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FINANCIAL SECTOR DEVELOPMENT AND REAL SECTOR GROWTH – ASSOCIATION, SPILLOVER AND CAUSALITY DURING PRE COVID AND COVID REGIMES

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Abstract. *In this paper, we propose an alternative approach to understanding the relationship between financial sector development and real sector growth in India. We use stock market sectoral indices available on National Stock Exchange (NSE) like Capital Goods Index, FMCG Index, Energy Index, Infra Index, Metal Index, Realty Index, and Auto Index to represent the real sector. To represent the financial sector, we consider Bank Index and Financial Services Index separately. The proposed framework examines the relationships at a granular level to understand the extent of association, spillover, and causality. We also analyze the relationship between the financial sector and the real sector in Pre COVID and COVID periods separately. Our research methodology includes the use of Detrended Cross-Correlation Analysis (DCCA), Wavelet Multiple Correlation (WMC), Wavelet Multiple Cross Correlation (WMCC), Diebold-Yilmaz spillover Framework, and Non-Linear Causality Test. Our granular approach has enabled us to examine the relationships in different periods and we observe that the results change. The intensity of the relationships also is different during the COVID period as compared to Pre COVID period.*

Key words: *Financial Sector, Real Sector, Detrended Cross-Correlation Analysis (DCCA), Wavelet Multiple Correlation (WMC), Wavelet Multiple Cross Correlation (WMCC), Diebold-Yilmaz spillover*

JEL Classification: C01, C22**.**

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1. INTRODUCTION

World Development Report (1989) dwells in great detail on the role of the financial sector in economic growth. The financial sector pools the savings of individuals and lends them for large investment projects which help in economic growth. Further, various financial instruments make it easier to trade and exchange goods and services and also make the cost of raising resources cheaper for firms. Self-financed investments have obvious limitations and profitable investment opportunities can be explored only in the presence of external finance. In today's world of globalization and with the growth of the internet, accessing finance has become easier, and the financial wealth of a nation is now no longer confined within its geographical boundaries.

The institutions in the financial sector, through their lending activities, also appraise projects for lending. This generates comfort to the savers that their savings are protected by people specializing in lending activities. Risk management and risk monitoring are done systematically and generate confidence in the savers, encouraging further savings with institutions. The financial sector, through its lending activities, also takes care of the agency problem thus encouraging shareholders to undertake projects, either for expansion or diversification. Some papers in this area include Jensen and Meckling (1976), Rozeff (1982), Easterbrook (1984), and Jensen (1986).

There is considerable literature on the relationship between financial sector growth and real sector growth. King and Levine (1993), Levine (1997), and Aghion et al. (2004) have laid the foundation of research in this area. In this context, different variables have been identified for understanding the relationship between financial sector growth and real sector growth. For financial sector development, variables like the ratio of liquid liabilities to GDP, the ratio of bank credit to total credit, the ratio of non-banking credit to total credit (except credit to the public sector), the ratio of bank credit divided by bank credit plus central bank domestic assets, the ratio of credit allocated to private enterprises to total domestic credit (excluding credit to banks), and credit to private enterprises divided by GDP have been considered. Growth in per capita output and growth in physical capital formation has been considered to represent real sector growth.

During the recent COVID-19 pandemic, the real sector came under pressure all over the world due to lockdowns, a standstill in world trade, closure of operations in factories, and shutdown in international and domestic travel (Özen and Özdemir, 2021; Jana et al., 2022; Babalola, 2022). In India, a few trains were running, airlines were running at low capacity, inter-state movement in the workforce went down significantly and factories were struggling to resume operations (Patil et al., 2022; Rajak et al., 2022). Loss of income and employment led to a fall in demand. The GDP growth rate has turned negative and there is little evidence of when things will get back to the pre-COVID stage. The banking sector and the non-banking financial services sector came under pressure as loan defaults had increased and fresh financial assistance was not being sought. The focus is on how to ease the financial burden of the borrowers. There was a huge requirement for liquidity and the Indian government used the banking sector to channel financial assistance to the needy. Mutual funds witnessed large redemptions as individuals faced liquidity constraints.

In this background, we propose an alternative approach to understanding the relationship between the financial sector and the real sector in India. We use stock market indices in India from the National Stock Exchange (NSE) for modeling and to represent the real sector, we consider Capital Goods Index, FMCG Index, Energy Index, Infra Index, Metal Index, and Auto

Index. To represent the financial sector, we consider Bank Index and Financial Services Index. We propose a framework where the relationship is examined at a granular level to understand the extent of association, spillover, and causality.

Although we will be using stock market indices which are financial sector indices, our contention is that company stock prices and consequently, sectoral indices, except for speculative waves, do reflect the state of the real sector. The sectoral indices that we have chosen, representing the real sector, reflect the fortunes of the companies within the sector, the state of that sector, and their growth prospects. Macroeconomic studies dealing with overall aggregative data fail to capture these sectoral characteristics.

The financial sector is represented by the banking sector index and the non-banking financial services sector index. In a similar vein, these reflect the state of the financial sector institutions and their future prospects. The bank index represents the health of the banking sector. It considers not only growth in assets and their profitability but also factors in the quality of assets and composition of assets. If banks are deploying more funds in government securities and government-sponsored directional lending, then the share of the private sector falls. This can impact the growth rate.

The Financial Services Index represents the state of the NBFC (Non-Banking Financial Services Companies) sector. Here again the growth in assets and the quality of assets step in. Also, such entities tend to be innovative in their asset allocation and more risk-taking as their cost of funds is higher. Their risk-taking can fund innovative ventures through different instruments. For our study, we have focused on the Indian economy predominantly due to two reasons. First, it has a strong and varied industrial structure with highly profitable and renowned companies, along with thriving micro, small and medium enterprises. This makes its requirements from the financial sector quite varied. Second, the COVID pandemic revealed the existence of a large migrant labor force who contribute to the supply chain and also constitute a significant part of the market for goods and services. The pandemic affected economic activities and, in turn, affected demand for financial services and products. Our framework can be applied to other economies and would reveal the structure of their real and financial sectors and the nature of dependence.

In this alternative approach, to understand the relation between financial sector development and real sector growth in different time scales, we use several non-parametric frameworks in conjunction with wavelet analysis methodology to enable multi-resolution examination. At first, Detrended Cross-Correlation Analysis (DCCA) is employed for extracting the nature association between the variables at different lags. Next, for expounding the time-varying traits of the association between the financial and real sectors, Wavelet Multiple Correlation (WMC) and Wavelet Multiple Cross Correlation (WMCC) techniques have been utilized. Diebold-Yilmaz Spillover analysis is used to critically evaluate the spillover connectedness among the assets. Finally, to comprehend the direction and extent of causal structure, Nonlinear Granger Causality Test has been used in conjunction with Maximal Overlap Discrete Wavelet Transformation (MODWT) in a scale-wise manner.

2. OBJECTIVES

For the Indian economy, the questions that we ask with respect to the relationship between financial sector development and real sector growth are:

- Is the relation similar in all time scales?
- How long do the impacts last?
- What is the nature of the association?
- Are the spillovers significant? If so, on what scale?
- Is the causality in the relationship between the two unidirectional or bidirectional?

We use a wavelet-based framework for our study which allows for granular analysis. Our framework enables us to understand, not only the directionality of the relationship, but also whether the relationships are strong or weak and during what time; do the relationships spill over, do short-term shocks have long-run consequences, are these relationships stable over all periods, and also are their lagged effects significant? Instead of using GDP as a proxy for the real sector, we study different real sectors separately. Our analysis will bring out the time-varying relationship between the financial sector and these sectors. Our study will also bring out which sectors correlate with the banking sector and the non-banking financial services sector separately.

3. PREVIOUS RESEARCH

Owing to practical implications, modelling financial and real sector interplay has received considerable traction in the literature. In this section, we briefly describe some of the previous research work that has investigated the relationship between the financial sector and the real sectors across different economies and different time scales.

Based on data from 1981 to 2000, Tang (2006) examined whether financial development would facilitate economic growth among the Asia-Pacific Economic Cooperation (APEC) countries. The paper considers the effects of three aspects of financial development on growth, namely the stock market, banking sector, and capital flows. Results suggest that among the three financial sectors, only stock market development shows a strong growth-enhancing effect, especially among the developed member countries.

Aizenman et al. (2013) suggested that developments in the financial sector had an asymmetric effect on the real sectors. The real sectors were sensitive to contractions in the financial sector, while they are not significantly responsive to expansion.

Samargandi et al. (2015) show that financial development does not have a linear positive long-run impact on economic growth. However, if a non-linear relationship is considered, then they find an inverted U-shaped relationship between finance and growth in the long run. This finding suggests that middle-income countries face a threshold point after which financial development no longer contributes to economic growth.

Ductor and Grechyna (2015) empirically evaluated the nexus of financial development, real sector, and economic growth. Their findings suggested the presence of nonlinear relationships and real sector growth heavily influenced the effects of financial sector development on economic growth.

Kenza and Eddine (2016) examine the impact of financial development on economic growth in the context of MENA countries. The measures of financial development they consider are private credit to GDP, M2/GDP, the ratio of commercial bank assets to the total of commercial bank assets, and central bank assets. Their results indicate that financial intermediaries had a negative effect on the growth rate and they suggest financial reforms to improve the quality and quantity of financial services.

Guru and Yadav (2018) examined the relationship between financial development and growth using the banking sector and stock market development indicators as independent variables and GDP per capita growth as the dependent variable. The banking sector development indicators are the size of the financial intermediaries, credit to deposit ratio (CDR), and domestic credit to private sector, and stock market development indicators are the value of shares traded and turnover ratio.

Radjenovic and Rakic (2017) examine the interdependence between financial sector development, particularly capital market development and economic growth in Serbia. The variables include capital market size, the extent of liquidity, government consumption, interest rates, and inflation rates. The Granger causality test is carried out to determine long-run causality between the variables. The results indicate that capital market development stimulates economic growth.

Silva et al. (2018) demonstrated the interconnection of financial and real sectors in the Brazilian market and that shocks from the real sector transmitted to government-owned banks. Their work suggested close monitoring of interlinks for estimating systematic risk.

Biplob and Rokeya (2018) examine the relationship between financial sector development and economic growth in Bangladesh using time series data for the period of 1977-2016. Using the Johansen Co-integration test and Granger-causality test in Vector Error Correction Model (VECM) framework, the study found significant long-run causality from financial development to economic growth.

Paun et al. (2019) selected 45 low-income, middle-income, and high-income countries covering ten years (2006–2015) and observed that financial sector development, sophistication, and performance had a statistically significant effect on economic growth.

Ghosh and Datta Chaudhuri (2020) explored the dynamic interplay of market sentiment, sectoral indices, and individual stock prices in India by applying wavelet-based methodologies. The presence of herding behavior in the long run after the global financial crisis was observed.

Raghutla and Chittedi (2020) show that BRICS nations' money supply, exchange rate, and inflation have a significant positive effect on economic growth. Thus, policymakers should increase the real sector expenditure and develop the financial sector.

Sharma and Kautish (2020) investigate the impact of financial sector development on GDP growth in the four middle-income countries of South Asia over the period of 1990–2016. Using pooled mean group (PMG) estimation, this study examines whether, for these developing countries, GDP growth has been affected by the size of market capitalization and size of market turnover in the long run which is used as a proxy for stock market development. The study finds that the impact of the banking sector on GDP growth has remained relatively low in the region.

Ibrahim and Acquah (2021) use panel data from 45 African countries from 1980 to 2016 to examine causal linkages between the financial sector and real sector variables. They apply the panel Granger Non-Causality test and find that the causal nexus between FDI and economic growth is conditioned on the indicator of economic growth. They also find feedback causality between FDI and financial sector development, and financial sector development and economic growth.

Ghosh et al. (2022) thoroughly explored the detailed dynamics of the futures market in India during normal and new normal time horizons applying appropriate indicators of spot counterparts, sectoral outlook, market sentiment, market fear, and volatility as explanatory variables. An ensemble of machine learning and explainable artificial intelligence-based frameworks suggested the futures prices of stocks belonging to different sectors were indeed predictable and predominantly driven by the spot markets and sectoral outlook.

Xu and Pal (2022) measured the impact of financial liberalization on the performance of the manufacturing sector in India using dynamic panel analysis. It was revealed that the financial liberalization policies exerted a positive influence on the overall productivity of the Indian manufacturing sector.

The impact of globalization and financial development on different socio-economic aspects in India has been documented in literature as well (Ohlan, 2017; Godil et al., 2021; Sethi et al., 2021; Panagariya, 2022). The said studies are, nonetheless, strictly restricted to a normal time horizon.

It can be observed that, although the existing literature has made considerable effort in decoding the interaction, it has remained confined to static analysis with limited variables. It, therefore, becomes imperative to extend the research towards modelling the dynamic time-varying nature of the interrelationship, and also at a granular level. Further, in the context of the current COVID pandemic which has caused worldwide instability, the relationship between the financial sector and the real sector has gained significance where demand and supply side effects have affected market outcomes and financial support in the form of interest waivers, liquidity infusion, increased government spending, and financial restructuring have gained importance. The present paper analyses whether the nature of the relationship between the financial sector and the real sector in the COVID phase is different from that of the Pre COVID phase.

4. DATA DESCRIPTION

Two separate modelings have been carried out to achieve research objectives. The first one examines the relationship between the Banking (Bank) sector with 3 real sectors, Metal, Capital Goods, and Energy. This set of variables has been referred to as Set A variables throughout the remaining portion of the paper. The other scenario deals with the evaluation of the dynamic interaction of the Financial Service (FS) sector with Automobile (Auto), Infrastructure, and Realty, as representatives of the real sector. These variables have been referred to as Set B variables onwards. To capture the interplay during Pre-COVID time horizons, daily closing returns of underlying variables from April 1st, 2019, to March 31st, 2020, have been compiled from the data repository of 'Metastock'. The same data source has been leveraged to compile daily closing returns of all variables from April 1st, 2020, to September 30th, 2020, to capture the nature of interrelationship during the COVID phase. Tables 1-4 outline the descriptive statistics of the underlying datasets of our study.

It can be clearly seen that Shapiro-Wilk and Jarque-Bera test statistics have emerged to be significant during both Pre COVID and COVID phases. Thus, the considered variables under the Set A category do not abide by normal distribution during both regimes. A clear presence of nonlinearity in all four sectors during Pre COVID phase is imminent from the outcome of Terasvirta's NN test. It is largely due to the slowing down of the Indian economy during the said time horizons which created uncertainty in the market. Interestingly, during the COVID phase, none of the variables demonstrate a sign of significant nonlinear traits. Extreme shocks and fear owing to the pandemic led the underlying variables to a bearish state. The dominance of unidirectional movement may explain the lack of nonlinearity.

Table 1 Properties of Set A Sectors Pre COVID

Properties	Bank	Metal	Capital Goods	Energy
Minimum	-0.17	-0.12	-0.15	-0.10
Maximum	0.08	0.08	0.08	0.09
Mean	-0.003	-0.002	-0.002	-0.001
Median	-0.0005	-0.002	-0.002	-0.001
Shapiro-Wilk Test	0.77***	0.94***	0.80***	0.86***
Jarque-Bera Test	3354.3***	199.61***	2433.1***	742.03***
Terasvirta's NN Test	6.03**	16.68***	9.11**	28.13***

Note: *** Significant at 1% level of Significance, ** Significant at 5% level of Significance, # Not Significant, Terasvirta's NN Test: Terasvirta's Neural Network Test

Table 2 Properties of Set A during COVID

Properties	Bank	Metal	Capital Goods	Energy
Minimum	-0.08	-0.08	-0.05	-0.03
Maximum	0.11	0.08	0.05	0.07
Mean	0.002	0.003	0.002	0.002
Median	0.002	0.004	0.001	0.003
Shapiro-Wilk Test	0.97***	0.96***	0.97**	0.97***
Jarque-Bera Test	24.23***	24.23***	8.22**	21.854***
Terasvirta's NN Test	0.073#	4.38#	0.14#	0.35#

Table 3 Properties of Set B during Pre COVID

Properties	FS	Auto	Infrastructure	Realty
Minimum	-0.16	-0.14	-0.12	-0.11
Maximum	0.09	0.1	0.07	0.06
Mean	-0.001	-0.002	-0.001	-0.001
Median	0.001	-0.002	-0.0003	0.0009
Shapiro-Wilk Test	0.75***	0.87***	0.83***	0.89***
Jarque-Bera Test	3000.6***	1244.9***	1337.3***	440.95***
Terasvirta's NN Test	74.51***	32.23***	79.28***	15.92**

Table 4 Properties of Set B Sectors Pre COVID

Properties	FS	Auto	Infrastructure	Realty
Minimum	-0.08	-0.07	-0.04	-0.07
Maximum	0.08	0.10	0.07	0.06
Mean	0.002	0.005	0.003	0.002
Median	0.002	0.004	0.002	0.004
Shapiro-Wilk Test	0.98**	0.91***	0.96***	0.98#
Jarque-Bera Test	14.01**	121.23***	61.47***	4.33*
Terasvirta's NN Test	5.96#	31.77***	10.3#	8.43#

It can be observed that the variables belonging to Set B emerged to be nonparametric during both Pre COVID and COVID regimes. The outcome of nonlinearity inspection through Terasvirta's NN test suggests during Pre COVID phase all four sectors appeared to be nonlinear in nature. Abrupt state changes in the financial market owing to economic slowdown during the said period have largely accounted for nonlinearity. On the other hand, during COVID regimes, barring the Auto sector, none of the sectors have shown signs of significant nonlinearity.

5. RESEARCH METHODOLOGY

5.1. Detrended Cross-Correlation Analysis (DCCA)

As the underlying variables of financial and real sectors have demonstrated traits of heteroscedasticity and nonlinearity, the mere usage of the orthodox correlation test would not be appropriate to draw insights into the prevailing association. Podobnik and Stanley (2008) proposed a new framework, detrended cross-correlation analysis (DCCA) based on the theoretical framework of detrended fluctuation analysis (DFA) for investigating power-law cross-correlation between two-time series need not abiding parametric properties. In this research, we have adopted an extension of the DCCA method namely, the DCCA cross-correlation coefficient proposed by Zebenede (2011) for measuring the magnitude of association between daily returns of two variables at a time. It is estimated using Eq. (1):

$$\rho_{DCCA}(s) = \frac{F_{DCCA}^2(s)}{F_{DFA}(x_i^1)(s) * F_{DFA}(x_i^2)(s)} \tag{1}$$

where, F_{DCCA} denotes the traditional fluctuation function derived from DCCA whilst F_{DFA} representing the fluctuation function generated from DFA, x_i^1 and x_i^2 denotes the two-time series under consideration. The computed ρ_{DCCA} measures the amount of cross-correlation at a selected time scale, *s*. The magnitude of the DCCA cross-correlation coefficient ranges between -1 to 1. A value close to -1 signifies a negative association whereas a positive association prevails when its value emerges close to 1.

5.2. Detrended Cross-Correlation Analysis (DCCA)

Fernández-Macho (2012) introduced WMC and WMCC techniques to overcome several computational drawbacks of scale-wise assessment correlation and cross-correlation. Basically, the frameworks are built upon generated wavelet coefficients, $W_{ijt} = \left(w_{1jt}, w_{2jt}, \dots, w_{njt}\right)$ on a multivariate stochastic process $X_t = (x_{1t}, x_{2t}, \dots, x_{nt})$, using MODWT at respective scales (λ_j). WMC $(\varphi_x(\lambda_j))$denotes a set of estimated multi-scale correlation figures by determining the square root of the regression coefficient of determination at each scale (λ_j) in a linear combination of wavelet coefficients having a maximum coefficient of determinism. The coefficient of determination regression of a variable (z_i) on a regressor set $(z_k, k \neq i)$ is computed using Eq. (2)

$$R^2 = 1 - 1/\rho^{ii} \tag{2}$$

where ρ^{ii} indicate the ith diagonal element of the inverse of the correlation matrix

Subsequently, the WMC is calculated using Eq. (3):

$$\varphi_x(\lambda_j) = \sqrt{1 - \frac{1}{\max diag\ P_j^{-1}}} \tag{3}$$

where P_j denotes the correlation matrix defined on W_{jt} and the max diag (.) operator is used for selecting the largest element.

The WMCC is computed by letting a lag (τ) between the actual and estimated figures of the criterion construct at each scale (λ_j) as shown in Eq. (4).

$$\varphi_x\tau(\lambda_j) = Cor(w_{ijt}, \widehat{w}_{ijt+\tau}) = \frac{Cor(w_{ijt}, \widehat{w}_{ijt+\tau})}{\sqrt{Var(w_{ijt})Var(\widehat{w}_{ijt+\tau})}} \tag{4}$$

5.3. Diebold-Yilmaz Spillover

To gauge the extent of volatility contagion, the spillover index (SOI) measure of Diebold and Yilmaz (2009), has been utilized in this work. It estimates the SOI by determining the forecast's error variance by implementing a vector auto-regression model. The present research has utilized the SOI index to estimate the intra-spillover rates among the four chosen sectors during Pre COVID and COVID phases.

5.4. Wavelet Decomposition

Using discrete wavelet decomposition, the original time series observation disentangled into a series of subcomponents of different frequencies reflecting linear and nonlinear components. Decomposed parts of lower frequency bandwidth prevail for longer periods whilst the components associated with higher bandwidth prevail for shorter periods. Several algorithms have been reported for implementing decomposition. In this research, MODWT has been used which has previously been successfully applied for modelling financial time series and is known for having several advantages over orthodox discrete wavelet transformation (DWT) (Ghosh and Datta Chaudhuri, 2019; Ghosh et al., 2019; Ghosh et al., 2021; Jana et al., 2020). The present research has utilized multi-resolution analysis using MODWT at 4 levels of decomposition considering the number of samples available for both Pre COVID and COVID time frames. Current work resorts to Daubechies least asymmetric (LA) wavelet filter of length 8 for the actual decomposition process. The said decomposition is combined with nonlinear causality test based on neural network models for capturing scale-wise causal structure.

5.5. Nonlinear Causality Test

The causal association of financial time series is predominantly explored via the Granger causality test. However, the said test is only capable of detecting linear causal structure owing to its fundamental properties. Literature reports several nonlinear causality tests for time series analysis. In this research, we have utilized the nonlinear Granger causality test of *the 'NlinTS'* package of R to detect the causal structure across the decomposed granular components obtained using MODWT. The said test is designed based on the incorporation of feed-forward neural networks based on two-way predictive analysis to account for nonlinearity.

6. RESULTS AND ANALYSIS

In this section, based on the methodology adopted, we examine the dynamic association of financial and real sectors across the specified time regimes.

6.1. Findings of DCCA

Tables 5-8 present the figures of DCCA-Cross-Correlation figures for underlying variables.

Table 5 Outcome of DCCA on Set A during Pre COVID Regime

	Time Scale (Days)		
	3	7	15
Bank-Metal	0.7233527	0.6798493	0.6781169
Bank-Capital Goods	-0.1339252	0.08462575	0.48167117
Bank-Energy	0.7419062	0.6684102	0.6760967
Metal-Capital Goods	0.03626816	0.14215420	0.40242120
Metal-Energy	0.8163277	0.801333	0.7822637
Capital Goods-Energy	0.001819431	0.153852819	0.456903162

Estimated DCCA coefficient figures suggest the existence of a strong positive cross correlation between Bank and Metal across all time scales. Cross-correlation between Bank and Capital Goods, on the other hand, has appeared to be relatively weaker and advocates the presence of negative association as well during 3 days lag. The Association of Bank and Energy sectors has emerged to be similar to that of Bank and Metal. Therefore, among the chosen real sectors, Metal and Energy share a comparatively stronger bond with the financial sector.

Table 6 Outcome of DCCA on Set A during the COVID Regime

	Time Scale (Days)		
	3	7	15
Bank-Metal	0.6936634	0.6437001	0.33075862
Bank-Capital Goods	-0.19594646	0.04006762	0.48167117
Bank-Energy	0.6270362	0.5595826	0.6337167
Metal-Capital Goods	-0.15978826	0.09168101	0.32339216
Metal-Energy	0.6519984	0.5794979	0.5504941
Capital Goods-Energy	-0.10206444	0.03918955	0.27305501

It can be noticed that Bank and Metal sectors are highly positively cross-correlated at 3 days and 7 days lags while their association observes a dip in 15 days scale. A relatively low degree of cross correlation has emerged for Bank and Capital Goods sector at a time scale of 7 days and 15 days lag. Bank and Energy sectors have been found to be positively associated across different time lags. On the other hand, DCCA among the subsectors of real sectors also demonstrates the presence of positive, negligible, and negative association patterns. Overall, the strength of association has seen a marginal decrease as compared to Pre COVID period.

Table 7 Outcome of DCCA on Set B during Pre COVID Regime

	Time Scale (Days)		
	3	7	15
FS-Auto	0.8092923	0.8008604	0.7772776
FS-Infrastructure	0.8675846	0.8445019	0.8246986
FS-Realty	0.7862788	0.7774274	0.7849782
Auto-Infrastructure	0.8449540	0.8191228	0.7842454
Auto-Realty	0.7372148	0.7240827	0.6979275
Infrastructure-Realty	0.7799858	0.7665851	0.7630102

Estimated DCCA coefficient figures clearly indicate the existence of a strong association across the time scales between all the pairs. All four sectors of Set B have been found to be positively associated with each other during Pre COVID regime. FS and Infrastructure sectors have emerged to share comparatively strongest association at a lag of 3 days. With the increase in time scale, the extent of association has declined for all constituent pairs. Amongst the real sectors, Auto and Infrastructure appear to be comparatively more linked to FS. This provides support to the fact that sales of these sectors depend on consumer/housing loans which are provided mostly by financial services companies.

Table 8 Outcome of DCCA on Set B during the COVID Regime

	Time Scale (Days)		
	3	7	15
FS-Auto	0.7197197	0.7095076	0.7516264
FS-Infrastructure	0.6961058	0.6592394	0.7261145
FS-Realty	0.6775208	0.6993603	0.7342715
Auto-Infrastructure	0.7566446	0.7707571	0.8004676
Auto-Realty	0.6806652	0.6648038	0.6913267
Infrastructure-Realty	0.6573807	0.6610222	0.7225326

It may be observed from Table 8 that in the COVID period, the strength of association among the pairs has diminished to some extent. However, with an increase in time scale, the extent of association has increased.

6.2. Outcome of WMC and WMCC

The following figures 1-4 exhibit the outcome of WMC-driven analyses.

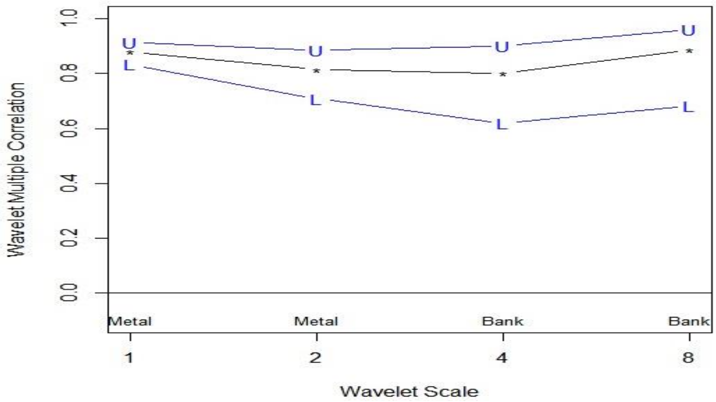

Fig. 1 Outcome of WMC Analysis of Set A during Pre-COVID Regime

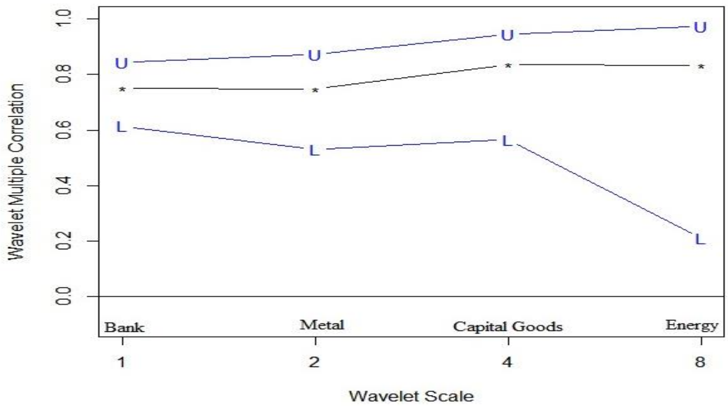

Fig. 2 Outcome of WMC Analysis of Set A Sectors during the COVID Regime

Figure 1 suggests the presence of a strong correlation between the financial and real sectors of Set A initially in scale 1 (2-4 days). It then experiences a marginal dip in scales 3 and 4 (weekly and fortnightly duration) and gains momentum again in scale 8 (monthly time horizon). Nevertheless, the co-integration manifested by WMC more or less remained stable and highly positive (0.7 on average) across the granular time scales which indicates that the considered sectors would offer very little diversification benefits during Pre COVID regime. Bank leads the co-movement in the long run while Metal dominates in the short run. On the other hand, during the COVID regime stable and positive co-integration can be observed across the scales, which also suggests little scope for diversification. Interestingly, Bank has appeared to be leading in the short run scale whilst Energy leads in the long run.

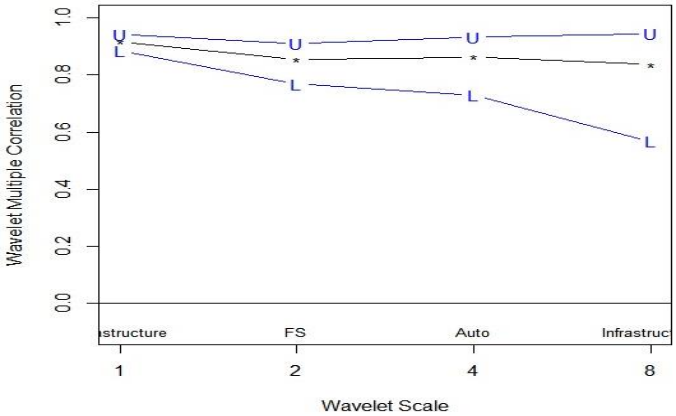

Fig. 3 Outcome of WMC Analysis of Set B during Pre COVID Regime

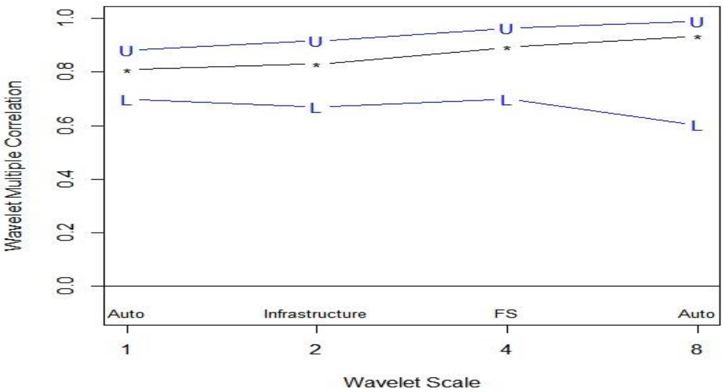

Fig. 4 Outcome of WMC Analysis of Set B during the COVID Regime

Financial and real sectors belonging to Set B demonstrate a strong positive co-integration structure during Pre COVID regime with a marginal dip in the strength of correlation on a higher scale as manifested by WMC. The average strength of correlation spanning across the four-time scales is above 0.8 roughly, which suggests the strength of co-movement of Set B sectors is relatively higher than the Set A counterparts which basically conforms to the findings of DCCA. Infrastructure has turned out to be the leader both in the shortest and longest time scales. FS and the Auto sector respectively lead in the intermediate time scales. Like Set A, Set B offers little scope for diversification. During the COVID regime (Figure 4), a monotonic increase in correlation from short to long-run scales can be observed among the underlying sectors. The auto sector and FS lead in the shortest and longest time scales, whereas infrastructure and FS lead in intermediate scales. The overall strength of association between Set B sectors has turned out to be comparatively greater than Set A sectors. However, the influence of the financial sector of Set B, i.e. FS sector, is not as impressive as that of the financial sector of Set A, i.e. Bank. We, next, present the findings of WMCC analyses for a lag of one month. In Figures 5-8, the color bar on the right-hand side indicates the strength of correlation and also the names of leading sectors across the scales.

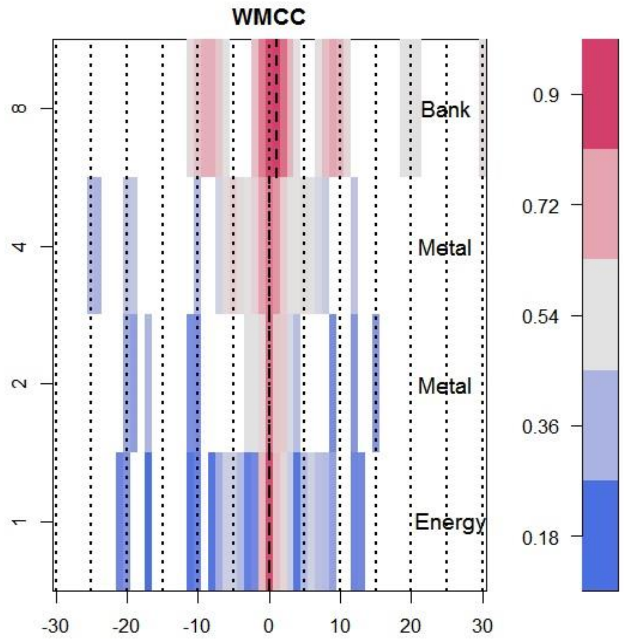

Fig. 5 Outcome of WMCC Analysis of Set A during Pre-COVID Regime

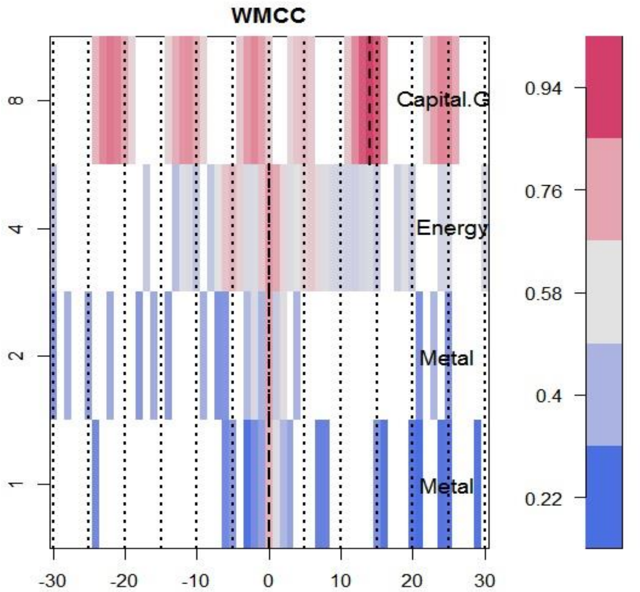

Fig. 6 Outcome of WMCC Analysis of Set A during the COVID Regime

For Set A, the strongest correlation during the Pre COVID phase can be observed at a lag of 10 days forward and backward direction. No sign of negative association can be observed. In other time scales (intraweek, weekly, and fortnightly periods), a marginal degree of association can be observed at different lags. Bank appears to be the leader in cross-correlation in long-run scales while Energy dominates the short-duration movement. During the COVID regime, the strongest correlation can be found to approximately spread across a lag of 25 days roughly at scale 4 of the monthly time horizon. It simply implies that the effect of the Pandemic has extended the prevalence of point-wise correlation across the lags. Similar to Pre COVID context, no sign of negative co-movement could be observed. A relatively low degree of correlation can be seen to be scattered across smaller time scales.

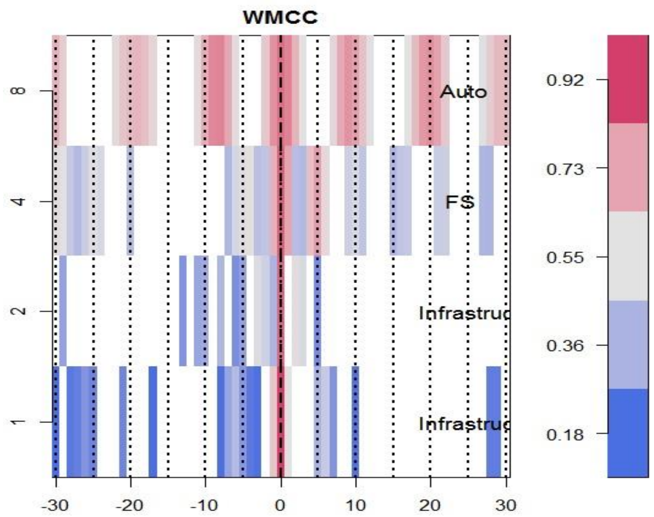

Fig. 7 Outcome of WMCC Analysis of Set B during Pre-COVID Regime

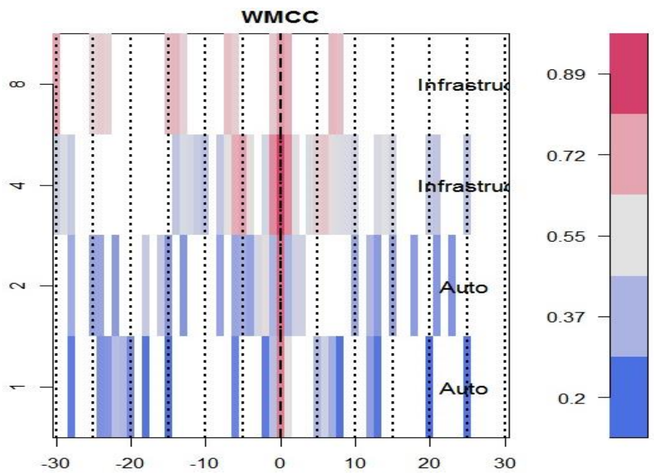

Fig. 8 Outcome of WMCC Analysis of Set B Sector during the COVID Regime

The concentration of the strongest correlation of Set B during Pre COVID context can be seen to span across entire 30-day lags at the highest time scale. Infrastructure leads in Scales 1 and 2 while FS and Auto sectors dominate scales 4 and 8, respectively. Likewise, in the earlier scenarios, no evidence of negative association can be found. For the COVID regime, the cross-correlation at different lags is lower, thus contradicting earlier cases. So FS and Sector B demonstrate different traits during the COVID pandemic.

6.3. Findings of Spillover Analysis

This section illustrates the findings of Diebold-Yilmaz spillover analysis to comprehend the nature and extent of volatility contagion from the Financial to Real sectors and inside Real sectors. The following tables 9-12 outline the results. Individual rows in the tables account for the quantum of received spillovers whilst the columns reflect the quantum of imparted spillovers.

Table 9 Outcome of Diebold-Yilmaz Spillover Analysis of Set A during Pre COVID Regime

	Bank	Metal	Capital Goods	Energy	From Others
Bank	40.21	6.09	43.34	10.36	14.95
Metal	4.49	68.93	24.94	1.64	7.77
Capital Goods	6.32	5.18	78.33	10.18	5.42
Energy	6.90	8.35	28.72	56.03	10.99
To Others	4.43	4.90	24.25	5.54	39.13

It can be seen that during Pre COVID phase Bank received high amount of spillover from the Capital Goods sector. Thus uncertainty in the Capital Goods sector resulted in a high degree of volatility in Bank sector. The metal and Energy sector received a considerable amount of spillover from the Capital Goods sector as well. Capital Goods on the other hand remained highly immune to significant contagion from other sectors. Overall it can be inferred that the shock in Capital Goods caused a ripple in the financial sector and other real sectors.

Table 10 Outcome of Diebold-Yilmaz Spillover Analysis of Set A Sector during the COVID Regime

	Bank	Metal	Capital Goods	Energy	From Others
Bank	16.99	54.45	12.76	15.81	20.75
Metal	19.48	44.79	8.31	27.42	13.80
Capital Goods	18.28	50.54	13.46	17.72	21.64
Energy	14.68	53.37	9.42	22.53	19.37
To Others	13.11	39.59	7.62	15.24	75.56

In the ongoing COVID regime, the Metal sector has emerged to be the top contributor to volatility spillover. It has affected Bank, followed by the Energy sector. Metal, on the other hand, has received the highest spillover from the Energy sector. Capital Goods, unlike Pre COVID time horizon, have remained largely dormant in transmitting volatility.

Table 11 Outcome of Diebold-Yilmaz Spillover Analysis of Set B during Pre COVID Regime

	FS	Auto	Infrastructure	Realty	From Others
FS	76.91	3.33	19.73	0.03	5.77
Auto	5.24	85.57	8.74	0.44	3.61
Infrastructure	9.27	0.28	90.07	0.39	2.48
Realty	2.54	2.37	5.58	89.52	2.62
To Others	4.26	1.49	8.51	0.22	14.48

In Set B during Pre COVID period, the FS sector received maximum volatility spillover from Infrastructure. Infrastructure has emerged to be the topmost contributor of volatility among the sectors. However, unlike Set A sectors, Set B sectors demonstrate relatively more resilience and immunity towards external shocks and interconnectedness through contagions.

Table 12 Outcome of Diebold-Yilmaz Spillover Analysis of Set B during the COVID Regime

	FS	Auto	Infrastructure	Realty	From Others
FS	12.68	26.49	11.39	49.43	21.83
Auto	13.52	28.88	9.09	48.52	17.78
Infrastructure	13.35	28.82	9.12	48.71	22.72
Realty	14.01	30.04	8.25	47.69	13.08
To Others	10.22	21.34	7.18	36.67	75.41

The structure of volatility spillover for Set B during the ongoing COVID regime, however, was completely different. It can be seen from Table 12 that FS has received maximum volatility spillover from the Realty sector, followed by the Auto sector. Defaults in auto EMI payments and housing loans have generated uncertainty in the financial services sector. In terms of imparting volatility, the Auto and Realty sector have again played a leading role. Inherent fear owing to the COVID pandemic has resulted in strong volatility transmission.

6.4 Outcome of Causality Inspection

To enable multi-resolution analysis, four levels of decomposition have been carried out using MODWT. Table 13 provides the time interpretation of scales of the decomposition process by MODWT.

Table 13 Time interpretation of different scales

Details	Wavelet Scales	Durations
D1	1	2 to 4 days(Intraweek scale)
D2	4	4 to 8 days(Weekly scale)
D3	8	8 to 16 days (Fortnightly scale)
D4	16	16 to 32 days (Monthly scale)

Tables 14-17 report the results of the nonlinear Granger causality evaluation. The bidirectional arrow, ↔ denotes the existence of bidirectional causality, and left headed arrow, ← indicates that the second variable Granger causes the first one, and the right-headed arrow, → suggests that the first variable Granger causes the second one.

Table 14 Results of Causal Assessment of Set A during Pre COVID Phase

	D1	D2	D3	D4
Bank-Metal	#	#	↔***	↔***
Bank-Capital Goods	#	#	↔***	↔***
Bank-Energy	#	#	↔***	↔***
Metal-Capital Goods	#	#	↔***	↔***
Metal-Energy	#	#	↔***	↔***
Capital Goods-Energy	#	#	↔***	↔***

Note: # Not Significant, *** Significant at 1% Level of Significance

It is evident from Table 14 that during the pre-COVID period for Set A, at short run time scales, intraweek, and weekly time horizons there was no significant causal interaction among the sectors. On the other hand, significant bidirectional causal interplay can be observed between all possible constituent pairs during fortnightly and monthly time scales.

Table 15 Results of Causal Assessment of Set A during the COVID Phase

	D1	D2	D3	D4
Bank-Metal	#	#	←***	↔***
Bank-Capital Goods	#	#	←***	↔***
Bank-Energy	#	#	↔***	↔***
Metal-Capital Goods	#	#	↔***	↔***
Metal-Energy	#	#	↔***	↔***
Capital Goods-Energy	#	#	↔***	↔***

Causal dependence analysis of Set A during the COVID regime indicates pretty similar findings as can be seen in Figure 15. However, on a fortnightly scale, the Bank sector has been causally driven by the Metal and Capital Good sectors in a unidirectional manner.

Table 16 Results of Causal Assessment of Set B during Pre COVID Phase

	D1	D2	D3	D4
FS-Auto	#	#	↔***	↔***
FS-Infrastructure	#	#	↔***	↔***
FS-Realty	#	#	↔***	↔***
Auto-Infrastructure	#	#	↔***	↔***
Auto-Realty	#	#	↔***	↔***
Infrastructure-Realty	#	#	↔***	↔***

For Set B, causality develops in higher time scales, i.e. fortnightly and monthly scales as bidirectional causality is observed for all concerned pairs (Figure16). The same result holds for the COVID phase (Figure 17).

Table 17 Results of Causal Assessment of Set B during the COVID Phase

	D1	D2	D3	D4
FS-Auto	#	#	↔**	↔***
FS-Infrastructure	#	#	↔***	↔***
FS-Realty	#	#	↔***	↔***
Auto-Infrastructure	#	#	↔***	↔***
Auto-Realty	#	#	←**	↔***
Infrastructure-Realty	#	#	↔***	↔***

7. Concluding Remarks

At the beginning of the paper, we mentioned that we will not be taking any position regarding the causality between real sector growth and financial sector growth. Our objective is not to establish whether financial sector growth leads to real sector growth or vice versa. Instead, we delve into exploring the relationship between the two at i) a granular level and ii) at different time intervals. The belief behind this approach is that some information may be lost when we take broad sweeps of time and analyze data at an aggregative level.

In terms of approach, our contribution has four distinct aspects. First, it tries to understand the relationship between financial sector development and real sector growth through stock market indicators. We contend that sectoral stock market indices represent the current and expected real future performance of the constituent companies. Second, we differentiate between the banking sector and the financial services sector as the two primarily serve two different sets of companies. This enables us to analyze one-to-one correspondence between specific sectors of the real economy with the corresponding segment of the financial sector. Third, we consider a granular approach where we break down the time series data into different time intervals and then analyze the relationships for various time intervals. Fourth, we separately analyze the data for both Pre COVID and COVID periods. This helped us in understanding the nature, intensity, and duration of the shock that India faced, along with the rest of the world.

Our analysis yields the following results. The linear correlation plots for the aggregative level data show that the association between the metal and the energy sector with the banking sector was strong in the pre-COVID period, but the strength of the association fell during the COVID period. This fall in the level of association between Pre COVID and COVID period is even more marked for the financial services sector with the auto, infrastructure, and the realty sector, the latter seeing the most decline. The decline in the overall relationship for the banking sector can be attributed to the slowing down of the economy. The result for the financial services sector is the result of loss in income and livelihood at the micro level.

The DCCA analysis gives more focus to the relationships for different time intervals. One can observe that the relationship between the banking sector and the metal sector decreased significantly during the COVID regime as the time interval increased from 3 days to 15 days. For the financial services sector, there has been an across-the-board reduction in the correlation levels in the COVID period as against the Pre COVID period for different time intervals. We can infer that as the virus spread, the effect of a fall in demand was felt by the financial services sector as time increased.

WMCC calculations for the banking and the corresponding real sectors suggest that during the COVID regime, the strongest correlation can be found to be approximately spread across a lag of 25 days as against a lag of 10 days in the Pre COVID regime. It implies that the effects of the pandemic have extended the point-wise correlation across the lags. While the capital goods sector has led the other sectors, including the banking sector, in a longer time horizon in the COVID period, the auto sector has led the financial services sector in the same period.

The results of the Diebold-Yilmaz spillover analysis suggest that in the pre-COVID regime, there was not much volatility spillover from the banking sector to the real sectors, whereas there was a strong spillover from the capital goods sector to the banking sector. This changed during the COVID regime when an increase in banking sector volatility was felt in the real sectors. Further, the metal sector did affect the banking sector significantly.

The extent of volatility spillover from the financial services sector to the corresponding real sectors was not significant in the pre-COVID period, although there was some spillover from the infrastructure sector to the financial services sector. This changed significantly during the COVID period where we observe a significant large volatility spillover from the realty sector, followed by the auto sector. Our results corroborate real-life relationships where many non-banking financial services companies suffered defaults and liquidity shortages because of a severe downturn in the realty sector during this period.

To understand causal interplay, a nonlinear Granger causality assessment has been carried out on decomposed components through MODWT. Our results indicate that for the banking sector, in the Pre COVID period there was significant both-way causality between banking sector development and real sector growth on fortnightly and monthly scales. However, in the COVID period, we observe one-way causality between the metal and capital goods sector and the banking sector on a fortnightly scale. For the financial services sector, significant two-way Granger causality was observed in the fortnightly and monthly scales. This persisted in the COVID period also.

The contribution of the study lies in breaking up the financial sector into the banking sector and the financial services sector and also relating specific real sectors with the corresponding part of the financial sector. This has enabled us to garner deeper insight into the relationship. Our granular approach has enabled us to examine the relationships in different time spans and we have observed that the results have undergone a change. We have not come across any paper in the literature that has used this approach.

The literature has not identified any specific relation between the financial sector and the real sector. Our approach supports that, but establishes that the relationship is bi-directional at granular levels. The methodology adopted enables analysis of the relationship between specific sectors of the real economy with specific sectors of the financial sector. It goes beyond the literature in looking at the relationship at different time intervals and also during pre – COVID and COVID periods. The results indicate an overall weakening of the relationships in the COVID period.

Our framework revealed which section of the real sector affected the banking and non-banking financial sector significantly, and at what time intervals. This has important policy implications as it brings to the fore which companies can get affected by external shocks and which assets can turn non-performing. The latter, in turn, has serious implications with respect to the financial health of the lenders, their capital adequacy, and policy intervention. Our approach highlights the need for sectoral asset monitoring by the financial sector in the presence of external shocks.

We have not explicitly considered the IT sector, the healthcare sector, the pharma sector, the FMCG sector, and the oil and gas sector in our study. This is on our future research agenda.

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RAZVOJ FINANSIJSKOG SEKTORA I RAST REALNOG SEKTORA – POVEZANOST, PRELIVANJE I UZROČNOST PRE I TOKOM KOVID PANDEMIJE

U ovom radu predlažemo alternativni pristup razumevanju veze između razvoja finansijskog sektora i rasta realnog sektora u Indiji. Koristimo sektorske indekse sa nacionalne Berze (NSE) kao što su: Indeks kapitalnih dobara, FMCG Indeks, Energentski Indeks, Infrastrukturni Indeks, Metal Indeks, Indeks Nekretnina i Auto Indeks kako bi prestavili realni sektor. Za predstavljanje finansijskog sektora, koristimo Bankovni Indeks i Indeks Finansijskih usluga odvojeno. Predloženi okvir proučava veze na granularnom nivou kako bi razumeli nivo povezanosti, prelivanja i uzročnosti. Takođe analiziramo odnost između finansijskog sektora i realnog sektora u periodima pre i za vreme Kovid pandemije odvojeno. Naša metodologija istraživanja uključuje korišćenje Detrended kros-korelacione analize (DCCA), Vejvlet multiple korelacije (WMC), Vejvlet multuple kros-korelacije (WMCC), Diebold-Yimlaz okvira prelivanja i ne-llinearni test kauzalnosti. Naš granularni pristup nam je omogućio da ispitamo povezanost u različitim vremenskim intervalima i primećujemo da se rezultati menjaju. Intenzitet veze takođe je drugačiji u vreme pre i tokom pandemije Kovida.

Ključne reči: *Finansijski Sektor, Realni Sektor, Detrended Kros-korelaciona analiza (DCCA), Vejvlet multipla korelacija (WMC), Vejvlet multipla kros-korelacija (WMCC), Diebold-Yilmaz prelivanje*