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Business and financial cycles in Rwanda

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Abstract

The global financial crisis has made it apparent that the financial cycle plays a more prominent role in macroeconomic dynamics. Cross-country studies have revealed significant links between business and financial cycles and have suggested policymakers closely monitor the likely impact of shocks from the financial sector on the real economy. Against this background, this paper explores the linkages between Rwanda's business and financial cycles.The empirical results from Wavelet analysisand Structural Vector Autoregressive (SVAR) model indicate that the financial cycle (proxied by overall credit to GDP gap) is closely related to the business cycle (proxied by the output gap), especially in the medium-term, with credit responding more to output. The results point out the presence of macro-financial linkages in Rwanda and highlight the potential risks of a shock from one sector to another.

JEL Classification Numbers: E30, E44, G10, G20

Keywords: Business cycle, Financial cycle, Wavelet analysis, SVAR, Rwanda.

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1 Introduction

The post 2007-2009 financial crisis has renewed interest in the linkages between macroeconomics and finance and put studies of interactions between business and financial cycles to the forefront of research (Caballero, 2010; Woodford, 2010; Claessens et al., 2012; and Yan & Huang, 2020), with a specific assessment of the effects of shocks originating from one sector to another. The Global Financial Crisis was characterized by sharp fluctuations in asset prices, credit, and capital flows, which dramatically affected the financial position of households, corporations, and sovereign nations. These disruptions were amplified by macro-financial linkages, almost bringing the global financial system to collapse,fueling the deepest contraction in world output in more than half a century,and resulting in unprecedented defies for fiscal, monetary, and financial regulatory policies.

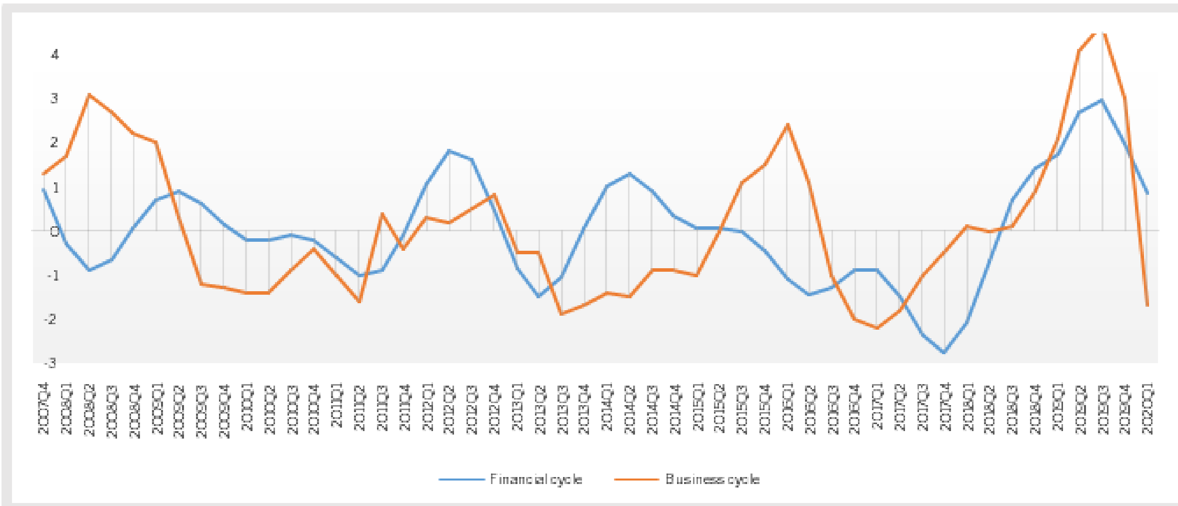
Macro-financial linkages are diverse. On the one hand, shocks from the real sector can be transmitted through financial markets, thereby amplifying business cycles. On the other hand, shocks can be originated from the financial sector, which, in turn, can lead to macroeconomic fluctuations. Overall, the abundance of theoretical as well as empirical studies has strongly argued for the linkages and interactions between financial cycles and business cycles, which led to the consensus among economists that the financial cycle plays an essential role in business cycle fluctuations (Caldara et al., 2016;Christiano et al., 2016) and vice versa.

Rwanda has experienced rapid economic expansion and relatively easy financial conditions over the last two decades. Except for a short and shallow recession caused by covid-19 in 2020, annual GDP growth averaged 7.2percent from 2000 to 2020. However, there have been some episodes where the growth was volatile; hence worth studying the business cycles. The financial system has also evolved from being almost purely financial intermediary-based to having a growing and active financial market. The banking sector is the largest, accounting for 67 percent of the total financial sector assets. The financial sector has deepened over time, with credit to private sector ratio to GDP steadily increasing from 4.0% in 1980 to 33.8 percent in 2010 and 56.6 percent in 2019. The total credit to the economy expanded very rapidly, more than doubling as a share of GDP, increasing from 10.3% in 2000 to 21.3 % in 2020.Similar to economic growth, some periods were characterized by volatility in certain financial sector components; hence, the fluctuations in both sectors may be linked.

Cross-country evidences suggest that co-movements between financial and business cycles can occur during economic and financial growth periods, with financial booms enhancing and lengthening output growth (Yong & Zhang, 2016) Again, some empirical evidence revealed that periods of easy financial conditions could amplify economic fluctuations and possibly lead to adverse economic outcomes. For example, Jorda et al. (2013) show that periods of strong credit growth are typically followed by periods of sluggish economic activity.

The illustration below of business and financial cycles for Rwanda indicates that they are positively correlated with some lags, with the business cycle leading in some periods and the financial cycle taking the lead in other periods. This co-movement supports the need for this study, bringing some instincts of the changes in the interaction between the two sectors overtime.

Figure 1: **Output gap and credit to GDP ratio gap in Rwanda**



Source:Authors' computation

No previous studies have attempted the same subject in the case of Rwanda, to the best of the authors' knowledge. Thus, it is critical to assess whether and how financial cycles are linked to the business cycle in Rwanda. Understanding these linkages would help predict and manage downturns and upturns in credit growth and the real sector and formulate appropriate macro-prudential policies.

Empirical results from Wavelet analysis and the SVAR model show the existence of the relationship between the business cycle and the financial cycle in Rwanda. Wavelet analysis indicates a co-movement, with the business cycle leading the financial cycle in the medium term, while impulse responses from SVAR suggest that credit responds more to output than output responds to credit. Contrary to some of the previous studies in other countries, the key insight for Rwanda is that influence of the business cycle on the financial cycle is relatively more important than the other way round; thus, policymakers have to take that into consideration to mitigate the possible effect on future credit growth and financial system stability.

The rest of this study is structured as follows: the next section reviews the literature. Section three explains the methodology used. Section four discusses the empirical results and section 5 concludes.

2 Literature Review

The fluctuations of real economic activity and aggregate credit are closely linked mostly through the wealth effects and financial accelerator mechanism (see, among others, Bernanke & Gertler,1989; Nobuhiro,1997, Gilchrist & Zakrajsek, 2009). In favorable economic conditions, optimistic growth prospects improve borrower credit worthiness and collateral values. As lenders usually respond with an increased credit supply, more abundant credit allows for more significant investment and consumption and further increases collateral values. In a downturn, the process is reversed.

Extensive practical experience and much formal research highlight the crucial supporting role that financial factors play in an economy's economic growth and prosperity. Just as a robust financial system promotes growth, adverse financial conditions may prevent an economy from reaching its potential. A weak banking system characterized by non-performing assets and inadequate capital or firms whose creditworthiness has eroded due to high leverage or declining asset values are examples of financial conditions that could undermine growth. The financial conditions may affect shorter-term economic conditions as well as the longer-term performance of the economy. Hence, it is logical that the financial and credit conditions changes are important in propagating the business cycle. Prior to and during the global financial crisis, the linkages between credit growth and GDP growth became more pronounced. In particular, the financial sector plays a significant role during the early stages of the crisis, while the real sector quickly takes over as the dominant source of spillovers.

There are three main channels by which disruptions in financial markets can influence real activity: a pullback in spending owing to reductions in wealth; balance sheet mechanisms that lead to a widening of credit spreads, which curtail the ability of households and businesses to obtain credit; and the direct effect of impairments in the capacity of financial institutions to intermediate credit.

It is commonly assumed that financial cycles are pro-cyclical and accelerate business cycle fluctuations (see, e.g., Borio, 2014). Recent research using cross-country data has revealed important links between business and financial cycles. However, the more likely tendency of the close relationship between real and financial sectors in developing countries, most available studies focused on developed and emerging economies, with SVAR as a dominant methodology applied and few adopting wavelet analysis. Since the macro-financial linkages primarily depend on economic structures, it is worth discussing the empirical literature based on countries' specific and group studies.

Studying the interaction of business and financial cycles in 21 advanced OECD countries and 23 emerging market countries from 1978Q1 to 2009Q4 for the latter and 1960Q1 to 2009Q4 for the former. Claessens et al. (2010) pointed to a strong interaction. They used the index developed by Harding and Pagan 2002 and tracked credit, house prices, equity prices, and exchange rates to measure the financial cycles, while the output was a measure of business cycles. The results show that financial cycles tend to be larger and sharper than business cycles and the business cycles are more synchronized with cycles in credit and house prices than in equity prices and exchange rates. Their results stress the importance of developments in credit and house markets for the real economy as a policy implication.

In another study, Claessens et al. (2012) used a comprehensive database for a large sample of advanced economies and emerging economies to provide a broad empirical characterization of macro-financial linkages. They report three main results. First, business cycles are more closely synchronized with credit and house price cycles than with equity price cycles. Second, financial cycles appear to play an essential role in determining recessions and recoveries and influencing the features of business cycles. In particular, recessions are more likely to overlap with financial disruptions, while recoveries are prospective to be linked with booms. Third, recessions associated with financial turmoil, notably house price busts, are often longer and more profound than other recessions.

Antonakakis et al. (2015) examined the business cycle and financial cycle spillovers in the G7 countries, using VAR- based spillover index approach introduced by Diebold and Yilmaz (2009) with data spanned from 1957Q1–2012Q4. By assessing the time-varying relationship between real credit growth and real GDP growth at business cycle frequencies for each of the G7 countries, their results showed spillovers between credit growth and GDP growth, which evolve heterogeneously over time across countries and increase during extreme economic events. Moreover, they found the bidirectional spillovers of shocks between the financial and the real sector.

Krznar and Matheson (2017) explored the link between Brazil's financial and business cycles from 1999Q1 to 2015Q3. They estimated cycles using various commonly used statistical methods with a small, semi-structural model of the Brazilian economy. Two approaches have been used to measure the financial cycle: the medium-term credit cycle and the Financial Conditions Index (FCI). The business cycle was measured by the output gap, calculated by the band-pass filter developed by (Christiano & Fitzgerald, 2003). Both model-based and statistical-based estimates of financial and business cycles conclude that the financial cycle has a longer duration and is larger than the business cycle. The results show that for every 1 percent rise in the output, credit increases by around 3 to 5 percent, on average. In addition, real GDP growth lags the financial conditions. Both facts suggest that financial sector developments are important for economic fluctuations in Brazil.The impulse responses indicate that credit responds more to output than output responds to credit. Private credit is more responsive to output shocks than public credit. Output responds strongly to shocks to financial conditions. Historical decomposition of the output gap suggests that short-term financial conditions and medium-term credit shocks are important in explaining fluctuations in economic activity.

Young and Zhang (2016) studied the linkages and interactions between financial cycle, business cycle, and monetary policy in the USA, UK, Japan, and China over the period 1987Q1-2015Q4, 1989Q1-2015Q4, 1989Q1-2015Q4, and 1998Q1-2015Q4, respectively. They estimated the equation using the GMM method, and their results showed that the financial cycle has an imperative impact on the business cycle in each country. Their study further investigated the role of financial cycle shock in macroeconomic fluctuations using a small macroeconomic model. The variance decomposition results for major endogenous variables of the model system in the four countries mentioned above showed that financial cycle shock plays a vital role in determining macroeconomic fluctuations.

Oman (2019) analyzed the synchronicity between business and financial cycles in the euro area, both within and across countries, for the period spanning from 1971 to 2015. He used the band-pass filter Christiano and Fitzgerald (2003) proposed for GDP growth, credit growth, credit-to-GDP, and residential property price growth. The results showed that Germany's financial cycle has been remarkably flat throughout the sample period. At the same time,Spain, Ireland, and Greece, which are "high-amplitude" countries, experienced significantly ample financial cycles after the introduction of the euro. The author found that average business cycle synchronization increased gradually over time, albeit with the similarity of the composite business cycle of high-amplitude countries falling in the boom period. He pointed out that the synchronization of financial cycles may influence resource allocation and generate asset price bubbles, hindering cross-country economic convergence and making a systemic financial crisis more likely.

A recent study by Yan and Huang (2020) studied the association between the financial cycle and the business cycle using Wavelet analysis and explored their interactions and dynamic mechanisms by the VAR model. The empirical results showed that the financial cycle is closely related to the business cycle; the business cycle leads the financial cycle with a high positive correlation. More importantly, the financial cycle was a key source of the business cycle fluctuations.

In summary, various studies on the linkages between financial and business cycles adopted the structural vector autoregressive models, wavelet analysis, and General methods of moment (GMM).We observe the key differences in the proxies of cycles across the studies,whereby financial cycles were measured by credit to GDP ratio gap, growth in the credit to the private sector, or the index of financial conditions, while the business cycles were mainly proxied by the output gap or the real growth of the economy. Despite some prevailing differences in magnitude and direction, the studies revealed evidences ofmacro-financial linkages. The main contribution of the present study is to analyze the linkages between real and financial sectors in Rwanda as one of the developing economies that lack empirical evidence in this area and have witnessed good progress, but with fluctuations in both sectors.

3 Methodology

This section presents the data source, transformation, and different analytical methods applied in this study.

3.1 Data source and transformation

We collect quarterly data with the sample period running from 2006:1 to 2020:1. The choice of the sample is motivated by the availability of quarterly data for some important series such as Gross Domestic Product (GDP), etc. All data were obtained from the National Bank of Rwanda database. To gauge how financial cycles co-move with business cycles, we compute concordance indices measuring the share of time over which two given cyclical series are in the same phase (expansion or contraction) over the observed period. We employ the band-pass filter developed by Christiano and Fitzgerald (2003) to isolate a quarterly seasonally adjusted series cycle, defined as a deviation of the series from their trends. In addition, variables such as the real monetary condition index and the United States real gross domestic product (US-GDP gap) are used in this study.

3.2 Analytical methods

We adopt two different methods to analyze the relationship between the business and financial cycles: Wavelet analysis and structural vector autoregressive models (SVAR).

3.2.1 Wavelet analysis

This approach has a huge potential in our analysis, as it allows one to unveil relationships between economic variables in the time-frequency space. Among the various analytical methods of wavelet analysis, we choose the cross-wavelet transform (CWT) that allows one to quantify the co-movement in the time- frequency space. That is, to analyze the interaction between two-time series x and y in the time-frequency domain and assess over which periods and frequencies are the co-movements higher (Rua, 2010).

In the spirit of Torrence & Compo (1998), the wavelet coherence of two-time series x and y can be defined as:

$$R_t^2 = \frac{|s(w_t^{xy})(s)x|^2}{s(s^{-1}|(w_t^x(s|^2).s(s^{-1}|w_t^y(s)|^2} \tag{1}$$

Where $S(.)$ denotes smoothing in both time and scale, wavelet coherence close to one shows a higher similarity between time series. In contrast, near-zero coherence depicts no relationship (Boako & Alagidede, 2016). Hence, from the wavelet squared coherency output, one can distinguish where and where the link is stronger and identify both time and frequency varying features.

We simultaneously computed the wavelet phase, which provides information about correlations and lead-lag relationships (causality) with different data series. According to Madaleno and Pinho (2010) and Torrence and Compo (1998), the phase for wavelet depicts any lead/lag linkages between two-time series and can be defined as:

$$\theta_{xy} = \tan^{-1}\frac{I\left\{w_t^{xy}\right\}}{R\left\{w_t^{xy}\right\}}, \theta_{xy} \in [-\pi, \pi] \tag{2}$$

An absolute value of xy less (larger) than /2 indicates that the two series move in-phase (antiphase, respectively), referring to the instantaneous time as time origin and at the frequency under consideration. At the same time, the sign of the phase shows which series is the leading one in the relationship. The phase vectors are indicated by arrows (Boako & Alagidede, 2017; Owusu et al., 2017).

If the phasedifference becomes zero, it is an indication that the timeseries move together at the specified frequency. If $x, y(0, /2)$, then the time series are in phase (or positive) relation, and x leads y; if $x, y(-/2, 0)$, then y leads x. If $x, y(/2,)$, the series are in antiphase (negative relationship), then y leads$x$; if $x, y(-, -/2)$, then x leads y.

3.2.2 Structural Vector Autoregressive model

Sims (1980)introduced SVAR models as an alternative to the large-scale macro-econometric models used during that time. Since then, the SVAR methodology has gained widespread use in applied time-series research due to various advantages, such as allowing for the incorporation of contemporaneous variables, an investigation into the impact of individual shocks, andidentification of specific independent shocks that are not affected by covariance terms. Thus, the SVAR models have become an appropriate tool for studying relationships and the effects of shocks in macroeconomics, considering the issue of endogeneity and the limited availability of proper instruments. The empirical analysis is based on the following structural VAR model:

$$AY_t = C(L)Y_t + \beta u_t \tag{3}$$

Where Yt is a vector of endogenous variables (business cycles, financial cycles,and real monetary conditions index), L is the lag operator,A, B, and C are matrices, and ut is a vector of normally distributed errors ($ut\ N(0, I)$).

A 4-variable benchmark model includes output gap as a measure of the business cycle,credit to GDP ratio gap as a measure of the financial cycle, based on an increasing amount of literature suggesting the effectiveness of the credit to GDP gap to spot the buildup of financial vulnerabilities (Drehmann & Tsatsaronis, 2014). Basel III recommends the credit-to-GDP ratio as the best-fitted measure of the financial cycle. In addition, the model includes the real monetary conditions (RMCI) measured as a weighted average of the real short-term interest rate and real effective exchange rate and the US GDP gap for consideration of external influence.

Regarding the identification strategy, we use recursive zero restrictions on coefficients (Cholesky decomposition). Our estimation considers the ordering of variables as follows: Variable representing business cycle is ordered first;the real monetary condition index is ordered second, and the financial cycle variable is ordered last. This ordering of the variables has the following implications: Monetary authorities consider the business cycle when making the decisions. The business cycle and real monetary conditions affect the financial cycle contemporaneously. The main reason for ordering the financial cycle at the last place is to assess the impact of shocks from credit to the economy, which is purely exogenous, i.e., eliminates the effect of output and monetary conditions.

4 Empirical Results

4.1 Unit root test

Before estimating models, the stationarity properties of each series are investigated using the Augmented Dickey-Fuller (ADF) test. All series stationary at the level $I(0)$. The below table reports the result of the stationarity tests.

Table 1: Results of unit root test

Variables	***Symbol***	***ADF***	
		Probability	***Level***
Output gap	Output_gap	0.0001	I(0)
Real monetary conditions index	RMCI	0.003	I(0)
Credit to GDP gap	Credit_ratio_gap	0.008	I (0)
US GDP gap	US_gap	0.0010	I(0)

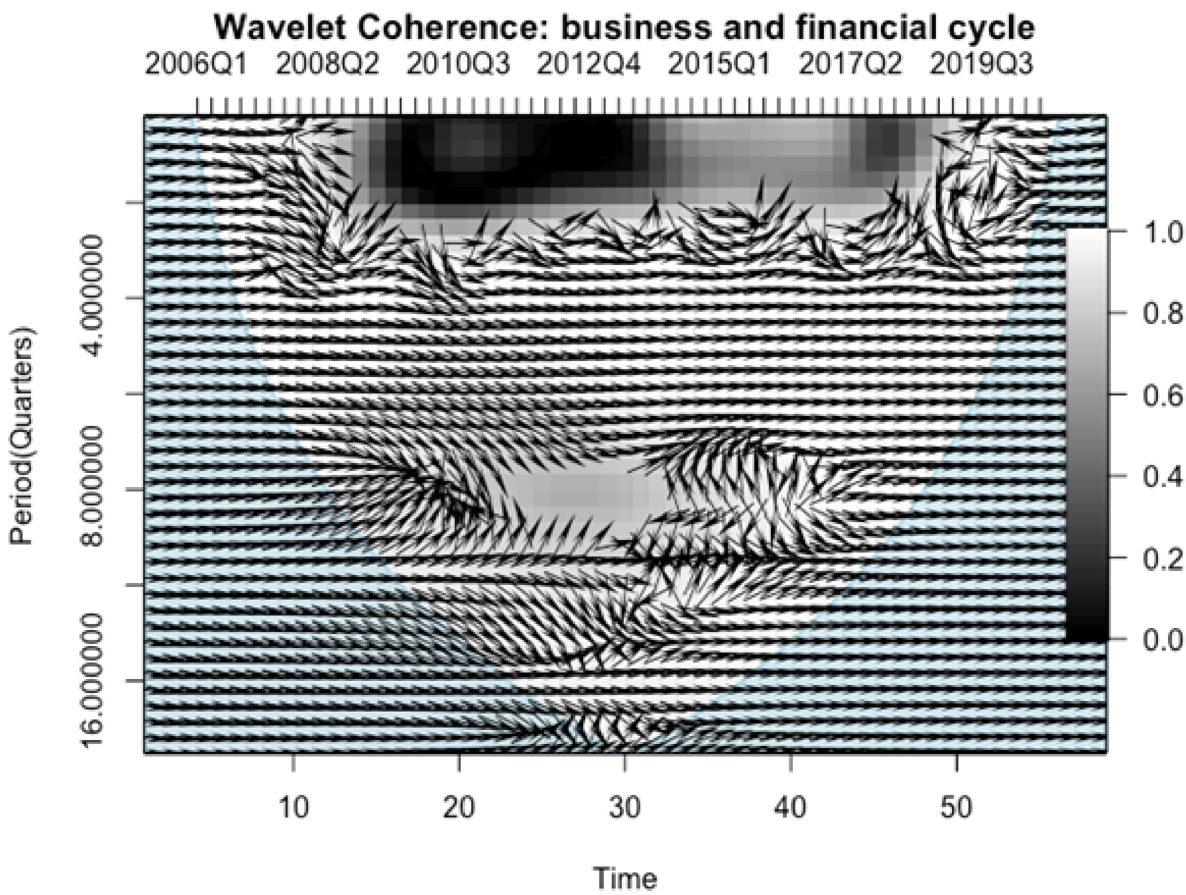
Source: Own computation

4.2 Results from wavelet analysis

According to Aguiar-Conraria et al. (2013), the interpretation of wavelet coherence can be summarized as follows. On the right-hand side, there is a bandwidth spectrum, which highlights the level of correlation oscillating from the lowest amount of correlation, 0, which is shown in the plot as deep black color, to the highest amount of correlation, 1, which is shown as a light grey color. We are looking for areas with this light grey color for high synchronization, indicating the co-movement of the business and financial cycles.

On the x-axis is the time - period shown, ranging from the beginning of the sample in 2006Q1 to the end of the sample in 2020Q1. The thick white contour in the coherence plot shows areas where the wavelet coherence is significant at the 5% level against red noise estimated from 1500 Monte Carlo simulations. The inverse bell-shaped cone is called the cone of influence (COI). It shows the region in the plot which is of substantial power, where the lighter shade is the significant region (Grinsted, et al., 2004). Furthermore, the direction of the phase-difference arrows inside the plots shows whether the two time - series are in - phase or leading/lagging each other. If the arrows are pointed to the right, it indicates that both time series are in phase with each other, and if it is pointed to the left, it indicates anti-phasing. If the arrow is pointed up, the first time - series is leading the second, and if the arrow is pointed down, the first time - series is lagging the other.

Figure 2: **below highlights the results of wavelet analysis**



Source:Authors' estimation using wavelet

The results point out a strong positive correlation between the business cycle and financial cycles in

Rwanda in the time and frequency dimensions, as the dominant color of the cone of influence is the light grey color.Limited correlation is only observed between 2010 and 2012 and the end of 2017, at a small scale of less than two quarters. Regarding which variable is leading or lagging through phasing, the arrows are mainly oriented to the right (they are in phase). Generally, the evidence shows that the business cycle leads financial cycle at a scale of 2 to 4 quarters, indicating that the booms (recessions) in the economic activities lead to booms (downturns) in credits to the economy after six to twelve months. As the arrows are mainly oriented to the right on a scale of four to eight quarters, both cycles are in phase, with none leading the other. We observe a two-directional correlation between the variables at a scale greater than eight quarters.

Keeping in mind that the wavelet analysis is robust in showing the correlation between series, it is essential to go further with structural VAR, which is more appropriate for judging the response of one sector to a shock from another.

4.3 Results of structural VAR

We estimate a VAR model, which has the advantage of providing evidence on the business cycle response to the financial cycle shocks and reactions in the financial cycle to the business cycle shocks and clarifies the causal relationship between the financial cycle and the business cycle.

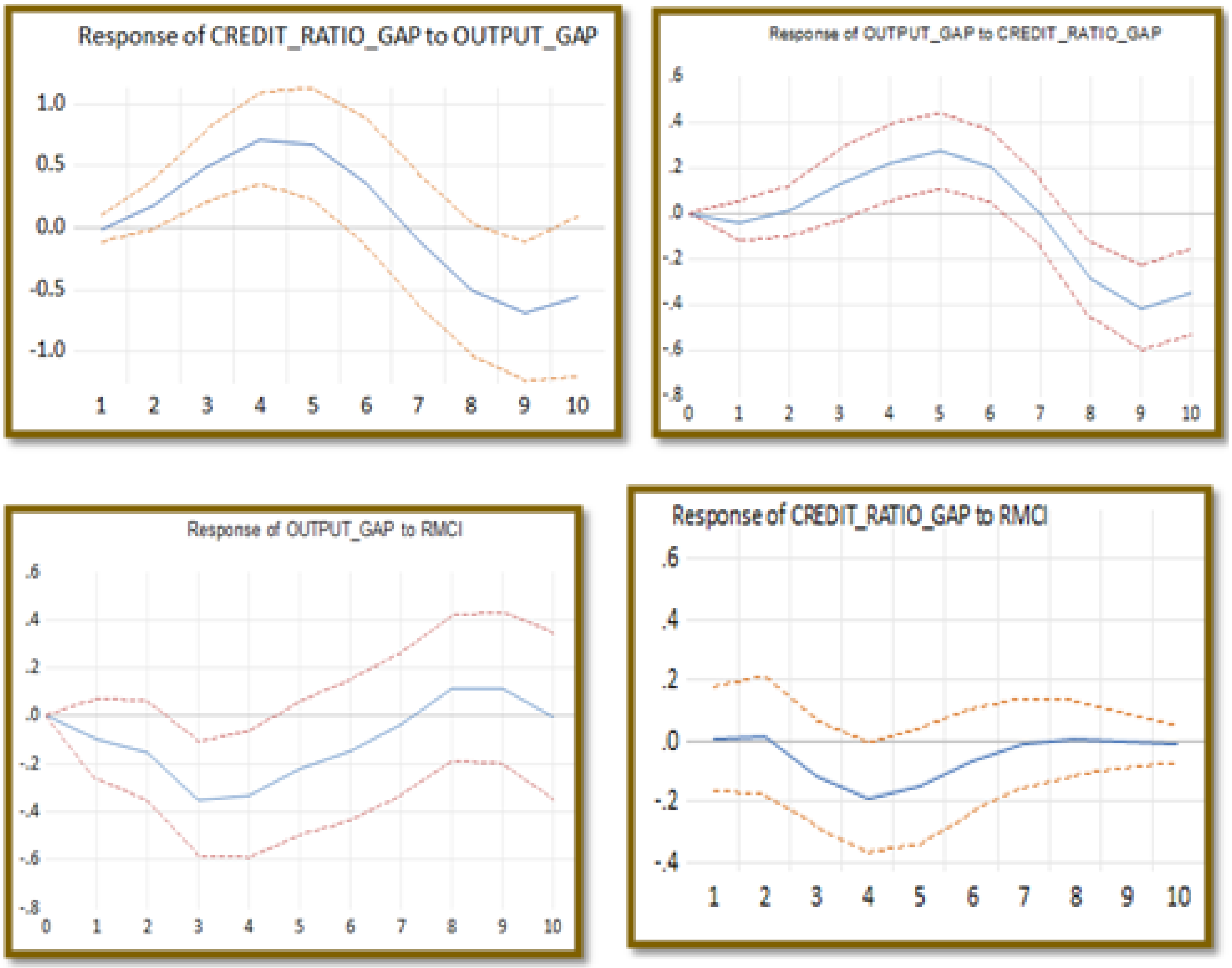
We use the Akaike information criterion (AIC) and the Schwarz information criterion (SIC) to determine thelag in the VAR model and find that the optimal lag period is 2. Figure is 3 shows the impulse response functions by using the Cholesky decomposition.Annexes highlight the diagnostics tests, justifying that errors are normally distributed, absence of autocorrelation, and the VAR satisfies the stability condition.

The impulse responses underline the importance of shocks from the real sector to the financial industry. The response of the financial cycle to a shock from the business cycle is quick at the 1st quarter and lasts about six quarters, implying that the boom in the economic activities leads to a boom in loans. However, the abundance in credits to the economy may result in the non-performing assets of lending institutions and later discourage and reduce the financing role, reflected in the negative and harsh impact on the business cycle realized after nine quarters. Our findings are in line with cross-country evidence suggesting that periods of strong credit growth are followed by periods of sluggish growth (Krznar & Matheson, 2017).

The business cycle responds to the financial cycle at the third quarter and lasts for three quarters before it turns negative at the eighth quarter, and the negative becomes stronger than the positive response. This indicates thatthe shock from the financial system leads to business cycle fluctuations.

The findings reveal that tight monetary conditions reduce the output gap, and the effect materializes in the second quarter but lasts for almost three quarters, in line with our policy horizon. Regarding the response of the financial cycle to monetary conditions, the effect is small and short, realized in the fourth quarter.

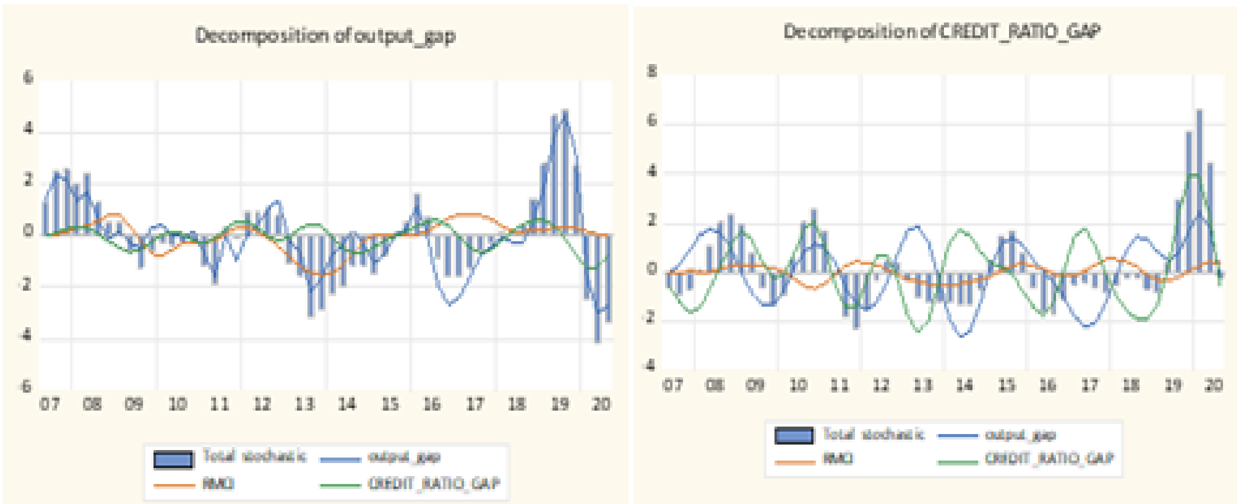
Figure 3: **Response to CholeskyOne S.D. Innovations 95.0% marginal confidence bands**



Source:Authors' estimation

Figure is 4 below presents the historical decomposition of the business and financial cycles through the lens of the identified structural shocks from the VAR model. On the left side of the figure, the historical decomposition of the output gap suggests that credit shocks have been important in explaining fluctuations in economic activity, especially during the global financial crisis (GFC) 2008-2009, and a relatively less significant role in other periods.On the right side, the results reveal that the business cycles have played an essential role in the fluctuations in financial cycles, particularly in post-GFC and in recent years of 2019-2020.

Figure 4: **Historical decomposition (HD) using Cholesky (d.f adjusted) weights**



Source:Authors' estimation

4.4 Discussion of the results

Empirical results suggest some similarities with previous studies on developed and emerging economies, but some differences also prevail, noting that the interaction between financial and real sectors depends on the structure of the two sectors and the economy in general.

Recent literature generally presented evidence of the relationship between the two sectors, with financial cycle shock playing a significant role in determining macroeconomic fluctuations. Similarly, for the case of Rwanda, the findings show the existence of the relationship between the business cycle and the financial cycle, with the former leading in the medium term. This implies that it takes a half to a full year for a good performance of the real sector to reflect into the financial sector, justifying that the periods of favorable economic conditions lead to optimistic growth prospects, followed by abundant credit.

Contrary to some of the previous studies in other countries, Rwanda's key insight is that theinfluence of the business cycle on the financial cycle is relatively more important than the other way round. The results are supported by the fact that the financial sector in Rwanda is dominated by banks, as previously discussed, which also rely on loans as the primary source of income; hence, the performance of the real sector observed through the demand for loans is likely to affect much the financial sector. It is also critical to note that Rwanda's big projects that drove the economic growth have much relied on external finance, including grants and loans. Nevertheless, as many firms and, to a large extent, households depend on bank loans for capital projects and large investments, the shock from the financial sector also affects the real sector, as supported by the results.

The results from historical decomposition revealed that the linkages between business and financial cycles in Rwanda became more pronounced during and after the crisis (e.g., in 2008-2009), as found in a study by Krznar and Matheson (2017). This calls for prudent macro-prudential policies to mitigate the likely impact of the current situation of the Covid-19 pandemic, which is affecting both sectors.

5 Conclusion and Policy implications

Based on Rwanda's quarterly data, from 2006:1 to 2020:1, this paper analyzes the interaction between business and financial cycles in Rwanda. We adopt the band-pass filter developed by Christiano and Fitzgerald (2003) to estimate cycles from seasonally adjusted series.

To bring more insights into the relationship between business and financial cycles in Rwanda, we adopt two different methods; (1) Wavelet analysis, which is an essential tool to assess simultaneously how two cycles are related at different frequencies and how such a relationship has evolved or which variable has been leading. (2) Structural vector autoregressive models (SVAR) as the appropriate tool for studying relationships and the effects of shocks in macroeconomics.

The results from wavelets analysis point out a strong positive correlation betweenthe business cycle and financial cycles in Rwanda, especially at medium-term frequencies (2–4 quarters), with the business cycle largely leading the financial cycle. This indicates that the booms (recessions) in the real sector lead to booms (downturns) in credit to the economy. At a scale greater than one year, two cycles tend to move in phase, and for a few episodes, the financial cycle leads business cycle.

The findings from SVAR confirm that business and financial cycles are closely linked in Rwanda. On the one hand, there is a significant and quick reaction of credit to shocks from the output at the first quarter, implying the importance of shocks from the real sector to the financial industry. On the other hand, the business cycle responds to the financial cycle at the third quarter, indicating that the shock from the financial system leads to business cycle fluctuations. In addition, the evidence reveals that tight monetary conditions affect more the business cycle than it does on the financial cycle.

Overall, the empirical analysis in this paper confirms the close relationship between the financial cycle and the business cycle in Rwanda and the critical impact of the business cycle shock on the financial sector. Policymakers should closely monitor the upturns and downturns in each sector and mitigate the likely propagation of shocks from one sector to another with appropriate macro-prudential policies.

Although the results came out with a significant contribution in explaining the dynamics between financial and financial cycles in Rwanda, with related policy implications, the study could not consider the financial condition index to measure financial cycles, which future studies may look at. Future studies may also consider a model-based approach that is advantageous in the sense that financial and business cycles can be jointly estimated, allowing information from all key economic relationships to be used consistently.

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Annexes

Annex 1: Normality test

VAR Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 02/03/22 Time: 11:36
Sample: 2006Q1 2020Q3
Included observations: 54

Component	Skewness	Chi-sq	df	Prob.*
1	-0.386693	1.345780	1	0.2460
2	0.338126	1.028960	1	0.3104
3	0.090171	0.073177	1	0.7868
Joint		2.447918	3	0.4848

Component	Kurtosis	Chi-sq	df	Prob.
1	3.925195	1.925968	1	0.1652
2	3.219120	0.108031	1	0.7424
3	2.273146	1.188714	1	0.2756
Joint		3.222713	3	0.3585

Component	Jarque-Bera	df	Prob.
1	3.271748	2	0.1948
2	1.136991	2	0.5664
3	1.261891	2	0.5321
Joint	5.670630	6	0.4611

*Approximate p-values do not account for coefficient estimation

Annex 2: Autocorrelation test

VAR Residual Serial Correlation LM Tests

Date: 02/03/22 Time: 11:40

Sample: 2006Q1 2020Q3

Included observations: 54

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df
1	4.641696	9	0.8644	0.509642	(9, 99.9)
2	8.066382	9	0.5275	0.900597	(9, 99.9)
3	5.053234	9	0.8296	0.555941	(9, 99.9)

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.641696	9	0.8644	0.509642	(9, 99.9)	0.8645
2	14.52572	18	0.6942	0.800396	(18, 108.0)	0.6959
3	18.34367	27	0.8927	0.656599	(27, 102.9)	0.8949

*Edgeworth expansion corrected likelihood ratio statistic.

Annex 3: VAR stability condition

VAR Residual Serial Correlation LM Tests

Date: 02/03/22 Time: 11:40

Sample: 2006Q1 2020Q3

Included observations: 54

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df
1	4.641696	9	0.8644	0.509642	(9, 99.9)
2	8.066382	9	0.5275	0.900597	(9, 99.9)
3	5.053234	9	0.8296	0.555941	(9, 99.9)

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.641696	9	0.8644	0.509642	(9, 99.9)	0.8645
2	14.52572	18	0.6942	0.800396	(18, 108.0)	0.6959
3	18.34367	27	0.8927	0.656599	(27, 102.9)	0.8949

*Edgeworth expansion corrected likelihood ratio statistic.