Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-024-03021-5 OPEN

Cyclical dynamics and co-movement of business, credit, and investment cycles: empirical evidence from India

Ridhima Garg[1]✉ & A. N. Sah[1]

The paper aimed to investigate the cyclical dynamics of the business, credit, and investment sectors in India. This was achieved by utilizing annual data from 1980 to 2021 and investigating the impact of domestic and global financial cycles on the business cycle. The cycles were derived using the Hodrick–Prescott filter, and structural vector autoregression (SVAR) and Granger causality tests were employed to establish the dynamic interactions among these cycles. The results of the study revealed a clear divergence between domestic and global financial cycles. Additionally, the SVAR analysis confirmed the presence of a long-run relationship between business, investment, and credit cycles. Notably, the findings suggest that credit cycles can provide valuable insights to manage business cycles in India. Finally, robustness checks were conducted to confirm the reliability of SVAR findings.

[1] School of Humanities & Social Sciences, Thapar Institute of Engineering & Technology (TIET), Patiala, Punjab 147004, India. ✉email: rgrg.ridhima@gmail.com

Introduction

The business cycle estimation and policy framework to monitor and control fluctuations in GDP is a well-known exercise carried out by various agencies internationally. However, the study of the financial cycle and its impact on the economy attracted the policymaker's attention in the aftermath of the 2008 Subprime crisis. Financial cycles analyze the state of the economy from the expansionary to contractionary phase. The expansion phase is characterized by increased economic activity and high growth rates. However, contractionary phases experienced a slowdown in economic activity. As proposed by Borio (2012), "self-reinforcing interactions between perceptions of value and risk, attitude towards risk and financing constraints which translate into booms followed by busts." Financial cycles are related to the trends in real bank credit, credit to GDP ratio, real equity prices, real effective exchange rate, and real house prices. Fluctuations in the stock market, bond markets, and foreign exchange markets are influenced by various economic factors such as policy-making, government intervention, speculation, and expectation.

Hyman Minsky, in his "financial instability hypothesis" outlined three stages of instability. During the period of Hedge, the credit demand remains moderate due to the recession losses. Recovery leads to increased credit demand, asset price booms, and economic growth, creating an increased debt burden in the speculative stage. Finally, during the Ponzi stage, the increased debt burden led to financial stress, asset liquidation, and declining asset prices which resulted in a recession. Credit rise stimulates the demand for houses, causing asset price growth. As a result, increased mortgage value reduces the demand, reversing the process. These self-reinforcing interactions cause disruptions. (Borio and Disyatat, 2011) discussed a 'policy drift', where a prolonged period of low-interest rates encourages borrowings and subsequent demand for money, which results in increased prices of houses, shares, and other assets causing financial stress and obligations.

Behra and Sharma (2019) explored the interactions between financial cycles and non-performing assets to examine uncertainties. There was a rise in non-performing assets. As of March 31, 2018, the total volume of gross NPA in the economy stands at Rs. 10.35 lakhs Crore. About 85% of these NPAs are from loans and advances of public sector banking. NPA of banks has expanded from 2.3% of total loans in 2008 to 9.3% in 2017, with it standing at 8.2% in March 2020. According to ICRA, gross and net NPAs were expected to increase to 10.1–10.6% and 3.1–3.2%, respectively, by March 2021. Simultaneously there was a decline in GDP at (2011–12) prices from 8.17% to 7.17% in 2017, then 6.12% in 2018 and 4.5% in Q2 (2019–20) from 5% in Q1. The GDP for the entire financial year (2020–21) contracted by −8%, causing a historic downfall in the Indian Economy attributed to the nationwide lockdown in response to the widespread coronavirus (Paul, 2018).

This paper attempts to incorporate the Digital transformation index (DTI) to capture the technology's role in the credit creation process. It is important to highlight that the banking industry in India has changed tremendously in operations and service delivery mechanisms since 1991. The advancement of loan and credit dispersal has been significantly influenced by technological advancement and the wireless revolution. Kolodiziev et al. (2021) established that digital transformation has enhanced banking competitive capacity. Additionally, this paper aimed to determine the cyclical components of the GDP, Credit, and Investment cycle and employed SVAR analysis to examine the dynamic interplay among them. The structure of the paper is as follows: The section "Literature review" provides comprehensive literature on the nexus among these variables in India. Section "Data and variable construction" presented the data and the variables utilized. The section "Economic methodology" describes the econometric methodology. Section "Empirical analysis and results " presents the findings obtained from the estimation, followed by sections "Robustness" and "Discussions and policy implications", respectively, and concluded in the section "Conclusion".

Literature review

Schumpeter (1911) focused on the importance of financial development in economic growth, especially in the R&D department and allowing new entries. Many studies such as McKinnon (1973), Goldsmith (1969), Gregorio (1999), Levine (1997), Arteta et al. (2001), Edison et al. (2002) have supported this view. Another aspect of the finance–growth nexus was the examination of cyclical fluctuations in macroeconomic variables. Several papers have focussed on the financial cycle in developed countries by researchers like Borio (2012), Claessens et al. (2011a, 2011b), Tobias Adrian and Shin (2010), and others. While business cycles have been highly discussed in the literature, financial cycles are still a work in progress and have recently gained attention. Business cycles are associated with financial cycles, and their theories helped us understand financial cycles.

The dynamic interactions between business cycles and financial cycles are important for the estimation of recessions and recoveries. Claessens et al. (2011a, 2011b) explored the interactions and found a strong relationship between them in 44 countries, shaping recessions and recoveries. The findings also revealed the synchronization of output cycles with credit and house prices, while equity price cycles show less similarity. Rünstler (2016) explored the US and five major European countries, revealing that financial cycles are longer than business cycles. Yong and Zhang (2016) emphasized financial cycles have a significant role in business cycles in the USA, UK, China, and Japan. Financial cycle shocks drive major fluctuations in macroeconomic variables, particularly during times of financial instability. Jawadi et al. (2022) revealed that information from business cycles is useful in forecasting financial cycles, particularly during expansion in the USA from 1987 to 2016. Sanvi and Matheron (2005) explored the lack of a strong link between stock prices and real activity except in the USA, highlighting the importance of the financial cycle and business cycle in strengthening the effectiveness of monetary policy.

Various methodologies have been employed to study the financial cycles, including the traditional method of Turning point analysis by Arthur and Mitchell (1946), Bry and Boschan (1971), and Harding and Pagan (2002), which identified longer and deeper financial cycles than business cycles. These were medium-term cycles, as explained in the literature. Financial variables have different frequencies and durations, necessitating the utilization of statistical filter methods such as the unobserved component model as employed earlier by Aikaman et al. (2010). Galati et al. (2016) observed that financial cycles, overall tend to be longer and have greater amplitudes than business cycles. Two commonly used methods for estimating cyclical behavior are the Hodrick–Prescott Filter and the bandpass filter. The HP filter, introduced by Hodrick and Prescott (1981), separates the series into trend and cycle components. Conversely, the BP filter, proposed by Christiano and Fitzerald (2003), functions as a two-sided moving average filter, effectively smoothing out fluctuations and underlying cycles and trends.

In India, studies about financial cycles such as Behra and Sharma (2019) have identified the existence of the financial cycle by examining their main characteristics using three methods: turning point analysis, spectral analysis, and bandpass filters, along with the quarterly data on credit, equity prices, house prices, and real exchange rates. Aravalath (2020) with the Wavelet-based causality test, revealed that financial shocks lead to business cycles and that financial cycles are larger than business cycles during the period Q1:1991 to Q4: 2019. These findings coincide with those of Kumar et al. (2020). Additionally, Paramanik et al. (2021) indicated a strong interdependency between real and financial markets between the years 2003 and 2020, emphasizing the importance of economic uncertainty. Conversely, Saini et al.(2021) found that the business cycle leads to the credit cycle in India at both aggregate and sectoral levels. Furthermore, the duration of the business cycle was approximately 4 years, whereas the credit cycle duration was 3 years.

The significance of global financial cycles has been investigated in various studies. Cerutti et al. (2017) explored the importance of global financial cycles in determining capital flows in 85 countries from Q1 1990 to Q4 2015. Through the utilization of panel regressions, national capital equations, and event studies, they revealed that global financial cycles are not important in understanding capital flows. however, their impact can be seen in other variables like credit and house prices. Similarly, Silvia and Hélène (2021) revealed that changes in monetary policy bring about developments in global financial variables, resulting in contractions in asset price, a decline in credit, a wider spread, and a downturn in capital flow globally. Consequently, the results indicate that US monetary policy serves as the key driver of global financial cycles.

This research aimed to address a gap in the existing literature by examining the impact of DTI cycles on business and credit cycles. To the author's knowledge, no prior studies have integrated these variables, particularly in India. Given the significant role played by the public and private sectors in India's growing digitization, characterized by deep internet and telecom penetration, the number of mobile subscribers is taken as a proxy for DTI. Olczyk and Kuc-Czarnecka (2022) found a strong relationship between GDP and digital transformation. Additionally, this paper incorporated the analysis of money supply and investment cycles, exploring the impact on the business cycle. Any time series data comprises four components, with one of the most important being the cyclical component evident in time series data, such as GDP, credit, and investment. According to Hawtrey's monetary theory of trade cycle, business cycles are caused by the expansion and contraction of bank credit. During the period of credit expansion, prices rise, profit increases, and aggregate output grows, constituting a boom period. Conversely, when bank credit falls, prices fall, profit decreases, and total production declines.

Moreover, Hayek (1943) suggested that business cycles arise from disequilibrium between actual and desired investments. The theories of Samuelson and hicks on trade cycles emphasized the interactions between the multiplier and accelerator principles. Thus, it is well documented in the literature that economies move in a wave-like manner. Accordingly, hypotheses were formulated in this study.

H_1: Cyclical components are present in GDP, credit, and investment

H_2: Credit cycles (NFGBC) have a causal relationship with GDP cycles

H_3: Financial cycles have a causal relationship with GDP cycles

H_4: DTI cycles have a causal relationship with GDP cycles

H_{4A}: DTI cycles have a causal relationship with credit cycles

Data and variable construction

This paper conducted an analysis utilizing annual data spanning from 1980 to 2021 at the aggregate level. Non-food Credit (NFGBC), comprising credit provided to agriculture, industry, services, personal loans, and economic growth (GDP), is examined as a primary indicator to analyze the interactions between the credit and business cycle. To account for potential measures of credit-business synchronization, we incorporate various macroeconomic factors as possible indicators like (a) Domestic credit to the private sector to capture deeper credit interactions with the business cycle, (b) Gross fixed capital formation (GFCF), higher level of investment indicates increased demand for credit and potential economic growth, (c) Broad Money (M3) as a proxy of money supply in the economy, changes in money supply impacts credit and growth, (d) GDP rate to proxy output, (e) the time-varying volatility of BSE, as a measure of fluctuations in financial markets, (f) Crude oil (Co-Brent) prices to represent the impact of the global financial market on the domestic market. (g) CPI (Consumer Price Index) to measure the increase in prices of goods throughout time. (h) Mobile subscription per 100 people to capture the impact of digitization (DTI) on economic growth and financial activities. However, for mobile subscribers' data, the focus was from 2000 to 2021. The annual data used in this study were collected from reliable sources like the World Bank database, the Reserve Bank of India, and BSE India.

The investment cycles are significant in India for estimating credit cycles and business cycles as they represent fluctuations in economic activity and are key indicators of growth. Food credit and non-food credit are formal measures of credit expansion. Non-food credit represents credit to various sectors and is considered a representation of a credit cycle (Banerjee, 2011; Saini et al., 2021). GDP is taken as a representative variable for the business cycle (Thomson and Vuuren, 2016). Turning points in the economy, named peaks and troughs, indicate the highest and lowest points that the economy can reach under current economic conditions (Jonung, 2009), while GFCF captures trends and cyclical movements in investment. Additionally, crude oil represents global financial cycles and their impact on the Indian market. Fluctuations in crude oil prices reflect global economic conditions and financial market dynamics.

Econometric methodology

The HP filter, a method developed by Hodrick and Prescott in 1981 is a commonly and widely used econometric model to separate the trend component from a cyclical component in a series. It is a linear filter that relies on the specification of a parameter called lambda (λ). Lambda helps in the determination of the smoothness of estimated trends and depends on the periodicity of data.

$$Y_t = \tau_t + c_t + \varepsilon_t$$

$$\min_{\tau_t} \sum_t (Y_t - \tau_t)^2 + \lambda \sum_t (\tau_{t+1} - 2\tau_t + \tau_{t-1})^2$$

The series Y_t denotes the time series decompose into τ_t—trend component, c_t—cyclical component, and ε_t—error component. This method helps in minimizing the deviation of the original series from the trend as well as the curvature of the estimated trend. The trade-off between the two is governed by the smoothing parameter λ; the higher the value smoother the estimated trend. The choice of λ depends on the frequency of data. Hodrick and Prescott (1981) originally proposed a value of $\lambda = 1600$ for quarterly data. For yearly data, no specific λ value is recommended. It is often selected from the range of {6.25, 100, 1600}. Baxter and King (1999) used a value of 10, while Backus and Patrick (1992) suggested a value of 100 which was suitable for their analysis (Ravn and Uhlig, 2002) suggested adjusting 1600 by multiplying it with the fourth power of 6.25 for annual data frequency variation.

Empirical analysis and results

The section discusses the results of various estimated cycles through the HP filter. This paper employs $\lambda = 100$ (Backus and Patrick, 1992).

Characteristics of cycles. Composite Fig. 1 demonstrates the trends and cycles of all the observed variables that have been computed using the HP filter. The HP filter helps in identifying the cyclical phases, which include duration, amplitude, and slope. Over the sample period, GDP exhibited 8 peaks and 9 troughs. Notably, the largest cycles were observed over 9 years (peak to peak) between 1999 to 2007 and 2010–2018. A significant downturn in GDP occurred in 1991, attributed to the BOP crisis, where the Government of India faced challenges in servicing external debt owing to a decline in foreign exchange reserves. The decrease witnessed in global economic growth between 2000 and 2005 could be attributed to events such as the terrorist attack, the collapse of the dot-com bubble, fluctuating oil prices, and decreased investments. Moreover, agricultural production was affected by drought. However, there was a significant increase in GDP in 2018–19, which may have been due to the subsiding of the effects of demonetization and an increase in economic activity. In 2020, an exceptional event occurred due to COVID-19 causing a major cyclical fluctuation in the GDP (−0.073). This led to a sharp decline in the GDP and an intense effect on the economy. Furthermore, the trough had a steeper slope than any of the identified peaks, implying that the change in GDP in a contraction phase was greater than the change during the periods of economic expansion.

Throughout the sample period, NFGBC exhibited 6 peaks and 7 troughs. The cycle duration remained constant at 12 years from 1995 to 2006. Initially, NFGBC experienced a continuous decline until 1985. In 1990, there was an increase in credit linked to an early phase of financial reforms and increased investment activities. However, there was a significant decline in NFGBC in 1993, which could be due to the tightening of monetary policy or policy change. The early 2000s marked a significant economic slowdown, resulting in a rise in NPAs within the banking sector. Interestingly, during the 2007 global financial crisis, NFGBC exhibited a sustained rise. However, demonetization and COVID-19 caused a sharp decline. Notably, the trough had a steeper slope than the peak, implying a quicker decline rate in credit. Meanwhile, the expansions during the peaks were relatively milder.

A total of 11 peaks and 8 troughs were observed in the provision of domestic credit provided to the private sector. Notably, two periods had exceptionally long cycle durations: 1992–2000 for 9 years and 2010–2020 for 11 years. From the early 1980s until 1990, there was a significant rise in credit possibilities due to financial reforms. However, a sharp contraction occurred in 1998. Also, there was a significant surge in credit during the Global financial crisis. Subsequently, a continuous decline was observed in 2016, which was followed by a gradual recovery and expansion. The decline was due to demonetization, which has a significant impact on private credit. However, the economy stabilized over time and credit demand increased. After the year 2019–20, there was a gradual rise in credit, possibly due to the stabilizing effects of economic events and government reform aimed at improving credit access for private sectors. The peak slope value was larger than that of the trough, implying faster credit expansion. While variations were observed, the magnitude of fluctuations was not extremely large.

Gross fixed capital formation (GFCF) has exhibited 10 peaks and 9 troughs in its cyclical pattern. Between 2011 and 2018, there was an extended period in which the cycles continued for a total of 8 years, with an average cycle duration of 5 years. In the early 1990s, there was a sharp rise in GFCF, possibly due to financial liberalization. The National Stock Exchange was established in 1992 to promote FDI in various sectors. Deregulation of interest rates also facilitated easy access to credit and capital, leading to a rise in GFCF. However, there was a decline in GFCF in 1994, 2000,

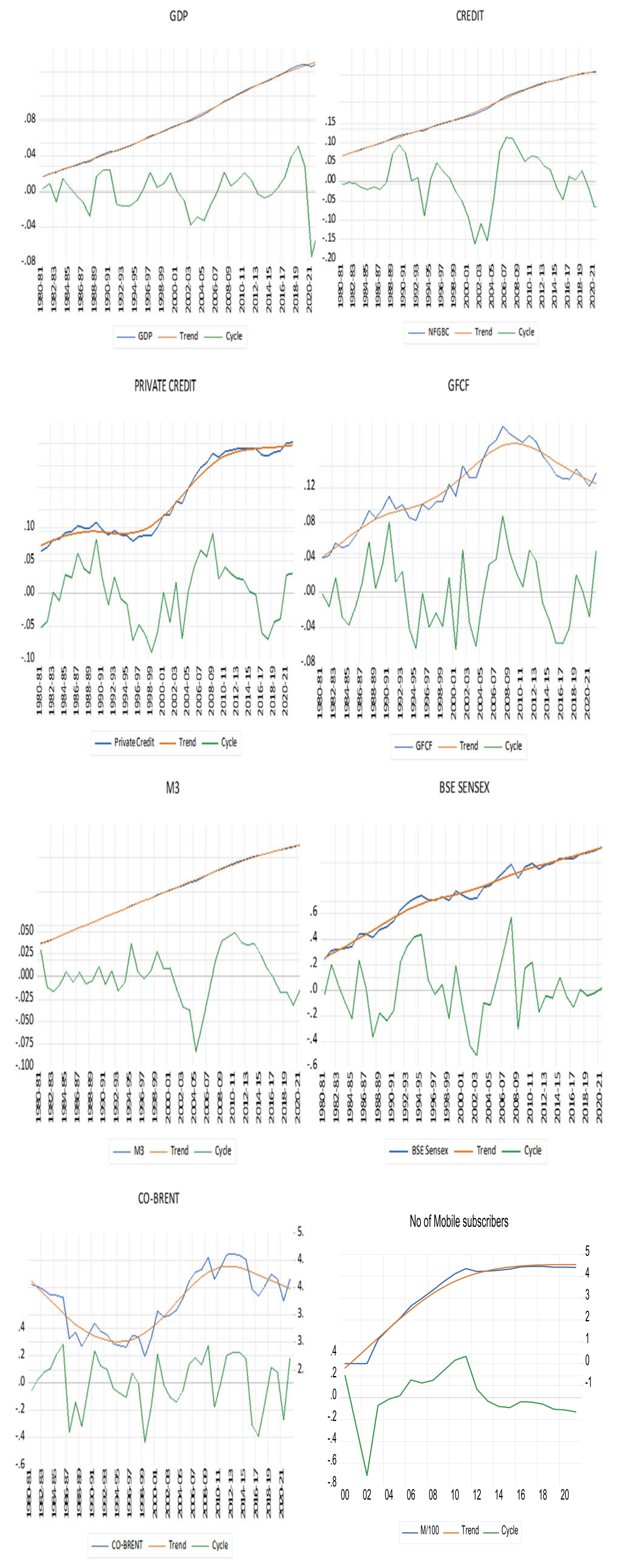

Fig. 1 Cyclical position of GDP, NFGBC, Private credit, GFCF, M3, BSE, co-brent, and mobile subscribers. Using the lambda 100 with the help of the HP filter, the authors have computed the cyclical position of these variables.

and 2003, which were likely caused by economic downturns, government policy shifts, and global domestic uncertainties. The Indian government implemented monetary and fiscal measures to counteract the effects of the Global financial crisis, which had a positive influence on GFCF. Demonetization marked a gradual rise in GFCF, while COVID-19 led to a sharp decline in GFCF. Also, the peak exhibited a larger slope than any of the troughs identified, indicating a faster and steeper rise in GFCF compared to contractions during troughs.

Throughout the years, the fluctuations in the money market have displayed cyclical trends with 6 peaks and 8 troughs. From 1998 to 2010, there was a notable variation in the length of cycles, with the largest cycle spanning 13 years, while the average cycle length was 3.8 years. There was a slight increase in M3 owing to economic liberalization in 1991 as the economy opened up and experienced liberalization. However, in 2004 there was a significant decline in M3, possibly due to changes in the government that may have impacted economic policies, including fiscal and monetary policy. From 2013 onwards, there was a persistent decline in M3 might be due to inflationary pressure in the economy. Additionally, growth achieved in M3 was supported by deficit financing contributing to its expansion. However, M3 experienced a decline during the periods of demonetization, as a significant portion of currency became invalidated, and there was a temporary shortage of physical cash. Further, COVID-19 led to a decline in M3 economic activity, contributing to a decline in money circulation. It's worth noting that the peak had a larger slope than the trough implying a significant rise in certain years and a robust expansion in M3.

Bombay Stock Exchange experienced a total of 9 peaks and 10 troughs, indicating multiple cyclical fluctuations in the stock market. Based on observation, the average duration of cycles was 3.5 years. Notably, the longest cycle lasted for 10 years, specifically between 1985 and 1994. Additionally, another cycle lasted for 9 years, spanning between 1999 and 2007. In 1981, a significant rise in BSE might be due to increased investor confidence and favorable economic policies following a sharp decline in 1984. While there was another sharp decline up to 1989. Increased FDI and privatization in 1991 led to increased market participation resulting in a substantial rise in BSE. However, there was a downturn in 2002. During the financial crisis, a rise in BSE was followed by a subsequent decline due to the crisis's impacts. The period of demonetization and COVID-19 events disrupted economic activities. However, the stock market has gradually started rising again. Further, the peak has a larger slope than any of the troughs, implying more pronounced upward movement in the stock market.

The prices of Brent crude oil displayed 9 periods of peaks and 8 troughs. Analysis showed that the average duration of cycles was 5.71 years. In the years 1985–86, there was a sharp increase in oil prices, possibly due to OPEC cutting production of oils, leading to increased prices Also, the Iraq–Iran war caused a rise in oil prices. Following the price surge in the mid-1980s, there was a sharp decline in oil prices until 1988. However, in 1990, increased prices could be attributed to geopolitical tension in the Middle East. In the year 1998–99, there was a substantial decline in oil prices. The period of 2008–09 marked a year of significant growth in oil prices. However, this was followed by a subsequent fall in prices as the global financial crisis exploded. From 2011 to 2013, oil prices remained stable. However, oil prices experienced a significant decline in the year 2016. Finally, the outbreak of Covid-19 had a profound impact on oil prices. Furthermore, peaks had larger slopes than troughs implying that prices of Brent oil tend to rise more rapidly during periods of peaks while the decline in prices in troughs may be relatively slow.

Number of mobile subscribers have displayed 1 peak and 1 trough over the specified time. In 2000, there was a remarkable decline in mobile subscribers, followed by a continuous rise in

Fig. 2 Interaction of observed variable cycles with GDP cycles. This figure displays how cycles of other variables interact with those of GDP.

Table 1 Correlation between GDP and NFGBC cycles.

	GDP	NFGBC
GDP	1	
NFGBC	0.505458	1

Table 2 Regression results.

Predictor variable	Coefficient	Standard error	*f*-value	*P*-value	*r*-square
NFGBC GDP = 4.76E−05 + 0.182444X_1	0.0182444	0.049244	13.72646	0.000639	0.255488
GDP NFGBC = −6.7E−05 + 1.400366X_1	1.400366	0.377974	13.72646	0.000639	0.255488

2003. Since then, there has been a sustained growth pattern in no of mobile subscribers, continuing until around 2010. Following that, there was a peak observed in 2011. There were over 20 million falls in subscriptions in July 2012, probably due to the entry of Reliance and the cleansing of non-operating numbers. In 2015, a temporary rise in the number of mobile subscribers was observed, following a continuous decline until 2021. India lost 1.7 crores of mobile subscribers in the lockdown period, particularly urban subscribers (Kumar, 2020). Moreover, peaks had larger slopes than troughs.

Synchronization of GDP cycles with other economic indicators. Figure 2 presents a comprehensive cyclical pattern of observed variables and their interactions with GDP cycles revealing a visible co-movement between GDP cycles and credit cycles. The cyclical position of GDP shows continuity, and it generally maintained the same sign and similar changes as the credit cycles. To investigate the relationship between the cycles, correlation and regression analysis was conducted. The correlation results in Table 1 indicate that GDP was positively related to NFGBC. The correlation coefficient between GDP and NFGBC was 0.50, which can be considered a moderate level of correlation. This also implies that with an increase in GDP, NFGBC also increases 50% of the time. The regression analysis in Table 2 revealed that GDP determined credit cycles in India. The *R*-square indicates that an increase in the GDP cycle component correlates with a 25% increase in the credit cyclical component. Additionally, the coefficient was statistically significant at the 5% level and had a higher value compared to when GDP was an independent variable. The findings supported the financial accelerator theory (Bernanke et al., 1999), which suggests that when the real economy grows, credit markets tend to be more stable and accessible.

It was observed that there was an inverse relationship between GDP cycles and domestic credit to private cycles. Both variables had opposite signs except from 2005 to 2015, when they moved in the same direction. The correlation results confirmed a negative relationship between GDP and private lending, as illustrated in Table 3. Specifically, a 1% increase in GDP led to a decline in credit of 20%. Furthermore, when GDP was the dependent variable and credit was the independent variable, results revealed a negative relationship and the coefficients were not statistically significant at the 5% level (Table 4). Similarly, considering credit as the dependent variable and GDP as the independent, the result showed a negative relationship, and coefficients remain statistically insignificant. This implies that the relationship between the two variables was not reliable in explaining either GDP or credit, also supported by the low *r*-square.

From 1980 to 1989, GDP and GFCF exhibited an inverse relationship. During this period, GFCF started rising, followed by a rise in GDP. Subsequently, after 1992, there was a sharp decline in GFCF, and GDP also started to decline. Moving forward, after 2001, both variables showed co-movements. However, GFCF exhibited higher cyclical fluctuations than GDP. Table 5 showed a positive correlation between the variables however it was very low. Furthermore, considering GDP as the dependent variable and GFCF as the independent variable, regression analysis revealed in Table 6 that the coefficient value of 0.05702 was statistically

Table 3 Correlation between GDP and private lending cycles.

	GDP	CREDIT
GDP	1	
Private credit	−0.20443	1

Table 4 Regression results.

Predictor variable	Coefficient	Standard error	*f*-value	*P*-value	*r*-square
Private credit GDP = 5.51E −05−0.10491X_1	−0.10491	0.079429	1.744519	0.194074	0.04179
GDP Private credit = 9.04E −05−0.39834X_1	−0.39834	0.301592	1.744519	0.194074	0.04179

Table 5 Correlation between GDP and GFCF cycles.

	GDP	GFCF
GDP	1	
GFCF	0.098943	1

Table 6 Regression results.

Predictor variable	Coefficient	Standard error	*f*-value	*P*-value	*r*-square
GFCF GDP = 0.000179 + 0.05702X_1	0.05702	0.090673	0.395457	0.53302	0.00979
GDP GFCF = −0.00232 + 0.171689X_1	0.171689	0.273018	0.395457	0.53302	0.00979

Table 7 Correlation between GDP and BSE Sensex cycles.

	GDP	BSE
GDP	1	
BSE	0.051765	1

insignificant at the 5% level. The R-square was very low, indicating a weak relationship between the variables. Additionally, when GFCF was the dependent variable, and GDP was independent, results showed that GDP had weak explanatory power in explaining GFCF.

Based on estimation, it was found that BSE cycles had significant ups and downs, while GDP showed moderate fluctuations. These variables exhibited opposite signs, indicating that they move in opposite directions. Correlation analysis confirmed a weak relationship between the two variables, with only a marginal 0.51% increase in BSE for a 1% increase in GDP, as displayed in Table 7. Regression analysis (Table 8) revealed an

Table 8 Regression results.

Predictor variable	Coefficient	Standard error	f-value	P-value	r-square
BSE	0.005184	0.015813	0.107472	0.74475	0.00268
$GDP = 4.89E{-}05 + 0.005184X_1$					
GDP	0.516893	1.576711	0.107472	0.74475	0.00268
$BSE = -0.00026 + 0.516893X_1$					

extremely weak relationship between the two variables, with an R-squared value indicating negligible correlation. The coefficient value of 0.005 obtained from the regression was statistically insignificant at a 5% level. These findings suggest that GDP and BSE have a weak and negligible relationship. Additionally, when BSE was the dependent variable, and GDP was independent, results showed that GDP had weak explanatory power in explaining BSE. Therefore, other factors likely drive fluctuations in the GDP and the stock market.

Until 2015, a continuous parallel movement was observed between GDP and M3 cycles. However, a notable shift occurred due to Demonetization, leading to a sudden decline in M3, which was subsequently followed by a decline in GDP attributed to the COVID outbreak. Correlation analysis supported these findings with positive results, showing a significant value of 0.33 (as detailed in (Table 9). Furthermore, the regression results also confirmed that M3 explains 11% of the variation in GDP cycles, and the regression coefficient was also statistically significant, as depicted in Table 10, implying changes in M3 and its influence on investment, consumption, and economic growth.

Co-Brent experienced high fluctuations as compared to GDP cycles in India, implying that variations in the global financial market do not drive variations in India's GDP. The correlation analysis in Table 11 depicted a positive relationship between the two variables; however, the relationship was weak, with a value of only 0.82% Thus, it has no significant impact on economic performance. When GDP was the dependent variable, and Co-Brent was the independent variable, *r*-square indicated no significant impact of Co-Brent on GDP and the coefficient value was not statistically significant illustrated in Table 12. Similarly, when GDP was the independent variable, the *r*-square value remained low, implying GDP has limited power in explaining Co-Brent and the coefficient was not statistically significant.

The rise in GDP corresponds to the increase in the number of mobile subscribers (MS). After 2003, both variables exhibited co-movements, but the increase in MS was more pronounced than the rise in GDP. However, after 2015, an inverse movement was observed, leading to a simultaneous decline in both variables. Moreover, there was a sharp downturn in both variables owing to the COVID-19 outbreak. The correlation analysis (Table 13) revealed a positive correlation between the variables, implying a rise of 0.32 in GDP for each unit rise in MS. However, the *r*-square in regression analysis in Table 14 indicated a weak relationship between the variables, with the coefficient being statistically insignificant.

To capture the interaction between credit cycles and mobile subscribers the paper also combined their cyclical graphs displayed in Fig. 3.

These variables exhibited a consistent co-movement pattern, with a notable exception in the year 2012, when mobile subscribers (MS) observed a sharp decline while NFGBC continued to increase. The correlation analysis in Table 15 also revealed a positive relationship with a value of 0.50, implying a noteworthy relationship between credit and mobile subscribers. Table 16 indicated when NFGBC was the dependent variable, the regression coefficient was found to be statistically significant, and the r-square value of 0.25 suggested that credit cycles can be

Table 9 Correlation between GDP and M3 cycles.

	GDP	M3
GDP	1	
M3	0.339392	1

Table 10 Regression results.

Predictor variable	Coefficient	Standard error	*f*-value	*P*-value	*r*-square
M3	0.289348	0.126799	5.207306	0.027888	0.115187
$GDP = 5.52E{-}05 + 0.289348X_1$					
GDP	0.398092	0.174452	5.207306	0.027888	0.115187
$M3 = -4.5E{-}05 + 0.398092X_1$					

Table 11 Correlation between GDP and Co-brent cycles.

	GDP	Co-Brent
GDP	1	
CO-Brent	0.082708	1

Table 12 Regression results.

Predictor variable	Coefficient	Standard error	*f*-value	*P*-value	*r*-square
CO-BRENT	0.009951	0.018958	0.275506	0.602559	0.006841
$GDP = 5.47E{-}05 + 0.009951X_1$					
GDP	0.687427	1.309667	0.275506	0.602559	0.006841
$CO\text{-}BRENT = -0.00075 + 0.687427X_1$					

Table 13 Correlation between GDP and MS cycles.

	MS	GDP
MS	1	
GDP	0.32731	1

explained by the number of mobile subscribers cycles. Moreover, the cyclical component of a number of mobile subscribers also has explanatory power on credit cycles.

Granger causality test. The Granger causality test in Table 17 reveals that NFGBC cycles do Granger-cause GDP cycles as the coefficients were statistically significant and GDP also Granger-cause NFGBC, implying a bi-directional causality between business cycles and credit cycles. Increased credit lending enhances economic activity, and higher GDP attracts more credit demand. So, there was a close interdependence between both cycles. Also, it revealed that no causality was found among private sector credit and GDP cycles; GFCF and GDP cycles; BSE and GDP

Table 14 Regression results.

Predictor variable	Coefficient	Standard error	f-value	P-value	r-square
MS	0.0408	0.02634	2.39968	0.13704	0.10713
$GDP = -1.9E{-}05 + 0.0408X_1$					
GDP	2.62599	1.69518	2.39968	0.13704	0.10713
$MS = 0.00045 + 2.62599X_1$					

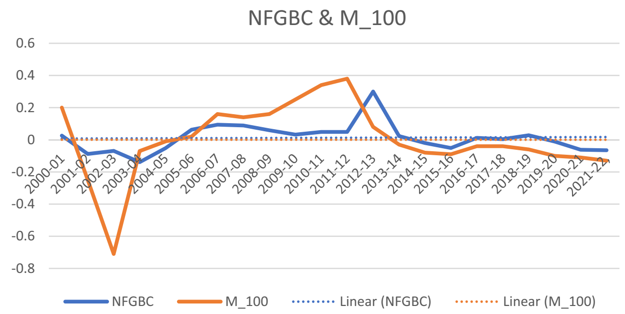

Fig. 3 Synchronization of credit (NFGBC) & no of mobile subscribers cycle. This figure shows the correlation between the cycles of credit and mobile subscribers to analyze how technology impacts the credit market.

Table 15 Correlation between NFGBC and MS cycles.

	NFGBC	MS
NFGBC	1	
MS	0.502977	1

cycles, and M3 and GDP cycles. No causal relationship was found between mobile subscribers and GDP cycles. Moreover, it was noteworthy that Co-Brent Granger caused India's GDP to be at a 10% level of significance, implying that changes in crude oil price cycles can influence GDP cycles. Likewise, it was interesting to note that mobile subscriber cycles had a causal effect on NFGBC cycles implying there was some interconnectedness between these cycles.

Structural VAR. Structural vector autoregression, commonly known as SVAR, was utilized to investigate the dynamic interactions among the cycles of various variables. The model aimed to estimate the relationship among business cycles (GDP), credit cycles (NFGBC), and investment cycles (GFCF). This paper employed an SVAR model to estimate the long-run pattern based on Blanchard and Quah's (1989) long-run restrictions identification scheme.

Structural VAR estimates on the long-run pattern matrix.

$$\begin{bmatrix} \text{variables} \\ GDP_{t-1} \\ GDP_{t-2} \\ GFCF_{t-1} \\ GFCF_{t-2} \\ NFGBC_{t-1} \\ NFGBC_{t-2} \end{bmatrix} \left\{ \begin{array}{cccccc} \varepsilon^{GDP_{t-1}} & \varepsilon^{GDP_{t-2}} & \varepsilon^{GFCF_{t-1}} & \varepsilon^{GFCF_{t-2}} & \varepsilon^{NFGBC_{t-1}} & \varepsilon^{NFGBC_{t-2}} \\ C_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & C_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & C_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & C_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & C_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & C_6 \end{array} \right\}$$

Optimal lag length criterion. The paper has employed five criteria for the estimation of optimal lag length: AIC, FPE, HQ, LR, and SC. The model exhibited in Table 18 implied two lags were adequate to capture the dynamics and relationship among the cyclical variables.

Structural VAR estimates on long-run pattern matrix. Estimating the long-run pattern matrix helps us understand the relationship and interactions among the selected cyclical variables over the long run. The results in Table 19 illustrate that GDP cycle lag 1 was positively and significantly related to its shocks in the long run. However, in lag 2, the coefficient of the GDP cycle was negative and insignificant to its shocks. The variable GFCF cycles at lag 1 and 2 had a positive and highly significant relationship with GDP cycles, implying a rise in GFCF cycles was associated with increased GDP cycles. Higher investment growth stimulates high economic growth. Further, NFGBC cycle lags 1 and 2 also had a significant and positive influence on GDP cycles.

Structural long-run impulse response function. To estimate the long-run IRF in SVAR, a structural decomposition technique was used for model identification, as represented in Fig. 4. One unit innovation in GDP cycles showed an immediate negative impact on all the variables except GDP itself. However, in the second period, GDP caused GFCF to decline by 0.0012 units and credit to decline by 0.0027 units, implying that a shock to GDP adversely affects GFCF and NFGBC. The analysis showed a diverse relationship.

Similarly, a one-unit innovation in GFCF cycles showed a negative repercussion on GFCF and NFGBC with a slight positive influence on GDP. Moreover, a one-unit innovation to GFCF in the second period led GDP to increase by 0.0088 units. It was noteworthy that there's a continuous positive influence on the GDP in the long run, while a negative response to GFCF itself and NFGBC in the long run.

Moreover, a one-unit innovation to NFGBC cycles caused a positive influence on all the variables in the short-run except GDP in the 4th and 5th periods. Further, NFGBC was positively impacting GDP, while negatively affecting credit GFCF and NFGBC cycles in the long run.

Structural long-run variance decomposition. The variance of GDP cycles can be explained by both GDP and NFGBC cycles, according to the results of structural variance decomposition illustrated in Table 20. In the initial period, 19% of the forecast variance of GDP was attributed to GDP itself, and 79% was attributed to NFGBC. This pattern continued in the short run. However, in the long run, the influence of GDP explained roughly 30% of the forecast variance of GDP, and the contribution of NFGBC declined to 63%. The results suggest that both GDP and NFGBC have a significant role in explaining GDP fluctuations in both periods, and GFCF has a slight but positive impact on the forecast variance of GDP.

Likewise, the variance decomposition of GFCF cycle results shows that GFCF cycles explain the variances in forecast error in both the short run and long run, with the remaining variables having limited explanatory power.

Lastly, the variance decomposition NFGBC cycles reveals that GDP plays a prominent role in explaining NFGBC forecast variance by 71% in the first period, which declines to 37% in the

Table 16 Regression results.

Predictor variable	Coefficient	Standard error	*f*-value	*P*-value	*r*-square
MS $NFGBC = 0.012228 + 0.196987X_1$	0.196987	0.075690	6.773273	0.017032	0.25298
NFGBC $MS = -0.015365 + 1.2842774X_1$	1.2842774	0.493468	6.773237	0.017032	0.25298

Table 17 Granger causality test.

Null hypothesis	*p*-value	Causality
GDP-NFGBC	0.0095	Bii-directional causality between non-food
NFGBC-GDP	0.0754	gross bank credit cycles and GDP cycles
GDP-CREDIT	0.7120	No causality between private-sector credit
CREDIT-GDP	0.8815	cycles and GDP cycles
GDP-CO-BRENT	0.5638	Uni-directional causality between crude oil
CO-BRENT-GDP	0.0808	(BRENT) cycles and GDP cycles
GDP-BSE	0.5815	No causality between BSE cycles and GDP
BSE-GDP	0.3955	cycles
GFCF-GDP	0.7513	No causality between gross fixed capital
GDP-GFCF	0.9334	formation cycles and GDP cycles
MS-GDP	0.8170	No directional causality between mobile
GDP-MS	0.1717	subscriber's cycles and GDP cycles
MS-NFGBC	0.0537	Uni-directional causality between mobile
NFGBC-MS	0.4815	subscribers' cycles and non-food gross bank credit cycles
M3-GDP	0.1374	No causality between money supply cycles
GDP-M3	0.3430	and GDP cycles
DTI-P		

last period. GFCF cycles still account for 27% of forecast variance in the last period and 34% in the long run.

Robustness

In this study, robustness checks on the SVAR results were also conducted to ensure the reliability of the findings. Firstly, we tested whether the residuals of the estimated SVAR model exhibited Autocorrelation, as shown in Table 21. The results of the Autocorrelation LM test revealed no autocorrelation up to 3 lags. This suggests that the model adequately captured the temporal dynamics of the variables. Secondly, we examined the normality of residuals with the help of Jarque–Bera (JB) statistics exhibited in Table 22 jointly assessed the skewness and kurtosis were, respectively, 0&3. The JB test indicated that GDP violated the multivariate normality assumption due to the inclusion of COVID-19 in the sample period. Other series were normal at a 5% significance level. Additionally, we tested for Heteroskedasticity in the SVAR residuals, including cross terms displayed in Table 23. The results showed no evidence of heteroskedasticity at the 5% level. Overall, the robustness check has suggested that results are unbiased and consistent across all observations.

Discussion and policy implication

The study's findings align with existing literature with prior research on the relationship between business and financial cycles. The study found a strong relationship between business and credit cycles (Claessens et al. 2011a, 2011b) (Rünstler, 2016). It is well-documented that credit availability and business activities are closely intertwined, and fluctuations in credit often precede or coincide with changes in economic activity. This suggested that regulating credit can be used as a controlled variable to mitigate the effect of the business cycle.

This study found a weak relationship between the investment cycle and other variables. Factors influencing investment behavior are complex, and its relationship with other economic variables may not be straightforward or strong. Furthermore, mobile subscriber cycles (MS) were significantly correlated to credit cycles, implying changes in technology and mobile subscribers can have a profound impact on credit markets. Therefore, policymakers and financial institutions need to be aware of these positive relationships and carefully monitor technological trends to make informed decisions that promote financial stability.

Conclusion

This paper examines the interconnectedness of the business cycle, credit cycle, and investment cycle as well as the impact of global financial cycles and domestic financial cycles on the business cycle of India. Employing annual data from 1980 to 2021, the HP filter was applied to identify economic cycles. The findings revealed that GDP had 8 peaks and 9 troughs, with the longest cycle lasting from 1997–2007 and 2010–2018, totaling 9 years. Similarly, NFGBC demonstrated 6 peaks and 7 troughs, with the longest cycle lasting from 1995 to 2006, spanning 9 years. Meanwhile, GFCF experienced 10 peaks and 9 troughs, with cycles persisting for a total of 8 years from 2011 to 2018.

The time series data on Indian GDP, banking credit, and investment cycles displays a significant cyclical component, indicating the requirement of regular monitoring to influence GDP. The results indicated that both business and credit cycles closely follow each other. The correlation analysis also confirmed the positive and significant relationship between the variables. The Granger causality test also confirmed the bi-directional relationship between business and credit cycles.

While GFCF had pronounced cyclical fluctuations, correlation analysis confirmed a weak relationship between the variables. Additionally, it was also evident from regression results and the Granger causality test. Furthermore, an explicit disconnect between business and domestic financial cycles proxy by BSE Sensex was observed. The changes in the business cycle can be partially explained by the money supply. Additionally, the Global financial cycle proxy through Brent crude oil did not demonstrate visible synchronization with the business cycle of India.

Remarkably, the study expanded its initial scope to include mobile communication technology as a proxy for DTI and diffusion of information and its impact on banking and credit delivery mechanisms through its impact on banking and financial transactions. The results demonstrated that GDP and the number of mobile subscribers' cyclical components were not significantly correlated. Additionally, the study highlighted that the MS cycle explained 25% of variations in the credit cycle. The regression coefficient of MS was also found to be statistically significant.

Finally, SVAR was employed to examine the interplay among economic, credit, and investment cycles, and the findings concluded a close interaction among the cyclical components of these variables. The Variance decomposition also revealed that the largest share of forecast variance error of GDP was attributed to NFGBC. Meanwhile, GFCF primarily explained its variance.

Table 18 Optimal lag Length.

Lag	Log*L*	LR	FPE	AIC	SC	HQ
0	214.7905	NA	2.89e−09	−11.14687	−11.01758	−11.10087
1	239.4450	44.11854	1.27e−09	−11.97079	−11.45365[a]	−11.78680[a]
2	251.0313	18.90412[a]	1.12e−09[a]	−12.10691[a]	−11.20193	−11.78493
3	258.8322	10.82631	1.26e−09	−12.01988	−10.72705	−11.55990
4	261.8322	4.545298	1.76e−09	−11.72801	−10.04733	−11.13004

LR sequential modified LR test statistic (each test at 5%), *FPE* final prediction error, *AIC* Akaike information criterion, *SC* Schwarz information criterion, *HQ* Hannan–Quinn information criterion.
[a]Indicates lag order selected by the criterion.

Table 19 Long run pattern matrix results.

GDP = α + 0.01861*GDP(−1)−0.00300*GDP(−2) + 0.05133*GFCF(−1) + 0.07203*GFCF (−2) + 0.09682*NFGBC(−1) + 0.06417*NFGBC(−2)

Variables	Coefficient	Std. error	*z*-statistic	*P*-value
GDP (−1)	0.01861	0.00208	8.94427	0.0000***
GDP (−2)	−0.00300	0.01139	0.26393	0.7918
GFCF (−1)	0.05133	0.01924	2.66789	0.0076**
GFCF (−2)	0.07203	0.00805	8.94426	0.0000***
NFGBC (−1)	0.09682	0.01483	6.52599	0.0000***
NFGBC (−2)	0.06417	0.00717	8.94427	0.0000***

***, **, and * indicate significance at 1%, 5%, and 10%.

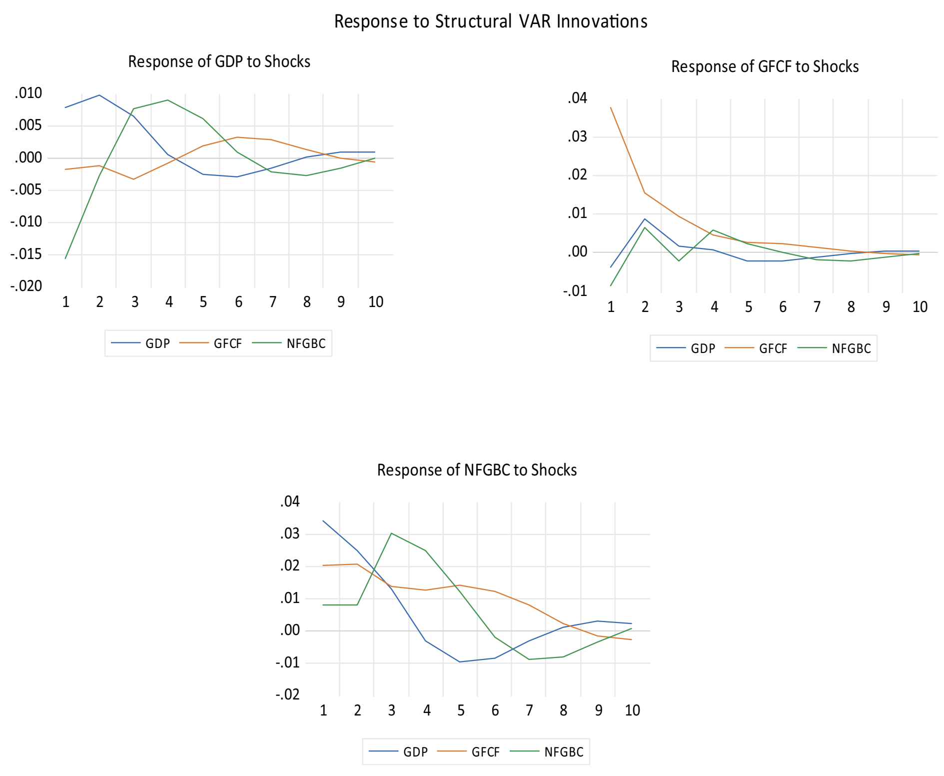

Fig. 4 SVAR impulse response function. Computed using E-views to understand the dynamic relationship between credit, investments and business cycles.

Moreover, every variable in NFGBC exhibited some level of explanatory power. Notably, GDP assumed a prominent role in influencing NFGBC dynamics. Furthermore, Robustness checks conducted on SVAR confirmed that the model was stable and unbiased despite the violation of the normality assumption by GDP due to COVID-19. It is important to highlight that this paper has employed a number of mobile subscribers as a proxy for the DTI, which offers a simple classification. For future studies, Information and Communication Technology (ICT) can be used to capture the bigger dynamics and interaction among the variables and better understanding of the technology landscape. Furthermore, the frequency domain approach, where series is a function of sine and cosines techniques such as the wavelet method, can be used for deriving cycles.

Table 20 SVAR variance decomposition.

Period	GDP	GFCF	NFGBC
Variance decomposition of GDP			
1	19.5407	1.1221	79.3371
2	37.5430	1.2472	61.2096
3	37.4177	3.2494	59.3328
4	32.3721	2.9615	64.6662
5	31.0757	3.2486	65.6755
6	31.5101	4.6660	63.8237
7	31.1718	5.6606	63.1675
8	30.7574	5.8109	63.4316
9	30.7230	5.7857	63.4912
10	30.7618	5.8541	63.3840
Variance decomposition of GFCF			
1	0.0919	94.2318	4.8484
2	4.9155	88.8449	6.2394
3	4.7962	89.0558	6.1479
4	4.6903	87.6257	7.6839
5	4.8597	87.2807	7.8632
6	5.0608	87.1118	7.8273
7	5.1130	86.9351	7.9518
8	5.1021	86.7520	8.1458
9	5.1123	86.6782	8.2093
10	5.1260	86.6661	8.2077
Variance decomposition of NFGBC			
1	71.1785	24.9849	3.8365
2	65.1029	30.2172	4.6798
3	48.4849	25.3133	26.2017
4	40.6842	24.3916	34.9241
5	39.1440	26.0972	34.7586
6	38.8429	27.7868	33.3701
7	37.9949	28.0958	33.9092
8	37.5150	27.8162	34.6686
9	37.4873	27.7404	34.7722
10	37.4837	27.8139	34.7023

Table 21 SVAR serial correlation LM test.

Lags	2 lags LRE*-Stat	*p*-values	1 lag LRE*-Stat	*p*-values
1	9.2235	0.41	9.2235	0.41
2	18.1632	0.44	4.4069	0.88
3	23.4618	0.67	12.1386	0.20

Table 22 SVAR normality test.

Components	Skewness	Kurtosis	Jarque-Bera
1	−0.7800*	5.4463**	14.0311***
2	0.2460	2.1466	1.6172
3	−0.5498	4.0030	3.6926
Joint	6.4763*	12.8647**	19.3410**

Table 23 SVAR heteroskedasticity tests (Includes cross terms).

Null hypotheses: Homoskedasticity		
Joint test:		
Chi-sq	**df**	**Prob.**
190.2896	162	0.0636

Data availability

The authors confirm that data supporting the findings of this study are available in the data set column.

Received: 15 November 2023; Accepted: 2 April 2024;
Published online: 15 April 2024

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Author contributions

The corresponding author wrote the main manuscript text, conducted analysis, interpreted the results and prepared all the figures. The second co-author oversaw the project and assisted with the analysis and interpretation.

Competing interests

The authors declare no competing interests.

Ethical approval

The paper does not contain any studies with human participants performed by any of the authors.

Informed consent

Consent was not deemed necessary for this paper, as the data collected is available on a public platform.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1057/s41599-024-03021-5.

Correspondence and requests for materials should be addressed to Ridhima Garg.

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