-0.076
NOGDP		1.000	-0.078	0.348
CGDP_CF			1.00	0.053
NOGDP_CF			0	1.000

From these correlations, we perceive that the CGDP is positively correlated with NOGDP, with a relatively moderate coefficient of 0.5828, while their cyclical components are very weakly correlated.

4.2. Univariate Filter and Cyclical Behavior of the Series

Empirical literature Borio (2014) and Drehmann et al. (2012) suggests that financial cycles are dominated by medium and long-term components (8-30 years), while real business cycles are characterized by short-term components (less than 8 years). To depict financial and business cycles in the case of Saudi Arabia, we implement the Christiano-Fitzgerald filter (CF), which is a pass-band filter. The CF filter is different from the HP filter in the sense that this filter removes from the time series those fluctuations that have frequencies that are too high or too low.

Following Drehmann et al. (2012), we set the upper bound parameter for the duration of each cycle that composes the financial cycle at 32 years and the lower bound at 8 years. As these authors note, the 32-year upper bound ensures that the medium-term cyclical component does not include a long-term secular trend. Figure 2 illustrates this strand of literature in the case of Saudi Arabia using the CF filter. We can observe that in Saudi Arabia, from 1970 to 2022, financial cycles are longer and more extensive than business cycles. The average duration of financial cycles is about 12 years, subdivided almost equally between upturns and downturns. However, the business cycle tends to be shorter in the last two decades, which may be a result of globalization, technological advancements, financial innovation, and policy responses. For business cycles, evolution is more erratic. The duration and amplitude of the cycle differ over time. On average, the duration is about 7 years, with periods of expansion more pronounced than contraction, especially at the beginning and the end of the cycle. These intuitive and preliminary results could reflect weak synchronization between financial and business cycles in Saudi Arabia.

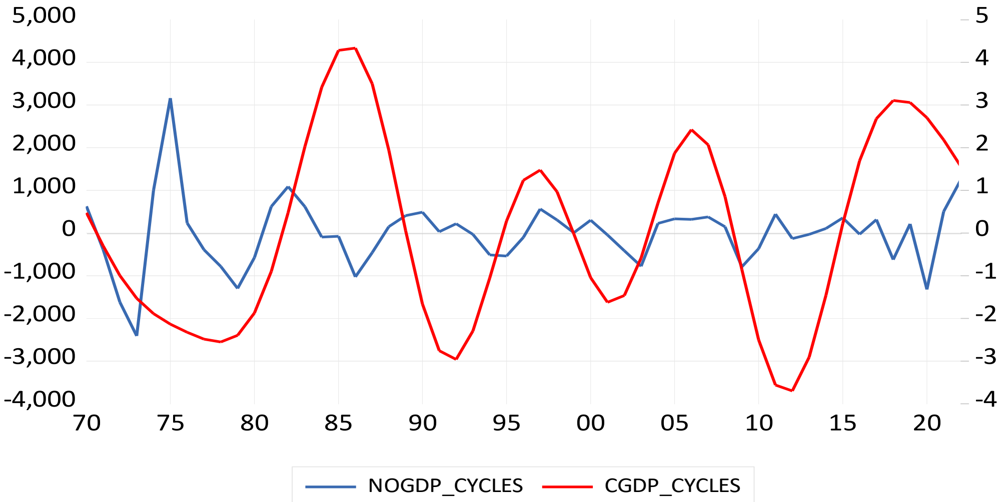

Figure 2. Financial and business cycles using the CF filter.

Note: On the left axis are movements around the trend of NOGDP in Saudi Riyals, and on the right axis are movements around the trend of CGDP in percentage.

Pearson's unconditional correlation, presented in Table 3, and univariate filters such as the CF filter offer limited information about the dynamics of business and financial cycles synchronization because they calculate only average static coefficients and neglect the time aspect as well as the frequency dimension characteristics.

Therefore, in the following section, we present results from three wavelet methods: the continuous wavelet transform (CWT) (including wavelet coherence and phase difference), the maximum overlap discrete wavelet transform (MODWT), and the wavelet quantile correlation transform (WQCT), which overcomes all the deficiencies of static correlation and univariate filter techniques. Then, we apply the MODWT-turning point analysis to identify periods of expansion (upturn) and periods of contraction (downturn) for business cycles and financial cycles.

The use of the wavelet method, as a non-linear method, is also justified in this paper because the series present non-linear serial dependence and non-stationarity. Table 4 summarizes BDS for non-linearity and the ADF test for non-stationarity.

From the BDS test results, we reject the null hypothesis that the time series are linearly dependent and corroborate the normality test results (Jarque-Bera test, Table 2) and reveal that the time series does not follow a normal distribution. Results from the ADF test suggest that the series are not stationary in level. These results support the use of wavelet methodology and help to avoid erratic outcomes and incorrect policy recommendations.

Table 4. BDS and ADF tests.

Variable	BDS					ADF			Result
	2	3	4	5	6	C	C&T	None	
CGDP	20.269	20.037	19.99	22.041	25.382	0.425	-1.225	-0.764	I(1)
NOGDP	20.752	21.367	22.46	23.807	25.901	-1.492	-1.583	0.467	I(1)

5. WAVELET RESULTS

We first analyze results obtained from the CWT as preliminary evidence to see whether similar oscillations in cycles are occurring at the same time and the same frequency using wavelet coherence and phase difference. This exercise will be conducted by analyzing the behavior of the CF cyclical component of CGDP and NOGDP following Njegić et al. (2017). Moreover, the algorithm for identifying turning points will be used to determine more accurately the characteristics of financial and business cycles in Saudi Arabia.

5.1. Wavelet Coherence and Phase Difference

To investigate the level of synchronization between financial cycles and real business cycles across different time scales, we have plotted the wavelet coherence and phase difference results between the CF cyclical component of CGDP and NOGDP in Figure 3.

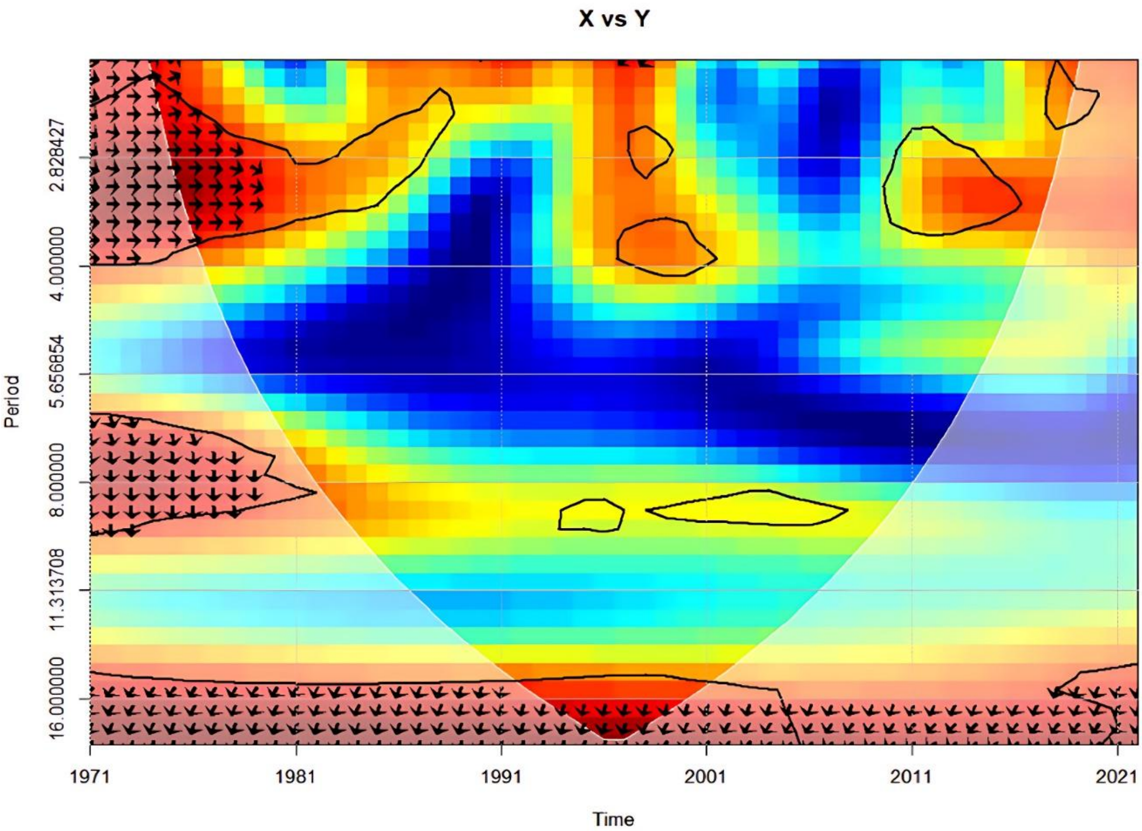

Figure 3. Wavelet coherence and phase difference between financial cycle (X) and business cycles (Y).

The interpretation of econometric results of wavelet coherence and phase difference follows the standard literature (see Aguiar-Conraria and Soares (2011)) and can be summarized as follows. The deep blue color indicates the lowest correlation and the absence of coherence between the two variables. It is interpreted here as the absence of synchronization between financial cycles and business cycles. In contrast, red areas indicate the highest correlation and coherence, representing strong synchronization between the two cycles. The dashed black contour outlines regions where wavelet coherence is statistically significant at the 5% level, based on red noise estimated from Monte

Carlo simulations using phase-randomized surrogate series. The cone of influence (COI), shown as light-colored areas, delineates regions of reliable power. The arrows indicate the phase difference and lead–lag relationships between the two time series: arrows pointing to the right (left) show that the variables are in phase (out of phase). Arrows pointing to the right and upward (downward) indicate that the first variable is leading (lagging), whereas arrows pointing to the left and upward (downward) indicate that the first variable is lagging (leading).

Figure 3, shows that, in Saudi Arabia, short-term (2-4 years) and medium-term (4-8 years) synchronization between financial and business cycles is observed only during 1970-1980 and 1970-1990 respectively, while in the medium-long-term (more than 8 years), synchronization is observed during the entire sample period 1970-2022. In the short-term, arrows are pointed to the right and up, indicating that financial and business cycles are in phase, with the credit to GDP ratio leading non-oil GDP. This result is symptomatic of oil-rich countries where the non-oil sector was unimportant during the first decades of development. In the medium-term, arrows are pointed to the right and down, indicating that financial and business cycles are in phase and CGDP is lagging. In the long-term, arrows are pointed to the left and down, indicating that financial and business cycles are out of phase, with NOGDP as the leading variable. Overall, the results of Figure 3 indicate that, in Saudi Arabia during 1970-2022, the synchronization between financial cycles and business cycles fluctuates significantly across frequencies and over time, with a predominance of lack of synchronization during the sample period.

5.2. Maximum Overlap Discrete Wavelet Transform

To consolidate results obtained from continuous wavelet analysis, we perform the maximal overlap discrete wavelet transform (MODWT) method (Gençay, Selçuk, & Whitcher, 2002). As mentioned earlier, CWT does not always provide higher power in detecting synchronization, whereas MODWT is more robust in decomposing cycles at different frequencies for this purpose. We construct an aggregate measure of financial cycles using the low-frequency wavelet detail component of the credit-to-GDP ratio. Next, we derive the basic characteristics of financial and business cycles using the turning point analysis proposed by Harding and Pagan (2002) and Harding and Pagan (2003). Following Lagesh (2022), the maximum overlap discrete wavelet transform with multiresolution (MODWT-MR) is applied using a Daubechies filter of length L=8 and the least-asymmetric family with "reflection" boundary conditions. This procedure generates five wavelet detail coefficients (D1, D2, D3, D4, and D5) and one smooth coefficient (S5). According to Drehmann et al. (2012), D1 corresponds to seasonal fluctuations; D2, D3, and D4 correspond to business cycle frequencies; and D5 corresponds to financial cycle frequency. Table 5 presents the interpretation of time–frequency characteristics for the different wavelet series.

Table 5. Scale and time frequencies of different wavelet series.

Scale	Time frequency	Interpretation
D1	0-1 year	High frequency fluctuations
D2	1-2 years	Business cycle
D3	2-4 years	Business cycle
D4	4-8 years	Business cycle
D5	8-16 years	Financial cycle
S5	> 16 years	Trend

Note: The decomposition is based on Drehmann et al. (2012).

In order to generate business cycles, we aggregate D2, D3, and D4 scale levels of NOGDP following Lagesh (2022), that is, we calculate $\sum_{j-2}^{4} X_j(t)$ according to Equation 7. Figure 4 presents the three levels of decomposition of the NOGDP series, and in Figure 5, we superimposed these combined series of scale levels reflecting business cycles (aggregation of D2, D3, D4) and the D5 scale level of CGDP reflecting financial cycles.

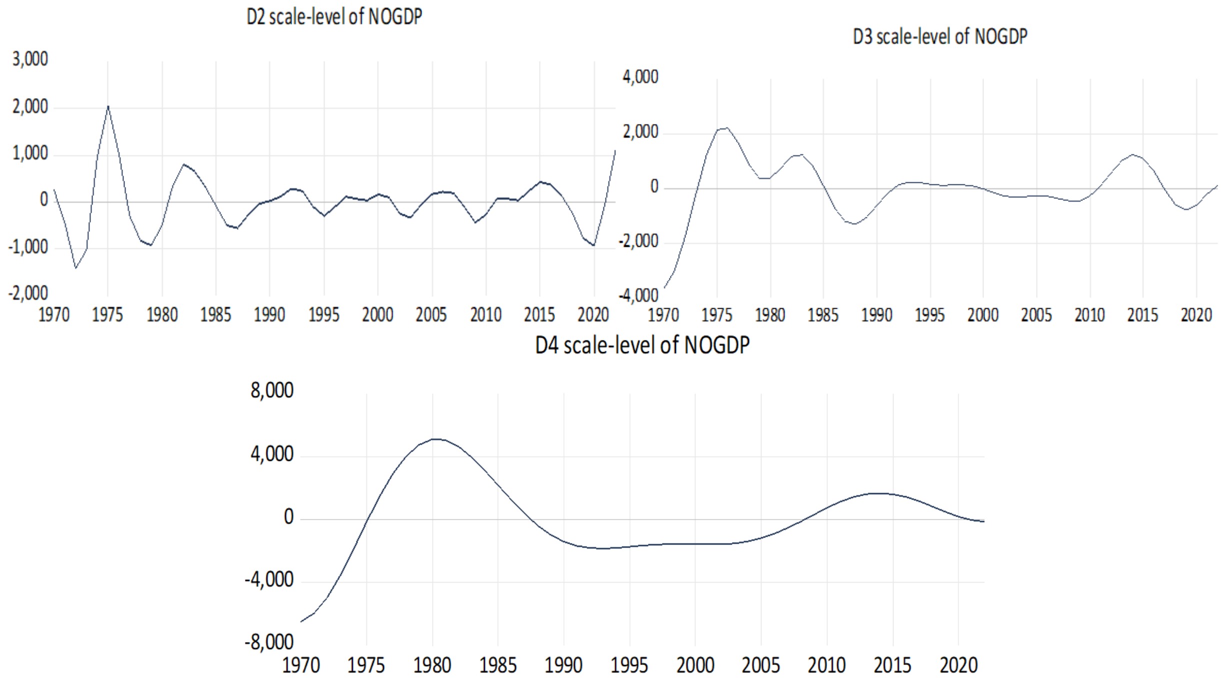

Figure 4. D2, D3, and D4 scale levels of Business cycles decomposed from NOGDP.

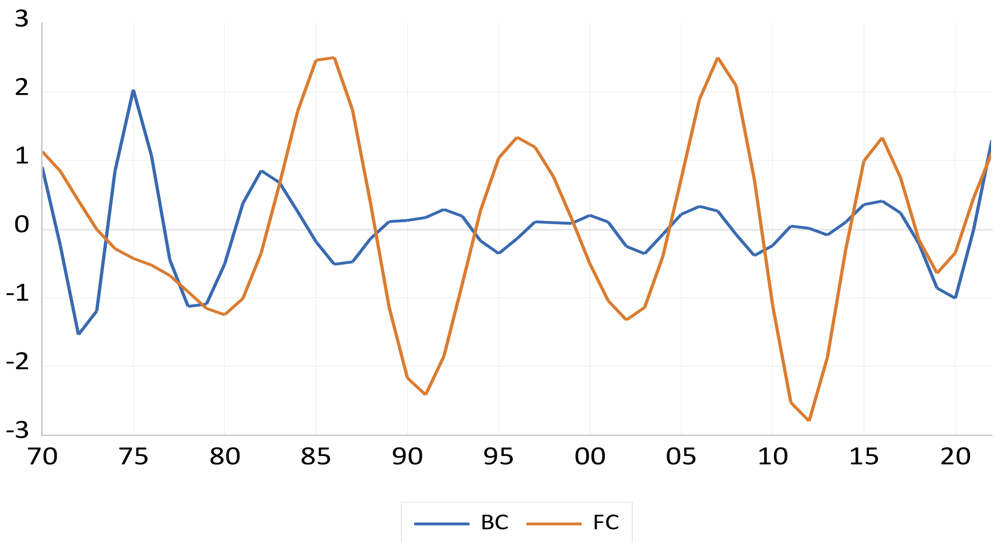

Figure 5. Business cycles (D2+D3+D4) vs financial cycles.

From Figure 5, we can observe that business cycle episodes are more frequent than financial cycle ones. During the period 1970-2000 BC, business cycles are leading FC, while during the recent period (2000 and after), FC are leading. This could indicate the development of the credit market, especially bank credit, in response to the development of the private sector and the adoption of an economic diversification strategy in Saudi Arabia since 2016. Also, Figure 5 reveals that economic crises are, in general, preceded by a peak in the financial cycle. We can depict these peaks, among others, for the stock market crash in October 1987 and the global financial crisis 2007-2008 caused by the American subprime mortgage crisis.

5.3. MODWT-MR-Turning Point Analysis

To study business and financial cycle episodes more rigorously, and to determine the duration of contraction and expansion phases, and to evaluate their synchronization, we perform the turning point analysis on the aggregate measure of business and financial cycles generated by the MODWT-MR method. As mentioned before, we use an adapted version of the Bry-Boschan algorithm to annual series developed by Inklaar (2003). For any annual time-series y_t, turning points are identified as follows:

- Peak occurs at time t if: $\{y_t > y_{t-k}, y_t > y_{t+k}\}$.
- Through occurs at time t if: $\{y_t < y_{t-k}, y_t < y_{t+k}\}$.

According to Inklaar (2003) $k = 1$ year for peak-to-through phase and $k = 2$ years for the peak-to-peak phase[3].

Table 6 presents the duration of expansion and contraction episodes of the business cycle, and Table 7 presents upturn and downturn episodes for the financial cycle. For the business cycle, results reveal that periods of expansion range between 1-6 years and periods of contraction between 2-4 years. This indicates that the Saudi economy takes a longer time to recover after a recession. The complete business cycle duration ranges between 4-10 years and has a mean of about 6.12 years, quasi-equally distributed between contraction and expansion episodes. In addition, the results of Table 8 show that periods of contraction are more frequent (54.7%) than expansion episodes (37.7%).

Table 6. Features for business cycles.

Dates			Duration (Years)		
Through1	**Peak**	**Through2**	**Expansion**	**Contraction**	**Cycle**
1971	1974	1977	3	3	6
1977	1981	1985	4	4	8
1985	1991	1994	6	4	10
1994	1996	1998	2	2	4
1998	1999	2002	1	3	4
2002	2005	2008	3	3	6
2008	2010	2012	2	2	4
2012	2015	2019	3	4	7

The duration of the financial cycle ranges between 8 and 16 years, with a mean length of approximately 12.2 years. Upturn episodes last between 4 and 6 years, while downturn episodes range from 4 to 10 years. The mean length of downturn phases (6.6 years) is longer than that of upturn episodes (5.6 years). Table 8 shows that periods of downturn are more frequent (60%) than upturns (32%).

Table 7. Features of financial cycles.

Dates			Duration (Years)		
Peak1	**Through**	**Peak2**	**Upturn**	**Downturn**	**Cycle**
1970	1979	1985	6	10	16
1985	1990	1995	6	6	12
1995	2001	2006	6	7	13
2006	2011	2015	6	6	12
2015	2018	2021	4	4	8

Table 8. General characteristics of business and financial cycles (Means).

Characteristics	Business cycle		Financial cycle	
	Expansion	**Contraction**	**Upturn**	**Downturn**
Duration (Years)	3	3.12	5.6	6.6
Frequency	37.7%	54.7%	32%	60%
Amplitude	28.3%	-12.7%	132.5%	-20.3%
Cycle (Years)	6.12		12.2	

[3] According to Inklaar (2003) for monthly data, the minimum peak-to-trough (trough-to-peak) period is 5 months and peak-to-peak (trough-to-trough) is 15 months. For quarterly data peak-to-through is 2 quarters and peak-to-peak is 6 quarters.

Overall, we observe that in Saudi Arabia and during 1970-2022, the financial cycle is longer and has a higher amplitude than the business cycle. This result is in concordance with other studies (see, among others, Drehmann et al. (2012) in the case of six developed countries; Paramaiah, Long, and Motelle (2021) in the case of India; Slaoui (2021) in the case of Morocco, and El-Baz (2018) in the case of Saudi Arabia).

Having identified turning points for business and financial cycles, we can seek for their synchronization using the concordance index (CI) of Harding and Pagan (2002) and Harding and Pagan (2003). For two time series x and y the index is defined as follows:

$$CI_{xy} = \frac{1}{T}\sum_{t=1}^{T}[C_t^x . C_t^y + (1 - C_t^x).(1 - C_t^y) \qquad (9)$$

Where C_t^x and C_t^y are binary variables defined as follows:

C_t^x= 0, if business cycle is in recession phase at time t.

C_t^x= 1, if business cycle is in expansion phase at time t.

C_t^y= 0, if financial cycle is in downturn phase at time t.

C_t^x=1, if financial cycle is in upturn phase at time t.

By construction, the *concordance* index ranges between 0 and 1. We have perfect synchronization if *the index* equals 1, and absence of synchronization if *the index* equals 0. Following this methodology, our results reveal that, in Saudi Arabia during 1970-2022, the *concordance* index is equal to 0.554, indicating that the business cycle and financial cycle are synchronized for 55.4% of the time. This result has implications in terms of policies Saudi authorities have to adopt according to episodes of financial and business cycles. In particular, when financial and business cycles diverge, the central bank should adopt macroprudential policies to complement monetary policy. In such a situation, monetary authorities can help banks to limit their losses in downturn periods by building up countercyclical capital buffers during boom times. Figure 6 presents the concordance index between Saudi Arabia's financial and business cycles from 1970 to 2022.

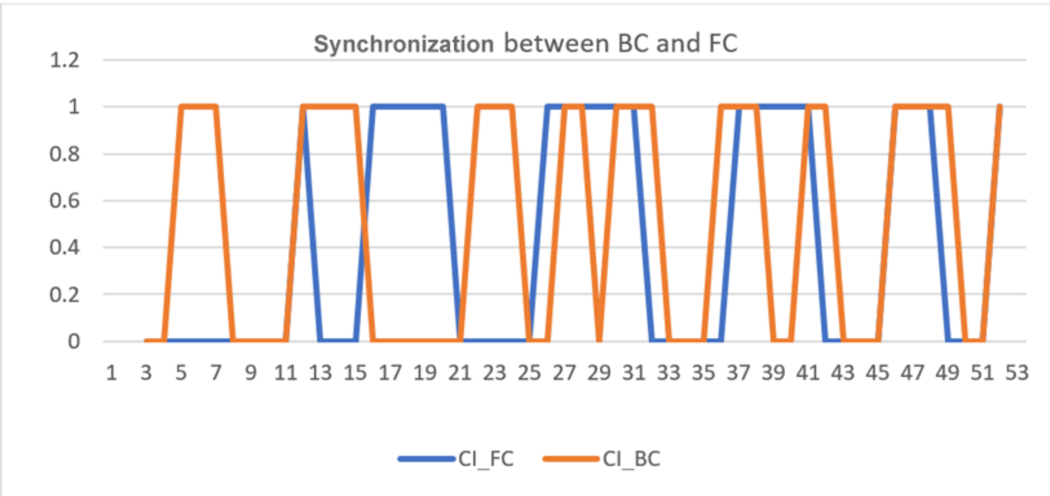

Figure 6. Synchronization between financial and business cycles.

5.4. Wavelet Quantile Correlation between Financial and Business Cycles

One of the contributions of this work to the existing literature on financial and business cycle synchronization is the use of the novel WQCT analysis. Kumar and Padakandla (2022) state that WQCT has the ability to identify information over different quantile frequencies as well as different time horizons. WQCT is also efficient in considering tail structure dependence over varying time scales. We perform the WQCT on CGDP and NOGDP (Figure 7a) and on business and financial cycles obtained from MODWT-MR decomposition. We extract information at the scales of (0-4) years (short-term), (4-8) years, (8-16) years (medium-term), and (16-32) years (long-term) to roughly capture the correlation between business and financial cycles through different periods and different frequencies. WQCT reveals some degrees of varying negative and positive correlations from the short, medium, and long terms between the two variables under consideration and between their cyclical components (business and financial cycles). For CGDP and NOGDP series (Figure 7a), we observe a relatively high positive correlation in the short term, while in the medium term, the correlation remains positive but minimal. In the long term, we observe deep black color boxes denoting a strong negative quantile correlation between the two variables.

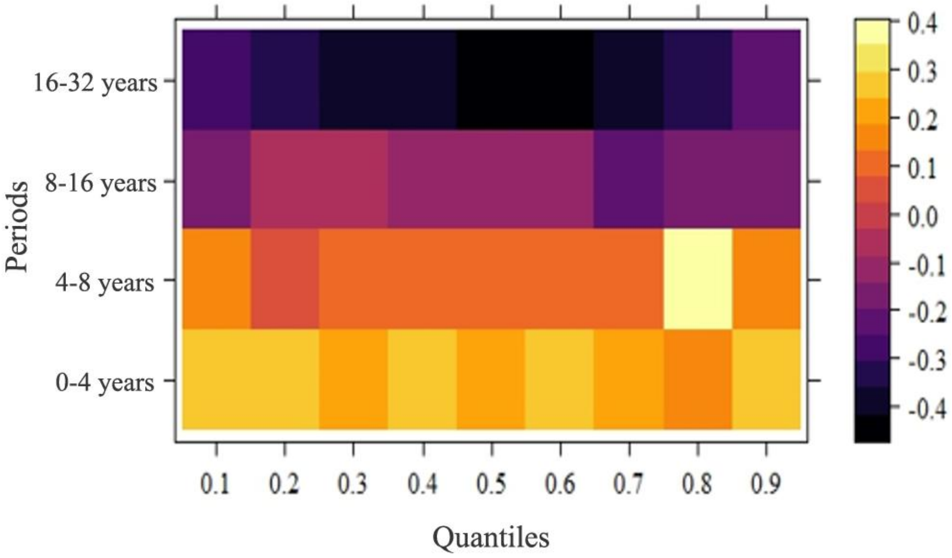

Figure 7a. WQCT between CGDP and NOGDP.

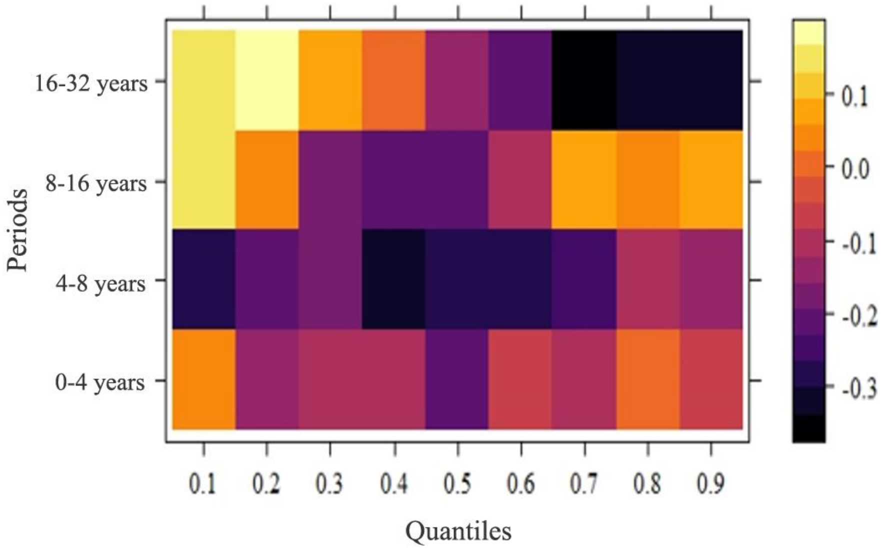

Figure 7b. WQCT between business and financial cycles.

For business and financial cycles, from Figure 7b, we depict a different WQCT distribution. In the short term (0-4 years), BC and FC are weakly and positively correlated for all quantile frequencies, while in the (4-8 years) period, they are rather negatively correlated for all quantiles. In the medium-long term, (8-16 years) and more, WQCT presents a very mixed structure. We observe a positive correlation between BC and FC only for low quantile frequencies (0.1-0.2) and a very strong negative correlation at high quantile frequencies (0.7-1). This result is in concordance with phase-difference results, where financial cycles and business cycles are identified to be out of phase. The previous technical analysis based on different wavelet approaches has shed light on co-movements and synchronization between business and financial cycles. Results have confirmed the episodic character of interactions between the credit-to-GDP ratio and non-oil GDP. In general, movements in NOGDP precede those of CGDP, inducing a lack of synchronization between business and financial cycles. During the last three years of the sample (2019-2022), the COVID-19 crisis has reversed the tendency. In fact, during that period, while economic growth slowed with a negative rate in 2020, credit to the private sector increased due to different programs initiated by the Saudi Central Bank to mitigate the negative impacts on small and medium enterprises.

6. CONCLUSION AND POLICY RECOMMENDATIONS

The taming of financial and macroeconomic instabilities requires the identification of financial and business cycle episodes. This study aimed to characterize the main features of business and financial cycles in Saudi Arabia and to identify the degree of their synchronization during the period 1970-2022. For this objective, we used novel and robust wavelet techniques, including the continuous wavelet transform (CWT), the maximum overlap discrete wavelet transform (MODWT), the wavelet quantile correlation transform (WQCT), and turning point analysis. These methods are appropriate because they allow for depicting the evolution of the series in the time-frequency domain, surpassing univariate filters, which postulate predetermined frequencies.

Our results show that financial cycles tend to be more ample and longer than business cycles, while the latter are more frequent. The average length of the financial cycle in Saudi Arabia (12.2 years) is around twice that of the business cycle (6.12 years). Wavelet coherence and phase difference indicate that the synchronization between financial cycles and business cycles fluctuates significantly across frequencies and over time. In the short and medium term, synchronization is observed only on subperiods of the sample (1970-1980 for the short-term and 1970-1990 for the medium-term), while in the long term, we observe high coherence during the entire sample period, but the two cycles are out of phase. These findings are corroborated by the use of MODWT-turning point analysis and the calculation of the concordance index, which shows that BC and FC are synchronized in about 55% of the time. The WQCT estimation offers more detailed results and suggests a very mixed correlation structure (positive, negative) depending on the term length and the level of quantile frequencies.

In sum, in Saudi Arabia and during 1970-2022, there is a lack of synchronization or episodic divergence between business and financial cycles. This result has implications for the policies and objectives of monetary authorities. In particular, this justifies the adoption of macroprudential stabilization policy that differs from traditional monetary and fiscal policies. Macroprudential policies are usually adopted to prevent and reduce systemic risk. When business and financial cycles diverge, the central bank cannot simultaneously achieve both price stability and financial stability through the use of monetary policy alone. In this scenario, the central bank should complement monetary instruments with macroprudential measures to limit risks to the financial sector, enhance its resilience, and smooth out the financial cycle.

The detection of periods of economic expansion (contraction) and financial upturn (downturn) is also crucial to the choice of an adequate macroprudential tool by the central bank to complement other policies. As an example, under the hypothesis of divergence between financial and business cycles, if the central bank adopts an accommodative interest rate policy to maintain price stability, it could worsen financial instability if there is unsustainable growth in credit to certain economic sectors. Therefore, in such a scenario, the central bank should supplement interest rate policy with macroprudential tools to attain both monetary and financial stability. According to Krug (2018) monetary policy instruments should focus on price and output stability, while macroprudential policy instruments suites better to maintain financial stability. To conclude, having macroprudential policy helps policymakers to address specific vulnerabilities and risks in the financial system, while allowing monetary policy to focus on maintaining price stability and promoting sustainable economic growth.

This study has at least two main limitations. The first is considering only one variable to apprehend financial cycles. In the literature, many other variables complement the credit-to-GDP ratio, including equity prices, asset prices, and house prices. This was mainly due to the unavailability of an exhaustive series of such variables for the total sample period. The second concern is the frequency of the data. We use annual data and not quarterly data for the reasons explained in the text.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The author states that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: Upon a reasonable request, the supporting data of this study can be provided by Salem Hathroubi.
Competing Interests: The author declares that there are no conflicts of interests regarding the publication of this paper.

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