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A Study on the Time-Varying Volatility Connectedness Between the Sectors in the Indian Stock Market

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ABSTRACT

The main purpose of this study is to examine the connectedness between the sectors in the Indian stock market for the period 01/2011 through 12/2020. It uses TVP-VAR (Time-Varying Parameter Vector Autoregression) based connectedness approach to measure the time-varying connectedness between sectors. For the whole study period, almost 84% of the forecast error variance is explained by cross-sectional shocks within the network of Indian stock market sectors. Thus, own impact only accounts for 16% of the total variability, suggesting a robust overall dependence among the sectors. In general, results suggest that cyclical stocks are usually net transmitters of shocks, whereas non-cyclical stocks are net receivers. Important political events in the past had profound impact on the connectedness between the sectors in the Indian economy. For the portfolio managers, the main implication of the findings is that they should not overly depend on sectors to diversify their portfolios – rather, they should look at the relationship between individual stocks in this regard. And, for the policymakers, the implication is that they should keep in mind that any policy changes (shocks) to cyclical sectors should be cautiously dealt with.

INTRODUCTION

Many events such as East Asian currency crisis in 1997 and the financial crisis of 2008 have showed that considering a market in isolation is not a good idea as far as portfolio diversification is concerned. This phenomenon is heavily related to the recent trend of globalization of business. Academicians and investors have been looking for new investment opportunities to achieve the benefits of portfolio diversification (Bekaert and Harvey, 1995). A portfolio of investments across multiple markets may seem to be well-diversified although they are inter-connected and vulnerable to human biases such as panics and excessive exuberance. Hence, information on the connectedness between markets or sectors may tell investors more about the real diversification benefits in extreme situations.

Studies of Eun and Shim (1989) and Hamao et al. (1990) show that the possible scenario of contagion effect – especially in the event of financial panics – has significant implication on portfolio construction across multiple markets. The availability of powerful statistical packages and reliable data of both developed and emerging stock markets have recently contributed to big explosions of studies related to the spillover tendencies between stock markets (Baele, 2005; Diebold and Yilmaz, 2012, 2014). Similarly, spillover effect between sectors is an important issue since it may contribute to the effective diversification efforts of investors. Especially it is true since sector sensitivity to systematic risk factors may not be the only factor for efficient diversification in the presence of behavioral issues.

India has two most traded stock exchanges – Bombay Stock Exchange (BSE) and National Stock Exchange (NSE). As of February 8, 2021, India's stock market was the seventh largest in the world with a market capitalization of US$ 2.7 trillion. In February, the BSE Sensex reached the 51,000 marks while the Nifty crossed the 15,000 mark for the very first time. The benchmark Nifty gained 6.9% during the first two months in 2021. Interestingly, Economic Times claims that the stock market of India is larger than that of Canada, Germany and Saudi Arabia. It is worth mentioning that India's stock market is the second-best performer among the top 15 stock markets in 2021 and it is expected that it will overtake France to become the sixth largest in the world. Total market capitalization of France now stands at US$ 2.86 trillion. The MSCI India index has gone up 21% during the December-February period compared to 19% and 12% by MSCI Emerging Market index and MSCI World index, respectively (Iyer, 2021).

Foreign portfolio investors have pumped in nearly US$ 4.05 billion in Indian stocks since January 2021, which is the second-best inflow performance among all the emerging markets during the same period. IMF projects that India’s growth will increase sharply to 11.5% and 6.80% in fiscal years 2022 and 2023, respectively. In this decade, the compound annual growth rate of this market is about 13.22%. According to Fitch ratings in 2020, The previous decade observed the global liquidity infusion of US$ 6 trillion. Liquidity infusion amounting US$ 20 trillion has happened again recently due to the Covid-19 pandemic (International Monetary Funds, 2021). Overall, Indian stock market has been an attractive market for global investors. Hence, it deserves a thorough investigation. In this backdrop, this study has chosen to examine sectoral behavior – more specifically, dynamic connectedness between sectors.

In this paper, we examine the time-varying connectedness across 17 sectors of the Indian stock market. This paper is the first in the literature to explore dynamic connectedness/spillover between all the sectors in the Indian market. This study uses the TVP-VAR (Time-Varying Parameter Vector Autoregressive) dynamic connectedness framework of Antonakakis et al. (2020). This framework, in fact, is based on the earlier methodology given by Diebold and Yilmaz (2009, 2012, 2014). This study focuses on the connectedness between the sectors in the Indian stock market for the period 01/2011 through 12/2020. A study by Chatziantoniou et al. (2020) on Indian stock market sectors is close to this paper. However, their study only covers 10 sectors whereas this paper covers the whole Indian market by considering 17 sectors for the period 2011-20. Moreover, this paper uses NSE sectoral index whereas the Chatziantoniou et al. (2020) have used BSE sectoral index. Obviously, our study is more comprehensive in terms of its scope.

This study should have strong implications for the investors, policymakers and academicians. First, this study primarily focuses on the dynamic connectedness of the Indian sectors by considering the volatility spillover of one sector to (and from) other sectors. Thus, this study tells an investor how sectors can behave differently with respect to important economic and political shocks. Second, an investor can achieve efficient diversification by avoiding/accepting investments in a particular sector. Specially, the knowledge of dynamic connectedness between sectors should help investors to take timely actions to safeguard themselves from potential spillover of panic or exuberance. In addition, policymakers and regulators can take the right policy decisions to protect the whole market in such a case. It is understandable that even if some sectors are highly connected, a policy decision for a particular sector cannot be taken by disregarding others. Since this investigation shows the time-varying connectedness between all the sectors of Indian economy, policymakers and investors will also effectively identify the leading and lagging sectors of the economy. It demonstrates how any shock spreads through the sectoral system, which helps policymakers to achieve efficient policy implementation.

The rest of the paper is organized as follows. Next section provides a brief review of studies related to spillover of volatility shocks (or in another word, connectedness) – especially related to stock market sectors. Section 2 provides information about the data and methodology used to estimate the spillover of volatility of sector returns. Empirical results are discussed in section 3. The last section concludes the paper with some implications for the investors.

1. LITERATURE REVIEW

Early research – such as Arshanapalli and Doukas (1993); Karolyi (1995) – focused on the correlations between the mature markets because investors were not that much interested in emerging markets before mid-1990s. Some studies prefer to use volatility spillovers as a measure of connectedness between two markets. King and Wadhwani (1989) examine volatility transmission between equity markets. When investors of a market collect information from other markets, sensitive information may transmit back and forth, resulting in an increase of overall connectedness. Their findings show that an increase in volatility contributes to further increase in volatility.

A study by Hamao et al. (1990) is probably the first one that applies univariate GARCH models to analyze relationship between cross-border markets. In this study, they use a two-stage approach to analyze volatility transmission among the stocks listed in New York, London and Tokyo stock exchanges. Tsai (2014) find that Germany and the United States were the main markets to transmit information to other important international markets. In a relatively recent study, Berg and Vu (2019) trace the spillover effect of the US stock market volatility on the economic activities of 17 mature markets. Their findings show that the US market influences the performances of these markets more than their own financial markets do.

The increasing importance of emerging markets in the global arena during the 1990s motivated the academicians to perform tests of spillover between these markets. Abbas et al. (2013) report that volatility transmission takes place between different regional markets if they are economically linked. Allen et al. (2013) investigate if volatility spillovers from the Chinese stock market to its neighboring and developed markets. Their results show that volatility spillovers took place among these markets during the pre-global financial crisis era. However, there is slight evidence of spillover from China to other markets during the crisis. For the period 2008-2013, Gomes and Chaibi (2014) report significant transmission of shocks between oil price movements and some of the 21 frontier markets under study.

Yarovaya et al. (2017) test the pair-wise spillover of returns and volatility shocks between nine developed and 11 emerging futures markets and find that there is asymmetry in returns and volatility spillovers between these markets. In a recent study, Arin et al. (2020) examine financial spillovers between four major GCC stock markets. There is evidence of volatility spillovers from Saudi Arabia to Qatar, Abu Dhabi, and Dubai. Moreover, spillovers from the larger markets have increased during the post-2014 oil crisis period. Chowdhury (2020) investigates the presence and direction of stock market sentiment spillover between the GCC stock markets. The findings of this study indicate that Kuwait and Qatar stock market sentiments are not connected to other markets' sentiment and that the stock market sentiments of Saudi Arabia and the UAE are connected as well as bi-directional.

The methodologies to detect connectedness between markets have also evolved over time. Diebold and Yilmaz (2009) propose a simple measure of connectedness of asset returns and/or volatilities. Their framework is able to detect trends and bursts in spillovers. In an analysis of 19 global stock markets for the period 1992-2007, they find that return spillovers display a smooth upward trend, whereas volatility spillovers display bursts without any trend. As an extension of this method, dynamic connectedness introduced by Diebold and Yilmaz (2012, 2014) focuses on the time-varying parameters (TVP) along with vector autoregressive model (VAR). The TVP-VAR framework shows the time-varying variance and covariance structure of given data with more flexibility. Antonakakis et al. (2020) use TVR-VAR along with Monte Carlo simulation to examine currency exchange rates' transmission mechanism. Their results reveal that the euro and the Swiss franc mainly transmit shocks to other currencies during 1975-2019 period.

Gabauer et al. (2020) have also used connectedness mechanism of TVR-VAR to examine the transmission structure of Asia-Pacific sovereign bond returns. They report that during the global financial crisis in 2009, dynamic connectedness increased sharply, which confirms that monetary policies of Asia-Pacific countries are interconnected – especially during periods of financial troubles. Gupta et al. (2020) apply rolling window estimation to examine several episodes of US financial crises during the 1936-2016 period. Their findings state that stock price returns reduce and volatility increases during financial crises. Lee and Lee (2020) investigate international transmission of volatility of Northeast Asian stock market returns. They report that there is a weak relationship between the Northeast Asian markets, and that the US market influences this regional market. They also observe a time-varying behavior of connectedness.

Academicians have published a good number of studies on Indian market's sector connectedness/spillover during the last decade. However, these studies mainly use GARCH based framework to detect volatility spillovers between sectors. Nateson et al. (2013) show that BSE Sensex volatility transmits to affect most of the Indian stock market sectors. However, power and technology sectors appear to be insensitive to shocks to Sensex. A study by Chatziantoniou et al. (2020) on Indian stock market sectors examines the connectedness between 10 selected sectors. Findings show that the Indian market's sectoral connectedness is time-varying.

Connectedness among the sectors reached the highest level during the 2008 financial crisis, the double-digit inflation and stock market crash of 2011, national election of 2014, and the historic and controversial demonetization of 2016. Purankar and Singh (2020) use DCC-GARCH framework to reveal a weak spillover relationship between the commodity and equity sectoral indices. Moreover, they are slightly negatively correlated with each other, indicating opportunities for portfolio diversification. Kumar and Singh (2020) use Granger-causality technique to explore the pattern of Indian sectorial indices and show that financial and banking sectors are the best two performers, whereas pharmaceutical and real estate sectors are the worst performers.

2. DATA AND RESEARCH METHODOLOGY

Seventeen sectoral indices have been considered in this study. The sectors are Automobile, FMCG, Real Estate, Pharmaceuticals, BPM (Business Process Management) & IT, Banking, Media, Financials, Steel, Energy, Healthcare, Services, Construction & Infrastructure, Public Sector Enterprises, Private Banks, MNC, and Consumption. Daily sector returns are calculated as the logged difference of sectoral indexes of two consecutive trading days. Data covers the period January 2011 through December 2020. Data are collected from www.niftyindices.com website.

The methodology followed in this study has been successfully used by Antonakakis et al. (2020), Antonakakis et al. (2018) to trace connectedness between two variables. These studies are based on Diebold and Yilmaz (2009, 2012, 2014), which provide an approach to identify and measure connectedness/spillover between markets. We use it to find the connectedness between sectors in the Indian stock market. In their influential papers, Diebold and Yilmaz basically use a rolling window with the help of a VAR estimation process. This estimation technique suffers from sensitivity to outliers and selection of rolling-window sizes. Thus, this paper uses TVP-VAR based connectedness approach given by Antonakakis et al. (2020), which bypasses above-mentioned two drawbacks. First, we estimate a TVP-VAR(1) model, which can be expressed as follows:

$$z_t = C_t z_{t-1} + u_t \qquad u_t \sim N(\mathbf{0}, S_t) \qquad (1)$$

$$vec(C_t) = vec(C_{t-1}) + v_t \qquad v_t \sim N(\mathbf{0}, R_t) \qquad (2)$$

where z_t and u_t represent $k \times 1$ vectors and both C_t and S_t are $k \times k$ matrices. Finally, $vec(C_t)$ and v_t are $k^2 \times 1$ vectors whereas R_t is a $k^2 \times k^2$ matrix.

Next, this study estimates the *H*-day forward generalized forecast error variance decomposition (GFEVD) by using the approach developed by Koop et al. (1996). Unlike the orthorgonalized forecast error variance decomposition of Diebold and Yilmaz (2009), GFEVD is not sensitive to the ordering of variables. Since there are no theory-based models for sectoral shock spillovers, an arbitrary selection of error structure may give invalid results; thus, a GFEVD framework is believed to be a preferred approach. A TVP-VAR can be transformed into a TVP-VMA model as follows,

$$z_t = \sum_{i=1}^{p} \boldsymbol{C}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{i=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}.$$

The scaled GFEVD ($\emptyset^{g}_{ij,t}(H)$) normalizes the unscaled version of GFEVD (($\emptyset^{g}_{ij,t}(H)$) in such a way so that each row adds up to one. $\tilde{\emptyset}^{g}_{ij,t}(H)$ measures sector *j*'s impact on sector *i* in terms of its share in forecast error variance. It can be defined as the pairwise directional connectedness or spillover from sector *j* to sector *i*. This indicator is computed by,

$$\phi^{g}_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} \left(\boldsymbol{\iota}'_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{\iota}_j\right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(\boldsymbol{\iota}_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{A}'_t \boldsymbol{\iota}_i\right)} \text{ and}$$

$$\tilde{\phi}^{g}_{ij,t}(H) = \frac{\phi^{g}_{ij,t}(H)}{\sum_{j=1}^{k} \phi^{g}_{ij,t}(H)}$$

where $\sum_{j=1}^{k} \tilde{\phi}^{g}_{ij,t}(H)$ equals 1, $\sum_{i,j=1}^{k} \tilde{\phi}^{g}_{ij,t}(H) = k$, and ι_j represents to a vector with unity on the *j*th position and zero otherwise. Based upon the GFEVD framework, Diebold and Yilmaz (2012, 2014) have estimated connectedness between two variables, which can be expressed as follows:

$$TO_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^{g}_{ij,t}(H) \qquad (3)$$

$$FROM_{jt} = \sum_{j=1, i\neq j}^{k} \tilde{\phi}^{g}_{ij,t}(H) \qquad (4)$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \qquad (5)$$

$$TCI_t = \frac{1}{k} \sum_{j=1}^{k} TO_{jt} \equiv \frac{1}{k} \sum_{j=1}^{k} FROM_{jt} \qquad (6)$$

$\tilde{\phi}^{g}_{ij,t}(H)$ estimates the impact an innovation in sector *j* has on sector *i*. Thus, Equation (3) estimates the total impact a shock in sector *j* has on all other sectors, which is defined as the *total directional connectedness to others*. Equation (4), on the other hand, estimates the total influence all other sectors have on variable *j*, which is defined as the *total directional connectedness from others*. Equation (5), the difference between equation (3) and (4), gives the *net total directional connectedness* which tells us whether a sector is a net transmitter or a net receiver of shocks.

Another important feature of equation (6) is to estimate the *total connectedness index* (TCI_t) between all the sectors, which is basically the average impact of all the spillovers between the sectors. A high *TCI* for the overall market implies a stronger presence of interconnectedness between the sectors.

3. DISCUSSION OF RESULTS

Table 1 gives the descriptive statistics for the returns of 17 individual sectors. All the sectors except PSE, METAL, and REAL have made positive returns during the study period. FMCG and BANK.P have performed the best with 6% return during the past 10 years. REAL's return was the most volatile among all the sectors. BANK, BANK.P, and MEDIA are other volatile sectors after REAL. First two sectors may be volatile because banking sector is usually considered to be pro-cyclical to the economy.

Table 1. Descriptive Statistics of Sector Returns

Indices	*Min*	*Mean*	*Max*	*SD*
MNC	-12.84	0.05	7.55	1.03
PSE	-10.66	-0.01	8.3	1.28
FMCG	-11.2	0.06	7.99	1.12
IT	-12.49	0.05	8.92	1.34
SERVICE	-14.68	0.04	7.91	1.21
BANK	-18.31	0.04	10	1.57
PHARMA	-9.35	0.04	9.86	1.23
AUTO	-14.91	0.04	9.9	1.39
FINANC	-18.3	0.05	9.03	1.49
METAL	-12.33	-0.01	9.39	1.76
INFRA	-12.84	0.01	7.24	1.35
HEALTH	-8.69	0.04	8.8	1.13
BANK.P	-19.7	0.06	10.49	1.58
MEDIA	-17.88	0.01	8.04	1.58
REAL	-12.33	0	8.09	2.1
CONSUMP	-12.05	0.05	8.38	0.99
ENERGY	-10.22	0.03	8.28	1.33

Table 2 provides the static connectedness between the sectors. The diagonal elements in this table provide the own-sector effects whereas off-diagonal elements provide effects from other sectors to a particular sector. MNC, PSE, SERVICE, BANK, AUTO, FINANC, INFRA, BANK.P, CONSUMP, and ENERGY are the net transmitters of volatility to other sectors. In fact, CONSUMP and SERVICE sectors are the two biggest transmitters of shocks. On the other hand, FMCG, IT, PHARMA, METAL, HEALTH, and MEDIA are the net receivers of shocks from other sectors. The IT sector is a very strong receiver of volatility spillover. MEDIA is the next strong receiver of shocks. TCI (Total Connectedness Index) is 83.67%, indicating that almost 84% of the forecast error variance can be explained by cross-sectional shocks within the sectors of the Indian stock market. This result also implies that own impact only accounts for 16% of the total variability, suggesting a strong overall dependence among the sectors. In such a case, a portfolio manager cannot expect to achieve portfolio diversification by just spreading investments across several sectors in this market. Thus, connectedness between individual firms is also an important consideration for effective portfolio diversification.

Table 2. Average Connectedness between Sectors in the Indian Stock Market

Indices	MNC	PSE	FMCG	IT	SERVICE	BANK	PHARMA	AUTO	FINANC	METAL	INFRA	HEALTH	BANK.P	MEDIA	REAL	CONSUMP	ENERGY	FROM
MNC	12.79	4.90	6.60	2.12	6.69	5.98	2.80	8.20	6.88	4.83	6.35	3.38	6.04	3.38	3.43	10.40	5.16	87.20
PSE	5.53	14.84	2.69	0.75	5.86	6.03	2.10	6.48	6.67	7.60	9.52	2.48	5.49	3.19	5.27	5.77	9.65	85.15
FMCG	10.29	3.63	19.66	2.30	6.19	5.16	3.03	5.50	5.98	2.62	4.70	3.48	5.21	2.44	2.46	12.82	4.46	80.33
IT	6.10	2.20	3.99	29.3	11.31	3.81	4.03	4.32	4.22	2.74	4.46	4.52	3.82	1.94	2.00	6.28	4.78	70.60
SERVICE	6.36	4.70	3.75	4.23	11.31	9.90	1.96	5.87	9.97	3.89	6.66	2.36	9.71	2.76	3.92	7.02	5.55	88.68
BANK	6.07	4.98	3.33	1.54	10.52	12.30	1.54	5.93	10.88	3.99	6.51	1.88	11.98	2.66	4.22	6.38	5.23	87.69
PHARMA	5.98	3.50	4.41	2.67	3.80	2.73	22.30	4.80	3.29	2.81	4.28	21.87	2.78	2.80	2.43	6.41	3.09	77.69
AUTO	8.59	5.65	3.76	1.53	6.47	6.01	2.62	14.00	6.96	5.21	6.92	3.07	6.02	4.27	4.13	9.60	5.11	85.99
FINANC	6.51	5.31	3.57	1.58	10.20	10.47	1.65	6.28	11.57	4.02	6.66	2.02	10.23	2.90	4.38	6.95	5.60	88.42
METAL	6.56	8.45	2.15	1.13	5.69	5.60	1.87	7.16	6.03	17.05	8.92	2.23	5.03	3.63	6.17	5.54	6.69	82.94
INFRA	6.21	8.23	3.15	1.46	7.04	6.55	2.18	6.43	6.94	6.57	13.24	2.63	6.00	3.21	6.06	7.09	6.93	86.75
HEALTH	6.40	3.72	4.50	2.74	4.17	3.07	19.66	5.10	3.71	3.03	4.63	20.22	3.09	3.04	2.75	6.79	3.31	79.77
BANK.P	6.32	4.61	3.46	1.61	10.56	12.24	1.60	6.02	10.85	3.64	6.10	1.95	12.65	2.70	3.92	6.56	5.10	87.34
MEDIA	6.31	5.44	2.81	0.97	5.12	4.90	3.06	7.66	5.48	4.99	6.39	3.59	4.79	21.22	5.02	7.74	4.43	78.78
REAL	5.10	6.63	2.07	0.80	6.32	6.78	1.81	6.09	7.37	6.85	9.45	2.27	6.11	4.40	16.9	5.43	5.53	83.06
CONSUMP	9.69	4.66	7.64	2.06	6.96	5.91	2.91	8.39	6.92	3.89	6.76	3.43	5.96	3.80	3.55	12.15	5.25	87.84
ENERGY	6.23	9.78	3.79	1.53	6.53	6.03	2.15	5.63	6.68	5.66	8.07	2.52	5.82	2.52	4.01	6.92	15.84	84.15
Contribution TO others	108.33	86.46	61.75	29.06	113.51	101.24	55.06	100.15	108.91	72.44	106.41	63.74	98.15	49.70	63.82	117.76	85.93	1422.45
Contribution including own	121.13	101.3	81.42	58.47	124.82	113.54	77.39	114.16	120.49	89.50	119.65	83.96	110.81	70.92	80.75	129.91	101.77	**TCI**
Net spillover	21.13	1.31	-18.58	-41.5	24.82	13.54	-22.62	14.16	20.49	-10.50	19.65	-16.04	10.81	-29.08	-19.2	29.91	1.77	**83.67**

Figure 1 provides the conditional volatility of all the 17 sector daily returns. Since it represents the period 01/2011-12/2020, there are 2,439 daily observations. Thus, the mid-point (slightly more than 1200th observation) of this figure corresponds to the year 2015. Throughout the study period, REAL sector suffers from consistently high level of overall volatility among all the sectors. The reason could be the fact that real estate business by nature is pro-cyclical with the economy. Approximately during the 2019 election period, volatility of all the sectors has gone up significantly. However, volatility of BANK, BANK.P, and FINANC was identical and each of them reaches about 40% in 2019 (this is about half way between the 2000th and the last observation). Banking and financial sectors are also considered to be cyclical industries. Hence, this result is not surprising. Overall, despite some volatility spikes, the conditional volatility for almost all the sector returns was within a healthy limit. That is also the reason for the investors to have strong faith in this market, which in turn caused the whole market as well as the Indian economy to reach a new peak during the period 2011-20. The nature of change of volatility over time has prompted us to examine the dynamic connectedness between the Indian stock market sectors.

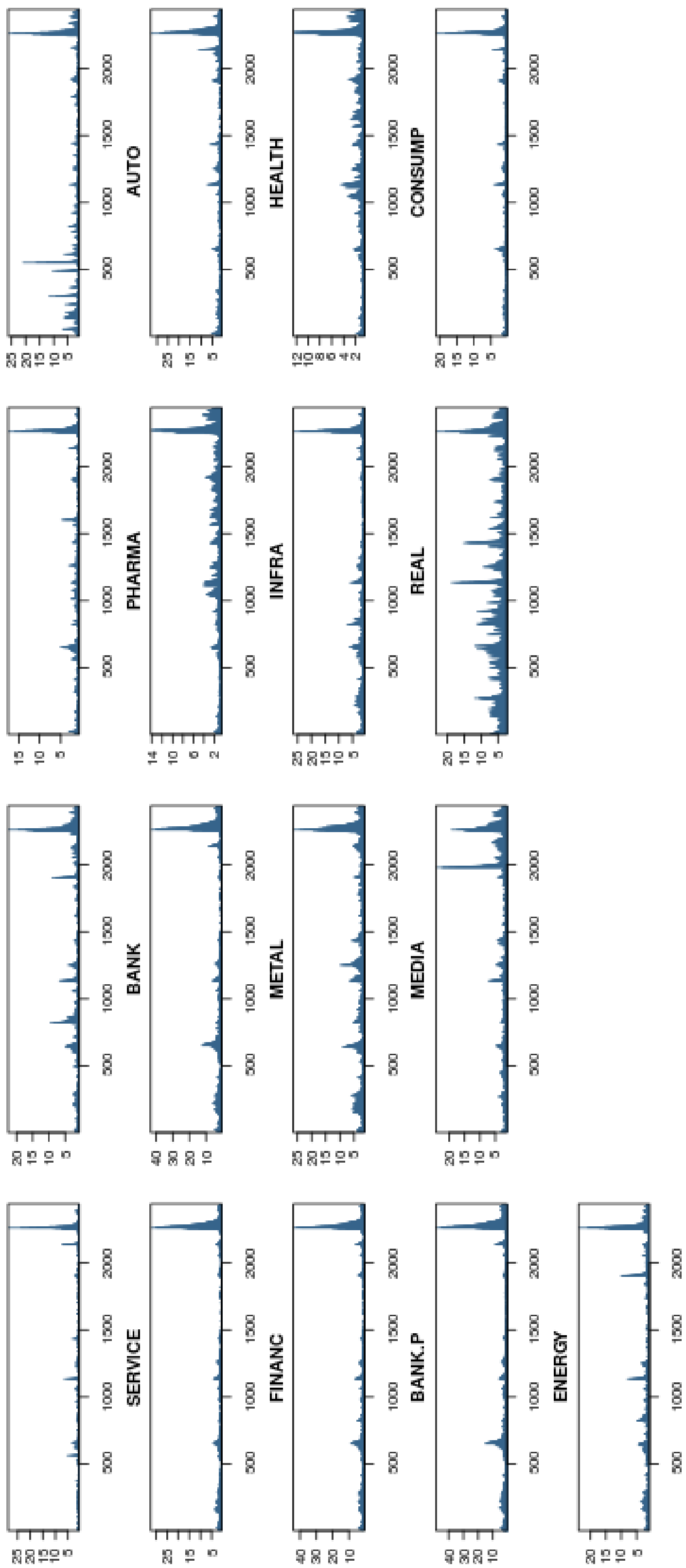

Figure 1. Conditional Volatility of Sector Returns

Figure 2 shows how sectors are interconnected through time. It is a better method to measure connectedness since this method considers a time-varying measure of dependence. The overall connectedness varies approximately between 77% to 91% during the study period. In 2012 (slightly left of start year, 2011), it reaches the maximum level (about 90%). Then it suddenly starts declining to reache approximately 79%. Overall, the total connectedness is high throughout the period, which supports the static findings in table 1. There is a very noticeable drop in connectedness in 11/2016 (close to the 1500th observation in the figure). On November 8, 2016, the Indian government announced the demonetization of all INR 500 and INR 1,000 notes. Government also announced the issuance of new INR 500 and INR 2,000 notes, which could be exchanged for the demonetized ones. This action was mainly taken to curtail the influence of underground economy and reduce the use of illegally earned and counterfeit money to finance unlawful business and terrorism. Initially, the impact is a substantial drop in connectedness around the time of demonetization. Afterwards, the effect runs through all the sectors, which increases the overall sectoral connectedness – thus, a lagged effect of an economic shock is observed.

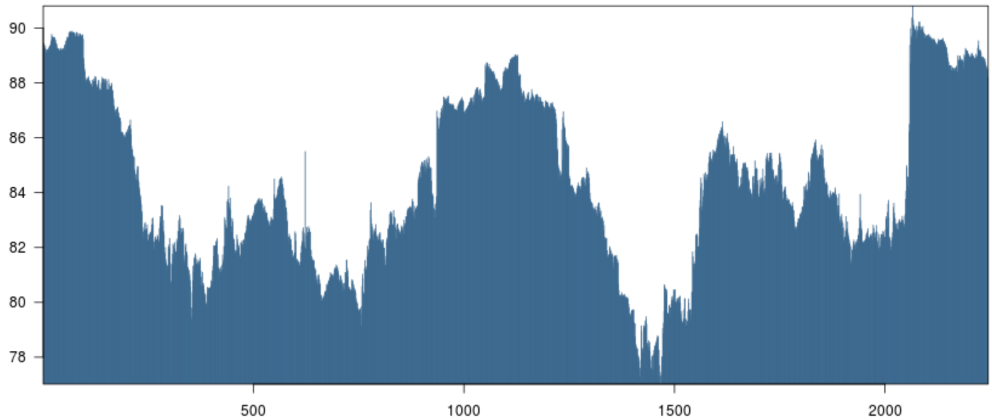

Figure 2. Total Dynamic Connectedness between Sectors in the Indian Stock Market

Effects of two election outcomes – that is, the victory of pro-business Modi government – are clearly observed in this figure. The win in 05/2014 election provides a slow yet positive impact on the connectedness. It corresponds to the time period close to the 1000th observation in this figure. However, the effect of 05/2019 landslide victory of the same government on connectedness is very vividly evident in this figure as the connectedness measure shoots up to 90% from 82% immediately. The effect of 2014 election is gradual whereas the effect of 2019 election is instantaneous. The government declared a corporate tax cut from 30% to 22% in September 2019. Interestingly, its impact on connectedness is not observed in this figure – perhaps, the effect is disguised by the re-election of Modi government or maybe the market has already expected this announcement.

There are three noticeable Indian Rupee depreciation during the study period: (i) between 04/2013 and 08/2013 the price of US dollar appreciates from INR 54.79 to INR 65.24; (ii) between 01/2018 and 09/2018 the price of US dollar appreciates from INR 63.16 to INR 73.86; and (iii) between 01/2020 and 04/2020 the price of US dollar appreciates from INR 71.23 to INR 76.67 (www.tradingeconomics.com). The impact of depreciation of INR is not clearly evident in this figure. The reason probably is that during the study period India was growing very fast and a currency depreciation was considered to be a positive news as it helped export. The double-digit inflation during the 2011-2013 period (www.ycharts.com) and sharp depreciation of INR in 2013 are the possible reasons for the overall connectedness to go down to about 80% in 2013. Overall, results indicate that connectedness increases (decreases) with respect to good (bad) news.

Figure 3 shows the net connectedness between individual sectors in the Indian stock market. That is, it shows if a sector is a net transmitter to or a receiver of shocks from other sectors. MNC, SERVICE, BANK, BANK.P, FINANC, INFRA, and CONSUMP are clearly transmitters of shocks to other sectors. The strong ability of finance and bank (both private and public) companies to transmit shocks indicates that these three sectors are the obvious channels through which the shocks to the economy are disseminated. Consumption sector is another one which ultimately affects other sectors as consumer confidence is greatly influenced by the fluctuations in the economy. On the other hand, HEALTH, FMCG, PHARMA, MEDIA, REAL are clearly net receivers of shocks. Thus, it can be suggested that these sectors are less efficient to react to major economic shocks and slow to react compared to some quick-response sectors. In general, this figure suggests that cyclical stocks are usually net transmitters of shocks whereas non-cyclical stocks are net receivers. Since cyclical stocks usually have high sensitivity to systematic risk factors, naturally these stocks react to any shocks in the economy quickly as well as sharply in terms of magnitude.

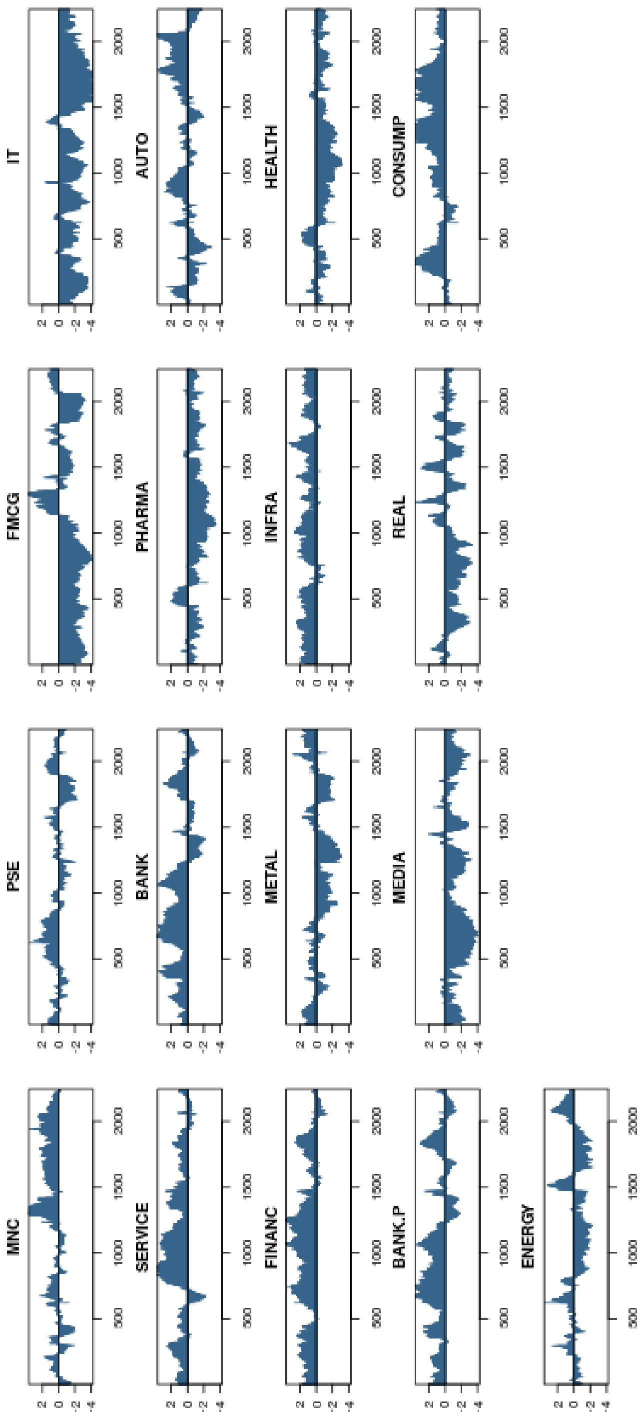

Figure 3. Net Dynamic Directional Connectedness between the Sectors

CONCLUSION AND POLICY IMPLICATIONS

This paper examines the connectedness between the 17 sectors in the Indian stock market for the period 01/2011 through 12/2020. TVP-VAR based connectedness approach is used to trace the connectedness between sectors. Results show that almost 84% of the forecast error variance can be explained by cross-sectional shocks within the sectors of the Indian stock market. It indicates that a sector's own impact, on average, only accounts for 16% of the total variability, suggesting a strong overall dependence among the sectors. In general, cyclical stocks are usually net transmitters of shocks whereas non-cyclical stocks are net receivers. Since cyclical stocks usually have high sensitivity to systematic risk factors, naturally these stocks react to any shocks in the economy quickly as well as sharply in terms of magnitude. Finally, our findings imply that any shock to economy spills from pro-cyclical sectors to non-cyclical sectors. During any crisis period, the connectedness between sectors decreases, implying that sectors react differently in a troubled time. On the other hand, in good times, sectors behave similarly and the overall connectedness increases. Interestingly, this finding contradicts with that of Chatziantoniou et al. (2021), where they report higher connectedness between sectors in crisis situation.

The leading effect of pro-cyclical sectors has an important implication for the policymakers – especially, in the event of key political and economic policy changes. Government should understand that the financial sector is extremely sensitive to relevant shocks and is a net transmitter of shocks to other sectors in the economy. Hence, the government will be more cautious in future to take economic decisions similar to demonetization in 2016. Since financial sector is a net transmitter of shocks, government must be more vigilant to pass information regarding monetary policy changes and exchange rate depreciation.

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