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Dynamic Connectedness among Business Cycle, Financial Cycle, and Policy Uncertainty Index in India

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Abstract

Purpose: Pervasive impact of uncertainty necessitates relooking at the traditional empirical approaches to gauge the nexus between the real economy and the financial market, especially after the 2008 financial meltdown. The recent pandemic and ongoing geo-political tension across the globe further emphasized the need for augmentation of the existing analytical framework to address the prime importance and influence of uncertainty on the real economy and financial market. This is why, in this paper, we empirically attempted to calculate the connectedness among the business cycle, financial cycle, and economic policy uncertainty in India. The major contribution of this work can be attributed to the TVP VAR model-based empirical investigation of time-varying connectedness among the aforementioned three variables for the Indian economy from January 1997 to May 2022. Unlike erstwhile works, the paper assesses the net transmitter and receiver of shocks in the multivariate framework too.

Design/methodology/approach: To estimate the dynamic connectedness among business cycle, financial cycle, and economic policy uncertainty, this paper integrates Diebold and Yilmaz's (2014) connectedness technique with Antonakakis and Gabauer's (2017) TVP-VAR methodology.

Findings: We found that the business cycle and financial cycle are the primary receivers of shocks whereas policy uncertainty is the primary transmitter of shocks.

Originality/value: To the best of our knowledge, this is the first empirical attempt to use such a technique in the Indian business cycle literature.

Practical implications: The findings of the paper suggest the need to augment the existing policy framework by incorporating the economic uncertainty component. A stable economic environment is congenial to promote investment and garner consumers' confidence to boost growth in developing nations like India.

Keywords: *Business cycle, Financial Cycle, Uncertainty, TVP-VAR, India*

JEL classifications: E32, D80, C32

1. Introduction

The notion of interconnectedness between real and financial markets has been long debated in economic literature. This debate has been recently reignited in the wake of the 2008–09 financial crisis (Antonakakis et al., 2015; Claessens et al., 2012; Drehmann et al., 2012). Theoretical underpinnings highlight that growth of the financial sector lowers market friction, increases domestic savings rates, and lures foreign capital. As a result, it increases capital accumulation and reduces the cost of external financing for firms which promotes overall economic growth. Growth, the prime objective of economic policy forums, also received fresher attention from theoretical and empirical perspectives over time. Even while it is still a major economic goal, determining GDP growth alone no longer suffices to determine an economy's overall health. The idea of the business cycle (BC), an otherwise unobservable phenomenon of output but an essential policy goal, is fostered by the latent fluctuation in output's dynamism. In their classic study, Burns and Mitchell (1946) presented the very first empirical definition of BC and since then, it has attracted the interest of both researchers and policymakers.

Recent research has highlighted oscillations in a number of financial variables and referred to this phenomenon as financial cycles (FC). These fluctuations are deviations from respective variables which are instrumental in determining the fundamentals of the financial markets. Variables related to the external sector, money market, and stock market are all reexamined from a fresh financial viewpoint. This opened up a new vista in economic literature where the relationship between the real economy and the financial market received revised attention. In particular, FC and its interaction with the BC have received significant attention for empirical investigations. Although there is disagreement in the literature regarding the nature of the relationship between these two cycles, there is a growing consensus among scholars that a deep nexus exists between them. We demonstrate how the Indian business cycle, as measured from industrial production output data, is firmly linked to the financial cycle.

Apart from gauging the dynamism of interdependence between the business cycle and financial cycle, the major motivation of our study is to relook at this nexus against the backdrop of a critical factor named economic and policy uncertainty. Uncertainty, an erstwhile pariah in the economic literature is attaining serious attention now. The pandemic and ongoing geo-political unrest across the world, especially deepened by the Russia-Ukraine war, necessitates assessing the economic models addressing growth-finance interdependence. Uncertainty, a disrupter to the investment environment and a discouraging factor to consumer confidence, leads to an eventual fall in output and financial market performance. Macroeconomic and financial stability are significantly impacted by economic policy uncertainty. When there is a high level of uncertainty, investors delay their investments, which decreases economic activity and hence adversely harms economic growth. In the presence of high uncertainty, financing cost rises, hindering investment activities and, as a result, leading to slow economic growth. To address the impacts of uncertainty factors on the business cycle and financial cycle, we included a measure of economic policy uncertainty

(EPU). However, the connectedness among BC, FC, and EPU is still an unresolved debate. The literature on network connectedness among the abovementioned variables for open emerging economies is silent. This motivated us to explore the nexus among them in an emerging economy like India. Researchers may be interested to know the nexus between Business Cycle and Financial Cycle against the backdrop of Economic Policy Uncertainty.

Two major contributions differentiate our empirical attempt from the existing body of work in literature. Firstly, unlike erstwhile works, we gauged the interdependence of the business cycle and financial cycle in conjunction with the economic policy uncertainty index. It helps us to gauge the degree of interconnectedness amongst all three aforementioned variables. Further, by employing the TVP-VAR-based spillover index approach developed by Diebold and Yilmaz (2009, 2012), we also empirically investigated time-varying connectedness among these three variables for the Indian economy from January 1997 to May 2022. This new technique can determine the dynamics across all three variables and the nature of interdependence among them. Generally, in multivariate time series models, static parameters from estimation signify constancy of the impact of one variable on others. Hence, the temporal dynamics of such a causal relation are completely overlooked in such an assessment. This is why we employed the TVP-VAR-based Diebold and Yilmaz model which unlike the traditional VAR model and its structural variants helps us gauge the temporal aspect of interdependence amongst all three variables.

Secondly, this paper also helps in identifying the nature of causal relations in a multivariate framework. In traditional VAR models, the causal direction is detected by the Granger-type test where pairwise causality is established for all variables. The novel spillover index approach developed by Diebold and Yilmaz (2009, 2012) is instrumental in identifying the net transmitter and receiver of shocks in a multivariate TVP-VAR framework. Our findings indicate that EPU is the primary transmitter of shocks to the financial and business cycles in India. In contrast, BC and FC are the primary receivers of shocks. To the best of our knowledge, this is the first empirical attempt to use such a technique in the Indian business cycle literature making the study unique.

The remainder of the article is organized as follows. We provide some theoretical and empirical background for the analysis of our paper in the literature section, setting it in the perspective of recent literature. In section 3, we discuss in greater detail the data and methodology used in our empirical work. Section 4 follows, including the empirical findings and a discussion of our results, and section 5 winds up with some concluding remarks.

2. Literature Review

Virtually all developed economies and a number of emerging markets have experienced recessions over the past two decades. These recessions were often accompanied by numerous financial disruptions, such as severe credit contractions and rapid drops in asset prices. Such trends have propelled the discussion to the forefront of research on how BC and FC interact. Literature on the nexus between BC and FC can be traced back to the fundamental work of Minsky (1977). His popular financial instability hypothesis postulates that BCs are consistently affected by FCs. Investors are motivated to take on high risk during stable periods when the stock price rises quicker than interest rates. As a result, they borrow more money and overpay for assets. Ponzi finance tends to become more prevalent as economic stability continues, usually resulting in the collapse of some financial organizations. If the use of Ponzi finance is sufficiently pervasive in the financial system, as it may have been in the case of the 2008 subprime mortgage crisis, then the collapse of fragile Ponzi schemes can also affect hedge borrowers, who are unable to secure loans despite the apparent soundness of the underlying investments (Knell, 2015). When speculative and Ponzi financing units get so indebted that they cannot continue borrowing, they are compelled to sell off assets to pay interest, which leads to an excess of assets that are then put up for sale. This debt deflation results in liquidity shortage and financial crisis (Mulligan, 2013). The entire process ultimately causes firms' debt structures to shift toward unsustainable Ponzi schemes, which eventually collapse and trigger an economic recession (Paramanik, Bhandari, and Kamaiah, 2022). Literature is laden with a similar mechanism where shocks to the financial sector result in an economic crisis. According to Claessens et al. (2012), the business cycle and financial cycle are strongly correlated. Yan and Huang (2020) show that the financial cycle and business cycle are closely related and there is a high positive correlation between them. There is a significant and strong time-varying nexus between the business cycle and financial cycles in the United States (Jawadi et al., 2022). Aikman et al. (2015) concluded that the length and amplitude of the financial cycle are higher than that of the business cycle. Anusha (2015) investigated the link between credit and IIP growth in USA and India and found that in the USA, credit drives output whereas, in India, output drives credit.

A connectedness method by Diebold and Yilmaz (2012) is used in some studies to investigate the transmission of spillovers between these two cycles. Using quarterly data from 1998 to 2018 in China, Li, Yan, and Wei (2021) investigated the transmission of spillover among monetary policy cycle, FC and BC. Their findings support the theory that the dynamics of BC depend heavily on financial factors, with a rising FC spillover on BC. Antonakakis, Breitenlechner, and Scharler (2015) used quarterly data covering the period 1957–2012 to investigate the dynamic interaction between credit growth and output growth for the G7 economies. They discovered that the US credit growth is the major transmitter of shocks to the real sector of other countries. For the Swiss economy, Uluceviz and Yilmaz (2020) analyzed the connectedness between the real and financial sectors. Their findings imply that the real sector of the economy functions as a net receiver of connectedness from the financial sectors.

Economic uncertainty has a major role in macroeconomic stability. Knight (1921) defined uncertainty as people's inability to predict the outcomes of future events. The analysis of macroeconomic and financial uncertainty and its impacts on the economy are of particular interest to economists and policymakers in the wake of the 2008 financial crisis and the great recession.

Since then, it has attracted the attention of researchers to find its role in the real and financial sectors. Uncertainty adversely affects the consumption and investment decision of households (Bernanke, 1983). It significantly impacts economic growth (Bloom, 2009; Balcilar, Gupta, & Segnon, 2016). An increase in uncertainty increases the cost of capital leading to lower investment and economic growth. Aye (2021) investigated the impact of uncertainty related to fiscal and monetary policy in South Africa. He found that uncertainty increases government expenditure, interest rate, and inflation rate as well as consumption and income tax and hence adversely hampers business activities and reduces economic activity. In a similar study, Aor et al. (2021) found a negative impact of US monetary and fiscal policy uncertainty on GDP and equity prices in advanced and emerging economies. A rise in economic uncertainty leads to a higher corporate tax rate (Clance et al., 2021). In times of high uncertainty, households delay spending and investment due to reduced personal income (Pastor & Veronesi, 2012). This demand shock results in a decrease in production and overall wealth of the economy (Bloom, Bond, & Van Reenen, 2007). As a result, uncertainty has a countercyclical relationship with BC. It peaks in recessions and bottoms out during booms (Bloom, 2014). These facts suggest that uncertainty is an exogenous factor of BC as well as an endogenous response to fluctuations of BC (Castelnuovo, Lim, and Pellegrino, 2017).

Recent literature focuses on the relationship between BC and EPU. Most of them show a negative nexus. An increase in the uncertainty of the leading economy results in a spillover effect on the BC and FC of other economies (Favero & Giavazzi, 2008). The United States transmits economic shocks to other countries worldwide (Diebold and Yilmaz, 2013). According to Colombo (2013), shocks to United States' policy uncertainty causes a substantial drop in industrial production in the Euro region. Nyawo and Wyk (2018) concluded that shocks to US policy uncertainty decrease Indian industrial production. Uncertainty shocks have a long run persistent unfavorable impact on BC (Cesa-Bianchi et al., 2018, Bonciani and Oh, 2019). It is possible to argue that policy uncertainty may directly impact the entire economy and eventually affect financial markets. Most of the empirical literature looks at how EPU and stock markets interact (Pástor and Veronesi, 2012; Antonakakis, Chatziantoniou, & Filis, 2013, Aor et al., 2021). They found that EPU negatively affects the returns of the stock market. According to Caldara et al. (2016), the United States business cycle is driven by uncertainty and financial shocks.

Although there is plenty of work studying the relationship between the business cycle and financial cycle in developed countries, very few studies examine the relationship in the context of emerging countries like India. In this paper, we empirically attempted to fill this gap by calculating the connectedness among business cycle, financial cycle, and policy uncertainty with the help of the connectedness measure of Diebold and Yilmaz (2014).

3. Data and Empirical Methodology

3.1 Data

We have taken monthly data on financial and macroeconomic variables for the time period from January 1997 to May 2022. We have used Index of Industrial Production (IIP) data to gauge business cycle dynamics instead of GDP as it is not available at monthly frequency. IIP is thought to be a suitable proxy for output because the value added by it makes up a large portion of GDP and is available at a monthly frequency. Recent studies have suggested that the cyclical component of the industrial production index might be a good proxy for business cycle analysis (Paramanik et al., 2022). It is evident from the literature that the relationship between real and financial variables is sensitive to the proxies used to represent the financial sector. A single indicator cannot describe the overall health of the financial sector. Therefore, variables related to the stock market and money market are generally used in the literature to make an index to measure the financial cycle. Our financial variables include nominal effective exchange rate indices (NEER), broad money indices, central bank policy rates, and the stock price index of leading Indian stocks. Broad money stocks represent the financial depth and overall size of an economy. The stock price is perceived as the barometer of the financial market. We took the policy rate from the money market and the exchange rate from the external sector. Our third variable, economic policy uncertainty is extracted from the database of Baker, Bloom, and Davis (2016). Using the X-12-ARIMA approach, every variable has been seasonally adjusted. Using the following formula, we have standardized all the variables by using the following formula:

$$Standardized\ variable = \frac{variable\ value - mean\ value}{standard\ deviation}\ .$$

Standardized and seasonally adjusted financial variables have been used to construct a financial index using Principal Component Analysis. Further, the financial index and IIP are used to construct FC and BC using the Christiano-Fitzergarld (2003) filtering technique. IIP and broad money are obtained from the Federal Reserve Bank of St. Louis database. The policy rate and NEER are obtained from the Bank of International Settlement database. The Asian Development Bank database is used to extract the composite stock price data, while the Baker et al. (2016) database is used to get the EPU data. The selection of the time period is based on the longest data set available, which spans from January 1997 to May 2022 and includes both periods of the pre-and-post-financial crisis.

3.2 Methodology

In order to investigate the time-varying transmission mechanism, this paper integrates Diebold and Yilmaz's (2014) connectedness technique with Antonakakis and Gabauer's (2017) TVP-VAR methodology. The following equations can be used to represent the TVP-VAR model:

$$Y_t = \alpha_t Y_{t-1} + \epsilon_t; \qquad \epsilon_t | F_{t-1} \sim N(0, S_t), \tag{1}$$

$$where \quad \alpha_t = \alpha_{t-1} + v_t; \qquad v_t | F_{t-1} \sim N(0, R_t). \tag{2}$$

where Y_t and Y_{t-1} are conditional volatilities vector and lagged conditional vector of dimension $N_p \times 1$ and F_{t-1} represents the information set before t-1, α_t is a time-varying coefficient matrix of dimension $N \times N_p$ depending on its past values α_{t-1} and on a $N \times N_p$ error matrix, ϵ_t is $N \times 1$ error disturbance vector having $N \times N$ time varying variance-covariance matrix S_t, and v_t with an $N_p \times N_p$ variance-covariance matrix R_t. The connectedness index created by Diebold and Yilmaz (2012) is based on the time-varying coefficients of the vector moving average (VMA) and uses the generalized impulse response function (GIRF) and the generalized forecast error variance decomposition (GFEVD), respectively, developed by Koop et al. (1996) and Pesaran and Shin (1998). VAR can be transformed into VMA form in order to calculate GIRF and GFEVD. From Equation (1), we have

$$Y_t = \alpha_t Y_{t-1} + \epsilon_t; \tag{3}$$

$$Y_t = A_t \epsilon_t; \tag{4}$$

$$A_{0,t} = I; \tag{5}$$

$$A_{i,t} = \alpha_{1,t} A_{i-1,t} + \cdots \ldots + \alpha_{p,t} A_{i-p,t}. \tag{6}$$

where $\alpha_t = [\alpha_{1,t}, \alpha_{2,t}, \ldots\ldots \alpha_{p,t}]'$ and $A_t = [\alpha A_{1,t}, A_{2,t}, \ldots\ldots A_{p,t}]'$ here α_{it} and A_{it} are $N \times N$ parameter matrices. I is the identity matrix. The term GIRF refers to the response of all variables following an impact in variable i. The following formula can be used to determine the gap between the J-step-ahead prediction of primary impact and the primary nonimpact variable i.

$$GIRF_t(J, \delta_{j,t,} F_{t-1}) = E(Y_{t+j} | \epsilon_{j,t} = \delta_{j,t,} F_{t-1}) - E(Y_{t+j} | F_{t-1}). \tag{7}$$

where J is the forecast horizon and the selection vector is $\delta_{j,t}$ with one on the jth position and zero elsewhere, F_{t-1} is referred to as information set before t – 1, and GFEVD is often known as the variance sharing of one variable to other variables and can be calculated. The variance shares must be standardized so that each row adds up to one row and that the sum of all the variables accounts for 100% of the variance in prediction error. The following is the computation process:

$$\breve{\emptyset}^{g}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,g}_{ij,t}}{\sum_{i=1}^{N} \sum_{t=1}^{J-1} \Psi^{2,g}_{i,j,t}}, \tag{8}$$

where $\breve{\emptyset}^{g}_{ij,t}(J)$ is J-step ahead GFEVD, $\Psi^{g}_{j,t}(J) = S^{\frac{-1}{2}}_{jj,t}\ A_{j,t}\ S_t \epsilon_{j,t}$ with $\sum_{j=1}^{N} \breve{\emptyset}^{g}_{ij,t}\ (J) = 1\ and\ \sum_{ij=1}^{N} \breve{\emptyset}^{N}_{ij,t}\ (J) = N$. We create the total connectedness index using the GFEVD by:

$$C^{g}_{t}\ (J) = \frac{\sum_{i,j=1, i\neq \mathrm{j}}^{N} \breve{\emptyset}^{g}_{ij,t}\ (J)}{\sum_{i,j=1}^{N} \breve{\emptyset}^{g}_{ij,t}\ (J)} * 100, \tag{9}$$

$$= \frac{\sum_{i,j=1, i\neq \mathrm{j}}^{N} \breve{\emptyset}^{g}_{ij,t}\ (J)}{N} * 100. \tag{10}$$

This concept of connectedness can show how a shock in one variable spills over to other variables. The initial step is to note that variable i transmit shocks to each other variable j. This is referred to as the total directional connectedness with other variables and is given by the following equation:

$$C^{g}_{i\rightarrow j,t}\ (J) = \frac{\sum_{j=1, i\neq \mathrm{j}}^{N} \breve{\emptyset}^{g}_{ji,t}\ (J)}{\sum_{j=1}^{N} \breve{\emptyset}^{g}_{ji,t}\ (J)} * 100. \tag{11}$$

Second, the total directional connectedness of all other variables, which is the directional connectedness that variable i receives from variable j, can be determined as follows:

$$C^{g}_{i\leftarrow j,t}\ (J) = \frac{\sum_{j=1, i\neq \mathrm{j}}^{N} \breve{\emptyset}^{g}_{ij,t}\ (J)}{\sum_{i=1}^{N} \breve{\emptyset}^{g}_{ij,t}\ (J)} * 100. \tag{12}$$

The net total directional connectedness, which is obtained by deducting the total directional connectedness of all other variables from the total directional connectedness, can then be used to estimate the ‘power’ of variable i or its influence on the entire variable network as shown in the following equation:

$$C^{g}_{i,t} = C^{g}_{i\rightarrow j,t}\ (J) - C^{g}_{i\leftarrow j,t}\ (J). \tag{13}$$

Positive net total directional connectedness of the variable indicates that the influence of variable i on the network is greater than that of the network whereas, negative indicates that the network is driving variable i. Finally, the net total directional connectedness can be broken down to investigate the bidirectional nexus by estimating the net pairwise directional connectedness (NPDC) as shown in the following equation:

$$NPDC_{ij}(J) = \frac{\breve{\emptyset}^{g}_{ji,t}\ (J) - \breve{\emptyset}^{g}_{ij,t}\ (J)}{N} * 100. \tag{14}$$

4. Empirical Findings

Table 1 presents the summary statistics of the variable series. It describes the BC, FC, and EPU statistics for the sample period. EPU is characterized by having the highest mean, whereas BC and FC have the lowest. Additionally, the BC has the lowest standard deviation and, hence, the lowest volatility, while the EPU has the highest.

Table 1. Summary Statistics

	BC	**FC**	**EPU**
Mean	-0.005	0	93.374
Variance	0.011	0.027	2113.849
Skewness	-1.911***	-0.419***	1.282***
	(0.000)	(0.003)	(0.000)
Ex.Kurtosis	7.489***	1.915***	2.052***
	(0.000)	(0.000)	(0.000)
JB	898.385***	55.535***	137.011***
	(0.000)	(0.000)	(0.000)

Note: BC, FC, and EPU represent Business Cycle, Financial Cycle, and Economic Policy Uncertainty, respectively.

The unconditional spillover effect between BC, FC, and EPU is defined as the connectedness measure and presented in Table 2. The table contains some crucial information that can be utilized to calculate the connectedness level's average value. It describes the unconditional spillover effects across the variables. The connectedness index in our model, which is based on the TVP-VAR model, is the variance decomposition with ten months. The total directional connectedness between all other variables and variable 'i' known as 'Contribution FROM others' computed as the addition of offline elements of row 'i'. Variable 'j' has a spillover effect on all other variables, which is known as its 'contribution TO other variables', as indicated by the total directional connectedness of all other variables computed as the sum of offline elements in column 'j'. The 'Net' row shows the difference between 'TO' and 'FROM'.

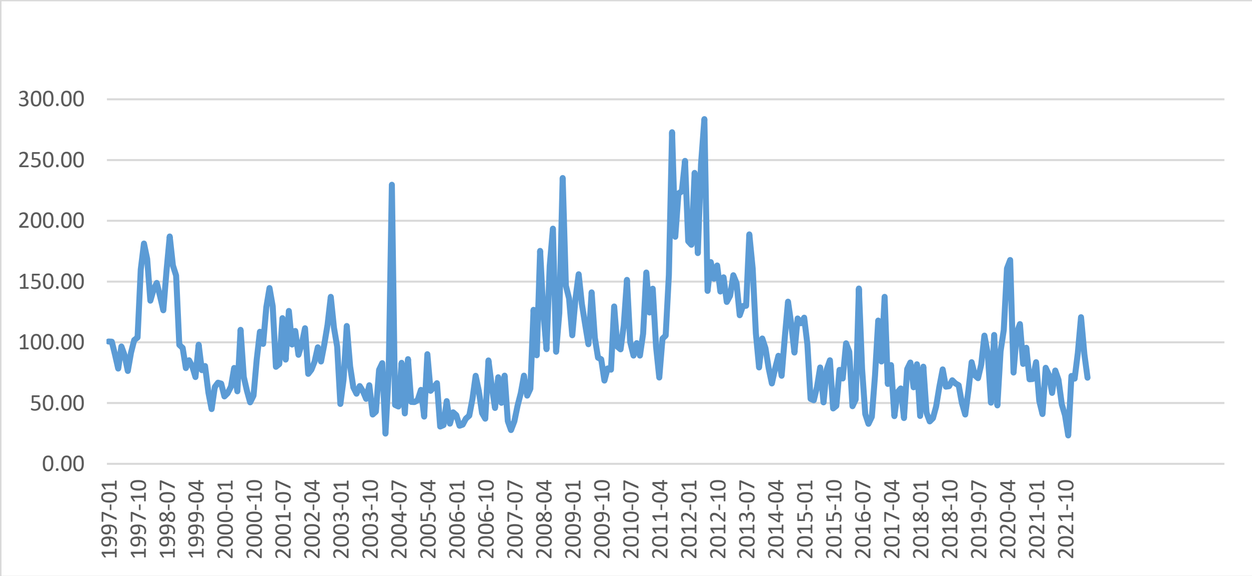
Results from Table 2 show that 15.89% of volatility (total spillover) between BC, FC, and PUI is due to their interconnectedness. For each variable in Table 2, the 'FROM' connectedness index shows that for BC, FC, and EPU, considerable contribution comes from FC, and EPU (12.19%, 14.62%, and 2.00%, respectively). Diagonal elements refer to their own connectivity which varies from 75.67 % to 96.51%. In general, EPU is relatively independent, with its shocks accounting for about 96.51% of the variance in forecast error variance, compared to 3.49% for all other variables. The EPU has the highest 'TO' connectedness (about 26.75%), and BC has the highest connectedness with other variables (about 24.33%). The BC has the lowest 'TO' connectedness (about 6.73%), and EPU has the lowest connectedness with other variables (about 3.49%). FC has 14.19% of 'TO' connectedness and 19.86% connectedness with other variables. The 'NET' line in table 2 represents the net spillover effect of various series, which is explained by the difference between 'To' and 'From'. For the study period from January 1997 to May 2022, the 'TO' connectedness of EPU (26.75%) exceeds its 'FROM' connectedness (3.49%) by 23.26%, making EPU the highest net connectedness among all three series. Therefore, EPU is the major transmitter of shocks (with a net connectedness of 23.26%). The table, however, reveals that the BC is the primary recipient of shocks (with 'Net' connectedness of -17.60%), while the FC is the second one (with 'Net' connectedness of -5.66%).

Table 2. Average dynamic connectedness table

	BC	**FC**	**EPU**	FROM
BC	75.67	12.19	12.14	24.33
FC	5.24	80.14	14.62	19.86
EPU	1.49	2.00	96.51	3.49
TO	6.73	14.19	26.75	47.67
Inc.Own	82.40	94.34	123.26	cTCI/TCI
NET	-17.60	-5.66	23.26	23.84/15.89

Note: BC, FC, and EPU represent Business Cycle, Financial Cycle, and Economic Policy Uncertainty, respectively.

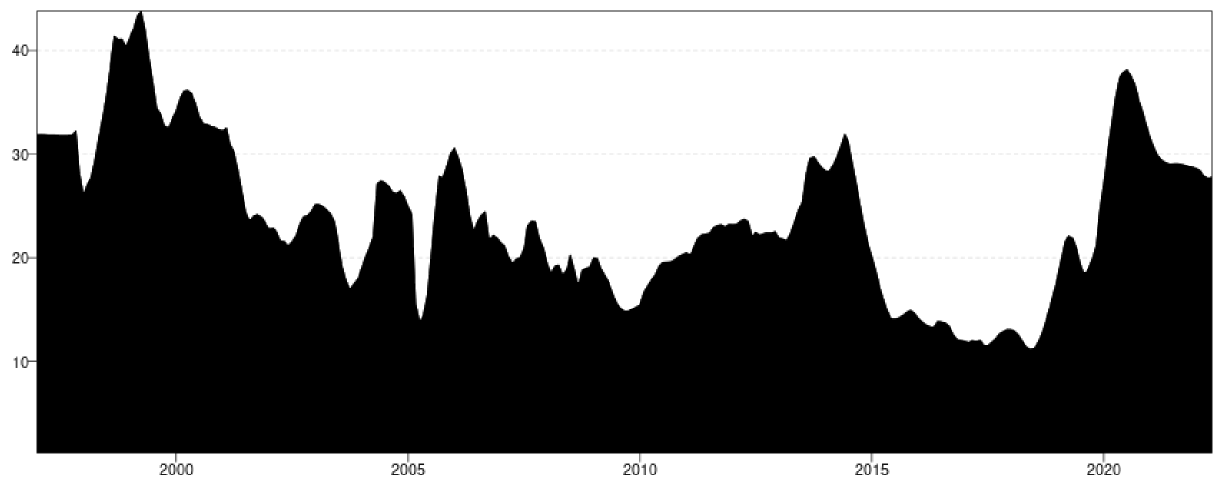
Figure 1. Economic Policy Uncertainty (EPU) Index for India, 1997-2022



Source: Baker, Bloom and Davis database

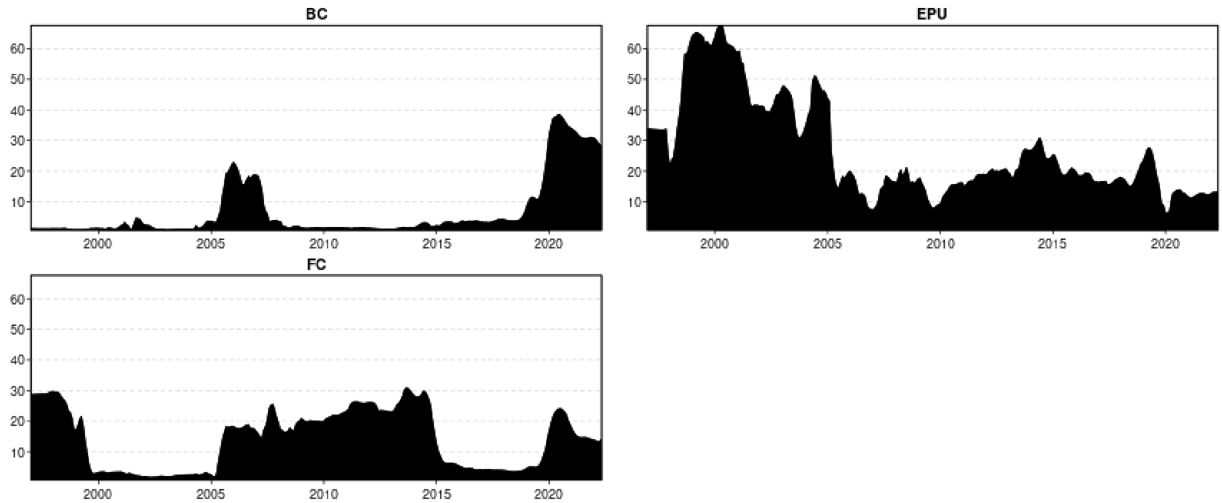
Figure 1 shows the evolution of economic policy uncertainty in India. The time period is represented on the horizontal axis and the index value is on the vertical axis. EPU has reduced significantly over the last decade. It was the highest in 2011-12; since then, EPU has declined sharply. Uncertainty increased in 2003-04 due to the Gulf War and in 2008-09 due to the Global Financial Crisis. Recently it has increased due to Covid-19 in 2020.

Figure 2. Dynamic Total Connectedness



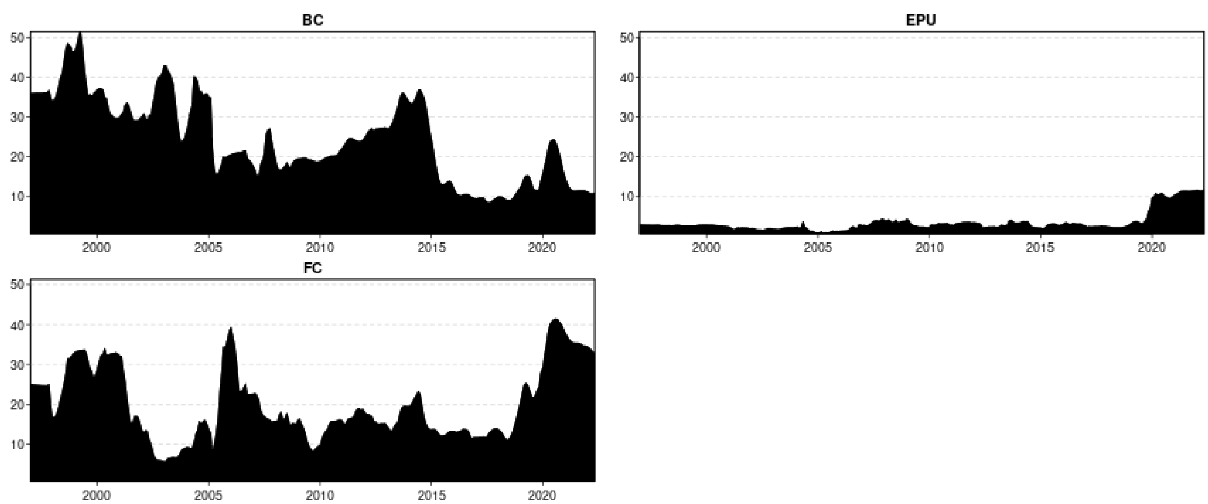
The evolution of the dynamic total connectedness index is depicted in Figure 2. The time period is represented on the horizontal axis and the connectedness index value is on the vertical axis. The total connectedness index has a range of 11.18% to 43.79%. By comparing Figures 1 and 2, we can conclude that total connectedness is high in a time of high uncertainty. This shows that uncertainty plays a major role in the evolution of BC and FC. According to Figure 2, the level of total connectedness between these three variables peaked around the Asian Financial Crisis of 1997, the Internet Bubble of 2000, the Global Financial Crisis of 2008 and the most recent global COVID-19 pandemic, demonstrating how the spillovers are highly responsive to extreme economic events. This finding further strengthens the relationship between these variables from a time-varying perspective.

Figure 3. To Others



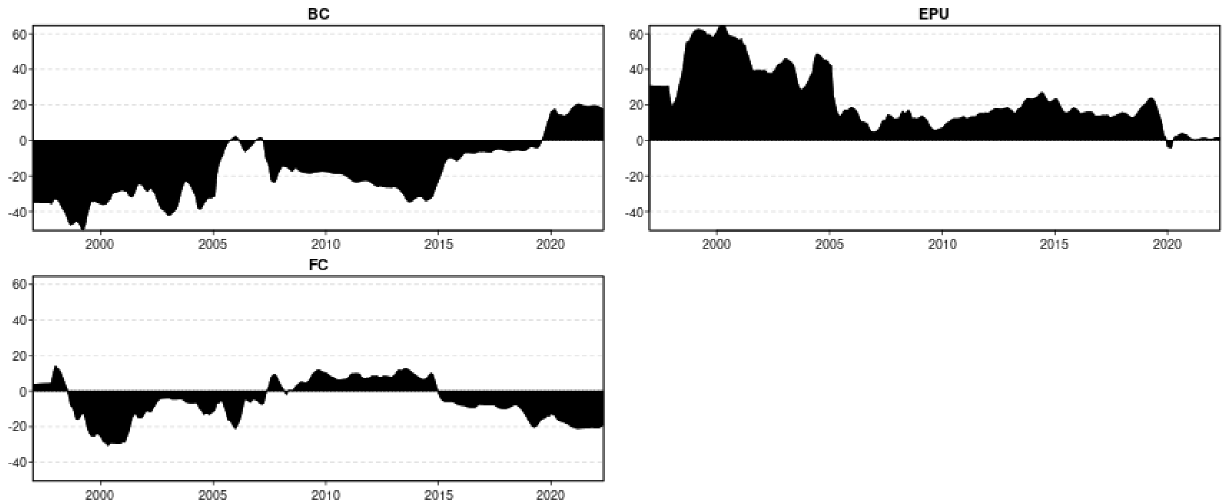
The directional connectivity of each variable with other variables is shown in Figure 3. It demonstrates the dynamics of 'TO' connectedness. The measure of spillover from respective variables to others is indicated on the vertical axis while the horizontal axis represents the time period. With an average of 6.72% and 14.19%, respectively, the spillover effect of BC and FC on other series is lower than that of EPU. With an average of 26.75%, the spillover effect from EPU to others is the largest.

Figure 4. From Others



The contributions 'FROM' others are depicted in Figure 4, which quantifies the directional connectedness between each variable and other variables. The measure of spillover from other variables to the respective variable is indicated on the vertical axis while the horizontal axis represents the time period. Other variables' spillover effects on the BC are significantly high. On the other hand, the EPU appears to be less sensitive to the impact of others. It shows that EPU is relatively independent. Other variables have less impact on EPU. The amount of spillover effect of other variables on FC is likewise very high.

Figure 5. Net Total Directional Connectedness



The net total directional connectedness is shown in Figure 5, which shows how the spillover connectedness index changes from the recipient of impact to the impact sender. The vertical axis represents the measure of spillover while the horizontal axis represents the time period. The BC and FC received shocks from others over most of the sample period. In contrast, the EPU transmitted shocks to the others throughout the study period.

Figure 6. Net Pairwise Directional Connectedness

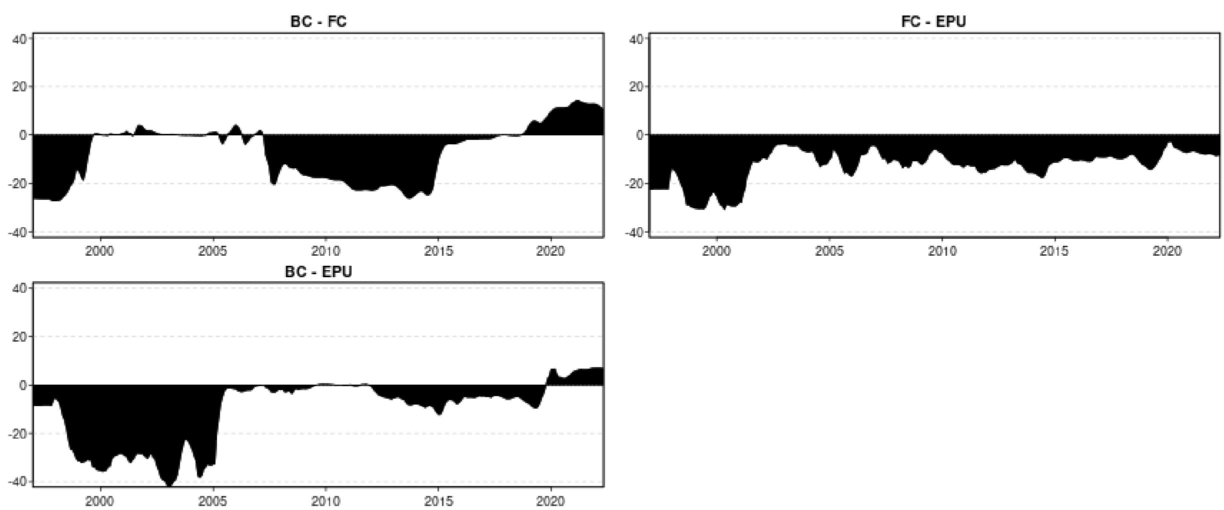
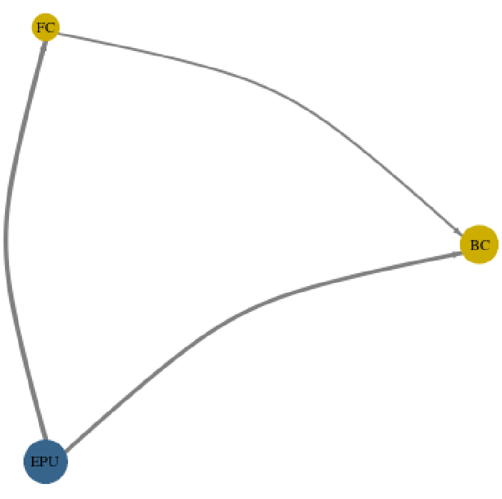


Figure 6, on the other hand, emphasizes the interconnectedness by displaying the net pairwise directional connectedness. The vertical axis represents the measure of pairwise interconnectedness while the horizontal axis represents the time period. We can see that FC could be said to be the net volatility receiver from EPU for the entire sample period. BC could also be said to be the net volatility receiver from EPU, but after the 2020 COVID-19 pandemic, it became a transmitter. For most of the period, BC is the net volatility receiver from FC.

A rise in uncertainty can have a negative impact on investment, a firm's productivity, and total employment, while increasing financial costs, household savings, and stock market volatility. All of these activities could delay the reallocation of resources to productive uses and hence adversely affect the BC. The bulk of the literature that examines the interactions between EPU and financial markets e.g. stock market and asset market, found that EPU negatively affects financial markets. EPU may increase risks, particularly in the financial markets, by decreasing the value of market protections offered by the government (Pastor and Veronesi, 2012). Changes in EPU have an impact on asset prices by altering both anticipated firms' cash flows and discount rates.

Figure 7. Network Plot



In Figure 7, the BC, FC, and EPU are abbreviated as 'node labels' in nodes. Sizes of link arrows represent pairwise directional connectedness 'to' and 'from'. We found that there is a connectedness between EPU to both FC and BC. Our empirical findings imply a unidirectional connectedness between FC and BC, whereas there is no connectedness between FC and BC to EPU.

5. Conclusion

Uncertainty, being the only certain thing in today’s economic order, needs special attention in empirical works of macroeconomics. In the recent past, the pandemic and the Russia-Ukraine war induced and deepened the intensity of such uncertainty which has disrupted the global economic order. Our study period also covers major events like the Asian financial crisis of 1997 and the great depression of 2008 which caused significant uncertainty owing to the financial market meltdown. Such events of crises accentuated the need to relook at the nexus between real and financial markets against the backdrop of prevailing economic uncertainty. Our empirical work is an attempt to gauge the interdependence between the business cycle, and financial cycle in the context of economic policy uncertainty. Conventional work assessed the relationship between real and financial markets and most of the studies in this area are based on standard time series models like VAR and structural VAR etc. To circumvent the limitations in the literature, in our paper, we examined the dynamic aspect of this nexus among the business cycle, financial cycle, and policy uncertainty index. Such dynamism is examined using the novel dynamic connectedness approach of Diebold and Yilmaz. The major advantage to address dynamic relations among business cycle, financial cycle, and policy uncertainty index for the Indian economy for this method relies on the underlying time-varying parameter VAR model. We have used monthly data from January 1997 to May 2022 for our study. Unlike the standard VAR model where parameters remain static for the given sample period, the TVP-VAR estimates temporally varying parameters in the model. Hence, the TVP-VAR-based spillover index can determine the dynamics of interdependence across all three variables. Further, this method also identifies the major transmitter and receiver of impact in this relationship in a multivariate framework. Empirical findings suggest that EPU is the primary transmitter of shocks to the other two variables. In contrast, the business cycle and financial cycle are the primary receivers of shocks.

Empirical findings from our work have practical policy implications. Well-documented literature on the growth-finance nexus is relooked at from the perspective of uncertainty, a very relevant and pervasive factor in today’s context. Findings from the paper necessitate augmenting the existing policy framework by factoring economic uncertainty component. Higher policy uncertainty leads to an unstable economic outlook through a disturbed investment environment and consumer confidence. This in turn eventually impacts financial market performance adversely. Hence, the reduction of uncertainty through favourable policy interventions is desirable to promote firm investment and growth in developing nations. Our findings corroborate that policy uncertainty, the major transmitter of shock, shapes the dynamics of the business cycle and financial cycle in the Indian economy. Owing to the unavailability of data on policy uncertainty, our study is limited to a certain time period. We also could not explore the nexus of other macro-finance prudential due to data limitations.

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