Uncertainties and Dynamic Connectedness Among Sectors: A Case of the USA, India, France, Germany and Russia

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Abstract

This study examines the connectedness among the sectoral indices for the USA, India, France, Germany and Russia stock markets pre and post-COVID-19. We use the Diebold and Yilmaz spillover index to examine the study's objectives. This study finds that volatility spillover is higher during COVID-19 than before COVID-19. In addition, the volatility transmission across the sectors demonstrated mixed results regarding net volatility receivers and transmitters. However, the degree of transmission is higher for the net volatility receivers than for the net volatility transmitters. This study will help policymakers draft related policies to immunise their economy and market from spillover contagions of international markets during varying pandemic scenarios. This study would also help potential investors, including foreign institutional investors, diversify their portfolios based on the sectors with net volatility transmitters and receivers.

JEL Codes: G11, G15, G41 **SDG:** SDG 17, Target 17.D

Keywords: USA, India, France, Germany, Russia, Sectoral Spillovers, COVID-19. Stock markets, Diebold, Yilmaz Index

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1. Introduction:

The globalisation of the financial markets has enhanced financial openness and helped in the broad integration of the world economy. However, some market segments remain relatively closed to outside investors, whereas others are integrated markets with an enormous scope for portfolio diversification. The local economy measures the risk of a segmented market, whereas the global economic market measures the risk of an integrated market (Bekeart and Harvey 2002). All over the world, 43,000 companies have been listed on the stock exchanges. Indian stock markets have the highest number of listed companies, contributing 12% to the world's listed companies, followed by the USA, which contributes 10% to the world's listed companies. Germany, France and Russia contribute 1% each to these listed companies. The countries under consideration for this study contribute approximately 28% of the world's listed companies.

This market structure and all the possible market intuitions work fine with the assumption of ceteris paribus, which was primarily violated when the World Health Organization declared the COVID-19 outbreak a pandemic and a "public emergency of international concern" in March 2020. Subsequently, the pandemic started spreading to different geographical locations worldwide, affecting human movement and activities. Nearly 100 million confirmed cases and approximately 2 million deaths were reported globally (See Figure 1). The economy faced significant setbacks due to shocks to the consumer and services industries, halting production and operations, resulting in difficulty in making employee payments, scarcity of employment opportunities, and disrupting the world economy. The financial markets worldwide were affected due to the unanticipated pandemic. This phenomenon was evident in the USA, India, France, Germany, and Russia (see Figure 1). At that time, there was no vaccine, and the number of deaths and new cases exponentially increased. To reduce the cases of infection, all countries imposed lockdowns and shut down many sectors except banking and securities markets, which were operated through work-from-home mode. These restrictions resulted in the slowdown of the economy and were reflected in the financial market and other sectors. Recent literature has shown the impact of COVID-19 on the global economy and financial markets (Baker et al., 2020; Caggiano et al., 2020; Ramelli & Wagner, 2020). Some studies attempted to explore the contagion effects of risk in different markets. Fasanya et al. (2020) found return and volatility spillovers between international exchange markets and epidemics.

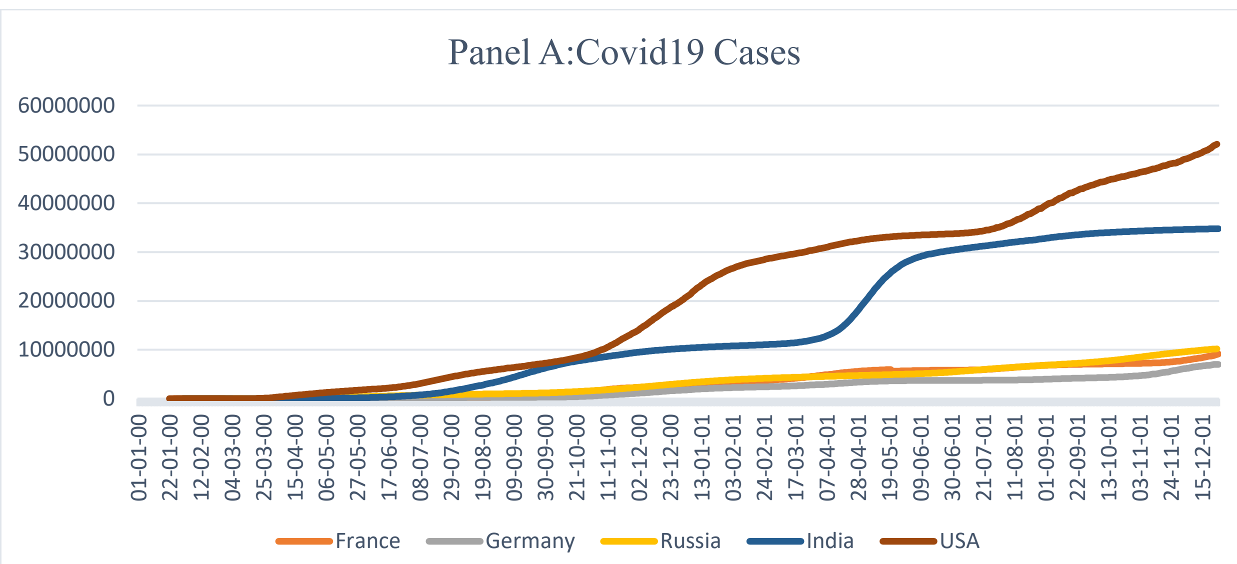
Some studies conclude that COVID-19 positively impacts sectors like healthcare, medicine, and internet industries in China (He et al., 2020) and other Asian regions (Sharma, 2020). However, COVID-19 also negatively impacts sectors like tourism and aviation, consumer goods, financial, utility and transport, energy, etc. Studies have also found varying degrees of transmission of volatility shocks during COVID-19. Some markets at the sector level are found as net receivers and transmitters of volatility shocks [Guru and Das (2021), Liu (2021), Wu et al. (2019)]. In some cases, we found mixed results in various sectors. We found the need for a comparative study to analyse whether the volatility shuck is high among the sectors during COVID-19 or not as compared to the pre-COVID-19. It is also necessary to quantify and understand the behaviour of the volatility transmission from one sector to other sectors as a transmitter or from other sectors to a particular sector as a receiver. In this study, we excluded China because most of the studies on volatility spillovers among sectors are already available in China.

While the above studies attempted to assess the impact of COVID-19 in various segments of markets and examine patterns of return volatility, a detailed study investigating the direction and extent of return and volatility transmission during the COVID-19 and pre-COVID-19 periods at the sector level has not been conducted. Hence, the present study is motivated to answer this research gap and examine the connectedness among the USA, India, France, German and Russian stock market sectoral indices during the COVID and pre-COVID periods. The sector-level analysis and the empirical implications of these nine most dynamic stock markets of the world that experienced substantial market dynamics during acute COVID-19 breakouts are the major contributions of the present study to the existing literature.

The study contributes to the existing literature in many ways. First, it attempts to determine the net transmitter and receiver of volatility during extreme scenarios like the pandemic. Second, unlike previous studies, the present study focuses on sector-level analysis of the world's nine most dynamic stock markets that experienced substantial market dynamics during acute COVID-19 breakouts. Third, the research design, the study period and the methodology have scope to bring out critical empirical implications. Finally, the study extends its scope to have a comparative analysis between during COVID and pre-COVID periods. The study is unique in that it helps policymakers draft related policies to immunise their economy and market from spillover contagions of international markets during varying pandemic scenarios. It may also help fund managers understand the risk exposure pattern and help them diversify their international portfolios.

The study finds a significant association between sector indices for both periods. However, the price changes of each sectoral indices are more significant during COVID-19 compared to pre-COVID-19. We use Diebold and Yilmaz volatility spillover to understand the volatility transmission between the sectors. In addition, it identifies sectors that are volatility net transmitters and receivers. We find that the utility sectors of India, basic materials of France, the financial sector of Germany, the consumer goods sector of the USA, and the utility sector of Russia and Germany are the highest net volatility transmitters. On the other hand, the primary material sector of Russia, the IT sector of Germany, the real estate sector of France, the utility sector of the USA, and the FMCG sector of India have the highest net volatility receivers. The study also finds that the degree of volatility transmission is higher during COVID-19.

The paper is organised as follows: section 2 contains a detailed literature review, section 3 discusses data and methodology, section 4 discusses empirical findings, and finally, section 5 concludes the study.



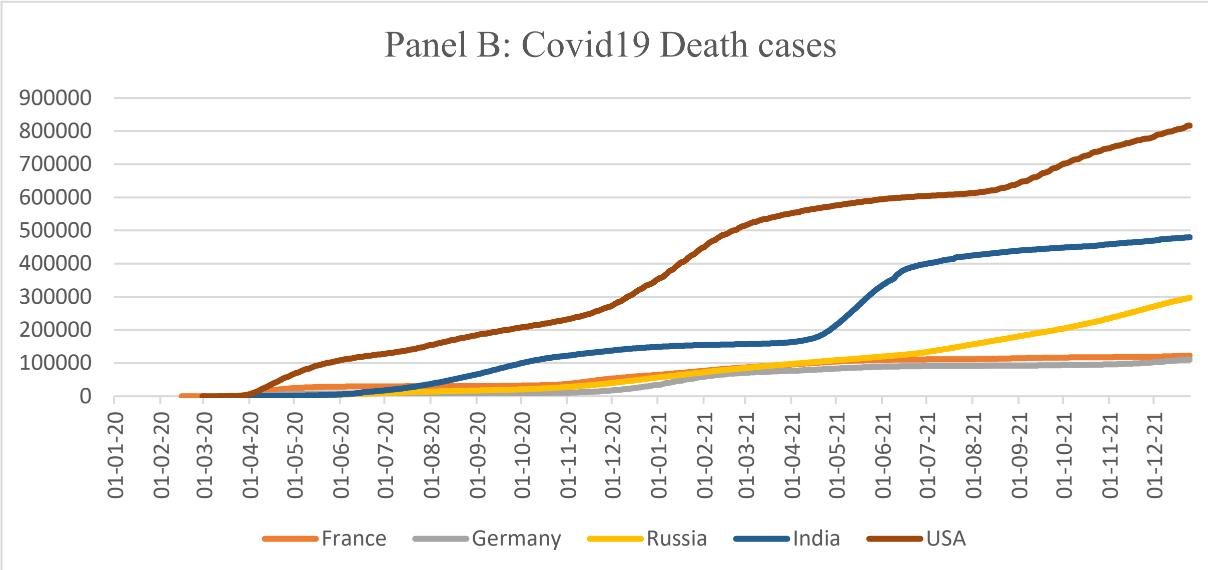


Figure 1: COVID Cases and Deaths. Source: World Health Organisation

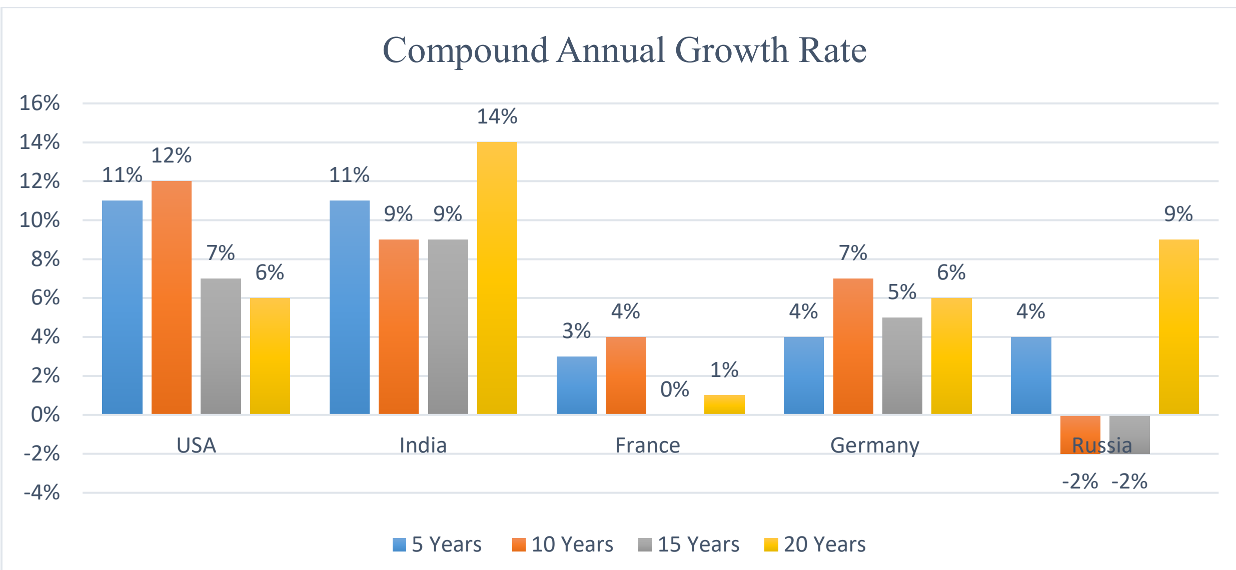


Figure 2: Compound Annual Growth Rate (CAGR). Source: Author's Calculation

2. Literature Review

Investment theories start with Markowitz's (1952) portfolio theory, which is based on probabilities of maximising the expected returns through minimising the expected risk. The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965) and Mossin (1966) depict the definitive existence of the market risk of the assets despite diversification to the maximum extent. Theories have categorised investment risks into two categories. One is the systematic risk, and the other is the unsystematic risk. Further, Fama et al. (1995, 1996, 2016 and 2017) have developed two factors, three factors, and a five factors model. The efficient market hypothesis of Fama and French (1970, 1991) attempted to capture the efficiency in weak, semi-strong, and strong forms. Black-Scholes-Merton (BSM) developed option pricing model (Black & Scholes, 1973; Merton, 1974). The arbitrage pricing theory of Roll and Ross (1980) considered the expected return of a risky asset and the risk factors of some macroeconomic variables to predict an asset return.

Guru and Das (2021) examined the sectoral spillover in 10 sectors of the Indian stock market, considering various shocks during the study period. Oil and gas received a major shock from other sectors, whereas the manufacturing sector experienced a negligible spillover impact. They found evidence of volatility spillover being the highest during COVID-19. Similarly, Shahzad et al. (2021) studied volatility spillover among sectors of the Chinese stock market and found that energy and utilities strongly influence each other. Moreover, they concluded that consumer discretionary and staples have lower connectedness than other sectors. Baruník et al. (2016) examined the spillovers among seven sectors of US stock markets such as financial, information technology, energy, consumer discretionary, consumer staples, telecommunication services, and healthcare. The results showed a clear spillover pattern in all sectors examined, but the consumer, health, and telecommunication sectors demonstrated a larger asymmetry spillover than the financial, technology, and energy sectors. Su and Liu (2021) investigated the volatility spillover structure of China's inter-sector stock indices. They found that sectors such as consumer discretionary, industrial index, and material index are systemically important industries and considered as the net volatility spillover for all industries. Kouki et al. (2011) investigated volatility spillovers between international stock markets in five sectors: banking, financial services, industrial, real estate, and oil. The result indicates three highly integrated sectors, bank, real estate, and oil, which received shock from the subprime and oil crisis; however, the financial and real estate sectors are less integrated.

Chiou-Wei (2019) posited the interaction between price volatility among five sectors and found that energy price and price volatility spillover to the corn and soybean market, and the ethanol price is intertwined between the energy and commodity markets. Mensi et al. (2013) studied the volatility spillovers between stock and commodity markets and found that the return from the S&P 500 influenced the gold and WTI indexes. Wu et al. (2019) investigated the interconnectedness in the Chinese stock market considering energy, material, industrial, consumer discrete, consumer staples, healthcare, financial, IT, telecom, and utilities sectors. Their study found these sectors to be connected. The industrial sectors were reported to be the top contributor to spillover, and telecommunication was the lowest contributor. Zhang et al. (2020) investigated a return and volatility spillover among North America and Europe's natural gas, crude oil, and electricity utility sectors. They found that European return and volatility spillover in the given time domain is stronger than that of North America. Arouri et al. (2011) examined the volatility transmission between oil and stock markets in Europe and the US at the sectoral level. Considering sectors such as automobiles and parts, financials, industrial, basic materials, technology, telecommunication, and utilities, they found significant volatility spillover between oil and other sectors. However, the spillover from oil to other European sectors is unidirectional, but it is bidirectional for the US. Choi (2022) examined the volatility spillover among the sectors in US markets during the pre-COVID period and reported that consumer discretionary and consumer staples are shock transmitters in both periods. Financial sectors transmitted less shock to other sectors in period II during COVID-19 (2 January 2018 to 31 December 2019) than in period I, pre-COVID-19 (January 2020 to May 2021). Still, these sectors also received shocks during period II. A lot of shock was transmitted from the energy and real estate sectors. Hanif et al. (2021) studied the impact of COVID-19 on the spillover between Chinese and US stock market sectors. The study found a bidirectional risk spillover from the US to Chinese sectors and vice versa during bull markets. The upside risk spillover is more profound from the US to China than from China to the

US for the broad index and nine sectors. The volatility spillovers from the US to China are from consumer discretionary, energy, materials, and telecommunications, whereas there are insignificant downside risk spillovers from China to the US. Ngene (2021) studied the dynamic connectedness of US equity sectors during the different business cycles by incorporating nine equity sectors and found that industrial, financial, consumer discretionary, and material are the higher net shock transmitters. In contrast, utilities, consumer staples, and healthcare are the net volatility receivers. It was also reported that energy and telecommunications are moderately related to economic cycles; thus, they are net volatility receivers.

Laborda and Olmo (2021) studied the volatility spillover between sectors of economic activity using network connectivity measures. They found that sectors such as banking and insurance, energy, technology, and biotechnology were the shock transmitters to the economy. Healthcare and pharmaceutical sectors were net receivers of shock, but biotechnology remained unaffected. Costola and Lorusso (2022) studied the interrelationship between the energy commodities (crude oil, natural gas, gold, and coal) market and the Russian stock market. The findings show a spillover effect from Russian oil and gas, metals, and mining to energy commodities such as crude oil and gold. The energy commodities were net transmitter rather than the net receiver. The study also found the sources of the spillover emanating from the financials and energy commodity market. Chowdhury (2021) examined the connectedness among 16 sectors in the Indian stock market and found that sectors such as MNC (Multinational Corporations), PSE (Public Sector Enterprises), service, auto, finance, infra, private banks, consumption, and energy were the net transmitters of volatility to other sectors. Out of these, the consumption and service sectors were the two biggest transmitters of shock, whereas the FMCG, IT, pharma, metal, health, and media were the net receivers of shock from other sectors. Lupu et al. (2021) examined the systemic risk spillover for European energy companies and determined the spillover from energy sectors to other economic sectors during COVID-19 and reported that sectors such as banks, capital goods, consumer services, diversified financials, retailing, and semiconductors were net volatility transmitters to the energy sector. In contrast, the remaining sectors were net volatility receivers from the energy sector.

The COVID-19 pandemic created a set of new issues that corroborated the problems associated with globalisation; for example, the markets are connected, and there is financial contagion (Nasir and Du, 2018; Baker et al., 2020; Ghabri et al., 2020). Directional spillovers and hedging have been well-researched for broad-based equity and country ETF Indices (Diebold and Yilmaz 2012, 2009; Yavas and Rezayat 2016). It is imperative to understand the aspect of volatility spillover for the portfolio design, allocation, and strategy and the benefits from hedging strategy between equity and other asset classes (Diebold et al., Diebold and Yilmaz, 2014., Kang et al., 2016; Mensi et al., 2016; Syriopoulos et al., 2015). In the process of deregulations, the markets have integrated; hence, the spillovers occurred, resulting in less scope for diversification. However, these processes have immensely helped investors access qualitative information (Forbes and Rigbbon., 2002; Markwat et al., 2009).

The present context warrants the regulatory lockdowns due to COVID-19. As a result, the real and financial markets have come under duress. The frequency of shock transmission has increased substantially in emerging and developing countries, showing greater volatility co-movement. Thus, it is better to identify and measure the interconnectedness for risk diversification and smoothening the effect of shock transmission. The stock market volatility in the Asian region comprising Hong Kong, Japan, South Korea, and Russia positively correlates with volatility at the country level during the COVID period (Sharma, 2020). The pandemic hit the Chinese aviation, tourism, and other services sectors, but sectors such as infrastructure, medicine, and internet industries scaled new heights. The performance of industries such as mining, transportation, electricity and heating in the market was poor, but healthcare, IT, and education did well during the pandemic (He et al., 2020). Moreover, industries with proportionate institutional investors and more vulnerability to the pandemic were adversely affected (Xiong et al., 2020). Zeng et al. (2019) ascertained the volatility and return connectedness among four hedging assets (bitcoin, crude oil, USD, and gold).

3. Data and Methods

3.1 Data

This study considers data from the USA, India, France, Germany and Russia based on the number of new COVID cases and deaths (see Figure 1). Each country's broad market and important sectoral indices are considered to understand the volatility transmission between the sectors. The sectors under consideration include IT, healthcare, financial, real estate, industrial goods, utilities, basic materials, communication and media, consumer goods, gas and energy. All daily data are sourced from Bloomberg. The study period is from 4 January 2010 to 7 June 2021, divided into pre-COVID-19 and during-COVID-19 periods based on the WHO announcement of COVID-19 as a pandemic on 11 March 2020. Based on the data available for all the respective countries' sectors, the study period has been considered. The details of the variables used and the study period are presented in Table 1.

Furthermore, all the countries under consideration (USA, India, France, Germany and Russia are the most dynamic stock markets of the world) are contributing approximately 53% to world market capitalisation, for which the USA appears to be the highest contributor (44%), followed by India and France (3% each), Germany (2%) and Russia (1%). Based on the Buffet indicator (Market cap as a percentage of GDP), all countries included in this study are undervalued except the USA and France. (*Source: World Bank*). Additionally, the compound annual growth rate (CAGR) represents the positive and high returns in different periods for these countries (see Figure 2).

The stationarity of the time series requires testing for further analysis; otherwise, the result will be spurious. We find the return data are stationary at a 1% level of significance as per ADF test results presented in Table 2.

Table No-1: Variables Used in this Study

Country	USA	India	France	Germany	Russia
Broad Index	S&P500	NIFTY Index	CAC40	DAX Index	RTS
Communication	Yes	--	Yes	Yes	Yes
CGoods	Yes	--	Yes	Yes	Yes
Energy	Yes	Yes	--	--	--
Financials	Yes	Yes	Yes	Yes	Yes
Industrial	Yes	Yes	Yes	Yes	--
REstate	Yes	Yes	Yes	Yes	--
Utilities	Yes	Yes	Yes	Yes	Yes
BMaterials	--	Yes	Yes	Yes	--
IT	Yes	Yes	--	--	--
Healthcare	Yes	Yes	Yes	--	Yes

Oil and Gas	--	--	Yes	--	Yes
Technology	--	--	Yes	--	
Material	Yes	--	--	--	Yes
FMCG	--	Yes	--	--	--
Media	--	Yes	--	--	--
Period of Study(daily)	04/01/2010-07/06/2021	4/01/2010-07/06/2021	31/08/2016 -07/06/2021	31/08/2016-7/06/2021	11/01/2010-7/06/2021

Table No.-2: Stationarity Test (ADF)

	USA	India	France	Germany	Russia
Broad Index	-14.63*	-13.67*	-10.85*	-10.58*	-13.97*
Communication	-14.33*		-10.62*	-10.18*	-13.90*
CGoods	-15.30*	--	-11.56*	11.76*	-13.15*
Energy	-14.03*	-13.11*	--	--	--
Financials	-14.41*	-13.66*	-10.01*	-10.46*	-13.52*
Industrials	-14.35*	-13.62*	-10.55*	-9.80*	--
REstate	-15.21*	-13.11*	-10.82*	-10.64*	--
Utilities	-15.30*	-13.47*	-10.52*	-10.44*	-13.18*
BMaterials	--	-13.51*	-10.53*	-9.78*	
IT	-14.72*	-14.24*	--	--	--
Healthcare	-15.77*	-13.85*	-10.95*	-10.95*	-13.33*
Oil and Gas	--	--	-11.98*	--	-14.45*
Technology	--	--	-1138*	-9.85*	
Material	-14.71*	--	--	-10.28*	-13.94*
FMCG	--	-14.51*	--	--	--
Media	--	12.61*	--	--	--

Note: '--' the data/sectors for the respective countries have not been considered due to unavailability of data.

3.2 Descriptive Statistics

The descriptive statistics of sectors are given country-wise for both periods. This helps understand the behaviour of price movement for each sector.

Table 3 presents the descriptive statistics of return and standard deviation of all the USA's sectors before and during COVID-19. The mean of the IT sector is the highest, followed by healthcare, S&P 500, industrial goods, and real estate. In contrast, the standard deviation of energy is the highest, followed by financials, materials, and real estate. The mean return during COVID-19 is the highest for energy and materials, followed by financials, IT, and S&P 500 sectors. The standard deviation of the energy sector is highest, followed by financials, IT, utilities, and industrial goods. Therefore, all sectors' mean returns and risk increased during COVID-19 compared to pre-COVID-19.

Table No.-3: Descriptive Statistics for the USA

	S.P500	CGoods	Healthcare	Industrial	IT	Material	REstate	Communication	Utilities	Financial	Energy
Pre COVID-19											
Observations	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657
Minimum	-7.60	-4.41	-5.25	-9.20	-7.56	-9.26	-8.48	-6.21	-5.64	-10.91	-20.08
Maximum	4.96	5.48	5.81	5.68	6.60	5.91	9.10	5.40	5.86	8.21	6.24
Mean	0.04	0.03	0.05	0.04	0.06	0.02	0.04	0.02	0.03	0.04	-0.01
Stdev	0.95	0.75	0.94	1.09	1.14	1.20	1.15	0.99	0.89	1.27	1.39
Skewness	-0.52	-0.27	-0.28	-0.57	-0.33	-0.41	-0.13	-0.28	-0.35	-0.46	-1.33
Kurtosis	6.17	4.42	3.56	5.42	3.97	4.19	6.31	3.20	4.08	6.95	18.45
During COVID-19											
Observation	324	324	324	324	324	324	324	324	324	324	324
Minimum	-11.98	-9.24	-9.99	-11.45	-13.91	-11.44	-16.55	-10.44	-11.54	-13.99	-14.28
Maximum	9.38	8.41	7.59	12.75	11.96	11.63	8.63	9.20	13.11	13.23	16.31
Mean	0.14	0.06	0.09	0.15	0.17	0.19	0.08	0.15	0.03	0.17	0.19
Stdev	1.82	1.48	1.62	2.11	2.21	2.07	2.18	1.79	2.14	2.45	3.26
Skewness	-0.61	-0.10	-0.26	-0.18	-0.28	-0.34	-1.13	-0.50	0.29	-0.06	0.16
Kurtosis	12.61	13.24	9.79	9.13	9.81	7.81	13.12	7.84	11.05	9.21	4.90

Table No.-4: Descriptive Statistics of India Pre COVID-19											
Parameter	NIFTY	Financial	FMCG	Healthcare	IT	Media	Energy	Restate	Utilities	Industrial	Materials
Obs	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657	2657
Min	-5.92	-6.55	-6.73	-6.99	-11.74	-16.37	-8.31	-11.60	-7.08	-7.48	-7.10
Max	5.32	7.82	5.38	5.21	9.33	8.37	5.47	8.43	7.51	8.16	7.11
Mean	0.03	0.05	0.06	0.03	0.04	0.01	0.02	0.00	0.00	0.01	0.01
Stdev	0.95	1.27	1.01	1.08	1.20	1.41	1.19	2.00	1.22	1.48	1.41
Skew	-0.11	0.13	-0.16	-0.21	-0.49	-0.61	-0.32	-0.25	-0.05	0.07	0.04
Kurtosis	2.34	2.59	3.40	2.45	7.99	8.56	2.77	1.99	2.18	2.32	1.48
During Covid-19											
Obs	63	63	63	63	63	63	63	63	63	63	63
Min	-3.53	-4.55	-2.28	-2.32	-3.28	-8.10	-4.41	-7.50	-4.64	-5.58	-4.40
Max	2.33	3.39	2.43	4.12	2.90	3.17	3.16	3.79	1.70	2.96	2.87
Mean	0.06	0.01	0.10	0.22	0.08	0.11	0.12	0.02	0.10	0.13	0.32
Stdev	1.04	1.49	0.91	1.16	1.12	1.74	1.31	1.83	1.12	1.44	1.33
Skew	-0.65	-0.19	0.14	0.79	-0.58	-1.75	-0.88	-1.17	-1.52	-1.02	-0.59
Kurtosis	0.95	0.84	0.75	1.53	1.18	6.18	1.68	3.39	3.80	2.81	0.95

Table 4 shows the descriptive statistics of the mean returns of all the sectors before and during COVID-19 for India. Before COVID-19, the mean returns of FMCG were the highest, followed by financial, IT, and other sectors, while the standard deviation of real estate was the highest, followed by industrial goods, basic materials, and media. During COVID-19, the mean returns of basic materials were the highest, followed by those of the healthcare, industrial, energy, and media sectors. The standard deviation of real estate is the highest, followed by media, financials, and industrial goods sectors. Therefore, the mean returns of all the sectors during COVID-19 are more than those before COVID-19, whereas the standard deviations of FMCG, utilities, industrial goods and materials have decreased during COVID-19.

Table 5 shows that before COVID-19, the average return was high for consumer goods, followed by healthcare sectors for France. The standard deviation is higher for oil and gas, followed by basic materials. During COVID-19, the mean returns were higher for consumer goods, followed by basic materials, whereas the standard deviations of real estate were higher, followed by oil and gas. Hence, the mean returns and standard deviation have increased during COVID-19 compared to pre-COVID-19 levels.

Table 6 presents the descriptive statistics of mean returns of different sectors before and during COVID-19 for Germany. Before COVID-19, the mean returns of utilities sector was the highest, followed by real estate. The standard deviation of the technology sector is highest, followed by industrial resources and healthcare. During COVID-19, the mean returns is the highest for technology followed by financial sector, whereas the standard deviation in the case of technology is the highest, followed by industrial goods and DAX Index. Hence the returns and standard deviation increased for all the sectors in Germany during COVID-19.

Table 7 shows that the mean returns and standard deviation increased for the all sectors during COVID-19 as compared to before COVID-19 for Russia. However, all sectors exhibited positive returns for both the periods. The oil and gas sectors yielded high returns with low risk before COVID-19, whereas consumer goods yielded high returns with low risk as compared to other sectors during COVID-19.

Table No.- 5: Descriptive Statistics of France

Parameter	CAC40	BMaterials	CGoods	Financials	Healthcare	Industrial	Oil.Gas	Technology	Utilities	REstate	Communication
Pre COVID-19											
Obs	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244	1244
Min	-8.39	-8.92	-6.07	-10.44	-5.66	-7.50	-16.85	-6.73	-8.27	-7.76	-6.59
Max	4.14	4.31	3.09	6.31	4.21	3.79	4.28	3.29	4.46	3.44	5.05
Mean	0.01	0.01	0.04	-0.01	0.02	0.02	-0.03	0.02	0.01	-0.06	-0.03
Stdev	0.87	1.17	0.94	0.98	0.90	0.91	1.25	1.08	1.14	1.01	0.94
Skew	-1.37	-0.68	-0.80	-1.29	-0.41	-1.09	-2.90	-0.60	-0.68	-0.66	-0.31
Kurtosis	11.18	4.45	3.98	16.13	3.68	7.53	35.83	2.92	5.00	4.46	5.18
During COVID-19											
Obs	324	324	324	324	324	324	324	324	324	324	324
Min	-12.28	-12.50	-9.06	-14.03	-7.87	-14.31	-14.47	-10.38	-15.83	-17.69	-11.39
Max	8.39	6.18	8.03	11.83	5.36	10.94	14.61	11.59	6.33	20.28	7.83
Mean	0.12	0.15	0.19	0.12	0.09	0.11	0.11	0.14	0.04	0.05	0.08
Stdev	1.72	1.69	1.59	2.36	1.26	2.31	2.72	1.86	1.96	3.59	1.51
Skew	-0.83	-1.18	-0.29	-0.38	-0.35	-0.50	0.38	0.16	-1.78	0.67	-0.83
Kurtosis	11.01	10.51	5.98	8.05	6.15	9.06	8.43	11.03	13.54	7.00	13.33

Table No.-6: Descriptive Statistics of Germany

Pre COVID-19											
Parameter	DAX.Index	BResources	CGoods	Financials	Industrial	HealthCare	Technology	Utilities	Restate	Materials	Communication
Obs	920	920	920	920	920	920	920	920	920	920	920
Min	-7.94	-9.07	-5.50	-7.84	-7.68	-6.52	-5.77	-6.96	-5.97	-9.41	-6.63
Max	3.37	6.33	4.00	3.58	3.85	4.98	6.21	5.83	6.14	5.10	4.93
Mean	0.00	-0.04	-0.01	0.00	-0.01	-0.01	0.02	0.05	0.02	-0.03	-0.02
Stdev	0.91	1.46	0.99	0.93	1.00	1.06	1.48	0.91	1.12	1.16	0.97
Skew	-1.08	-0.31	-0.61	-0.95	-0.78	-0.37	-0.21	-0.50	-0.42	-0.69	-0.28
Kurtosis	7.51	2.35	3.15	6.53	4.93	3.04	1.19	6.94	3.42	5.77	4.63
During COVID-19											
Obs	324	324	324	324	324	324	324	324	324	324	324
Min	-12.24	-11.45	-10.48	-12.22	-12.57	-10.16	-10.82	-7.47	-8.24	-11.67	-10.72
Max	10.98	8.16	8.39	9.77	9.10	6.35	9.82	5.47	7.72	8.92	6.39
Mean	0.14	0.22	0.09	0.15	0.16	0.08	0.21	0.07	0.07	0.14	0.09
Stdev	1.77	2.03	1.65	1.73	2.15	1.41	2.15	1.20	1.62	1.98	1.55
Skew	-0.47	-0.27	-0.35	-0.81	-0.63	-0.73	-0.60	-0.64	-0.33	-0.49	-0.77
Kurtosis	11.73	3.95	7.36	11.20	7.03	9.31	4.22	5.51	6.34	5.72	8.72

Table No.- 7: Descriptive Statistics of Russia

Pre COVID-19								
Parameter	RTS	Oil.Gas	EUtilities	Telecom	Fianncial	CGoods	Healthcare	Material
Obs	2652	2652	2652	2652	2652	2652	2652	2652
Min	-13.02	-11.10	-15.79	-12.83	-13.95	-12.65	-8.19	-13.81
Max	14.16	5.65	8.30	14.22	13.18	10.85	8.91	7.16
Mean	0.00	0.04	0.00	0.01	0.01	0.02	0.00	0.01
Stdev	1.71	1.24	1.41	1.36	1.40	1.09	0.61	1.70
Skew	-0.34	-0.53	-0.86	-0.42	-0.65	-0.78	0.89	-0.40
Kurtosis	7.83	5.07	10.28	10.73	10.60	17.43	101.42	4.16
During COVID-19								
Obs	324	324	324	324	324	324	324	324
Min	-11.03	-7.93	-10.77	-7.70	-10.03	-8.35	-8.18	-11.80
Max	9.23	10.25	7.37	5.85	7.47	4.41	8.91	14.77
Mean	0.15	0.11	0.07	0.06	0.23	0.17	0.002	0.14
Stdev	2.09	1.71	1.33	1.09	1.60	1.14	0.57	2.22
Skew	-0.62	0.49	-0.96	-0.87	-0.54	-1.24	0.94	-0.02
Kurtosis	6.52	6.43	17.44	11.60	6.27	10.27	114.18	9.47

3.3 Methods

Based on the literature review, it is noted that standard deviations do not adequately reflect the large asset price movements that are of most concern to policymakers. Engle (1982) developed the Autoregressive Conditional Heteroskedasticity (ARCH) model to overcome these problems. Accordingly, the principle of calculating realised return volatilities has been used for this study by applying the GARCH model. This study used the spillover index developed by Diebold and Yilmaz (2009, 2012) to capture the volatility spillover across markets.

To estimate the volatility spillover index, we first employed a univariate GARCH model with each of the sectors. We generated the conditional volatility series using the conditional volatility series of all the sectors. This spillover index helps to estimate the fraction of P-step ahead of forecast variance in one asset due to past shocks of other assets in the VAR framework. The Index is an aggregate measure that helps capture cross-market spillover, the share of cross-market error variance relative to the total variance of the asset under consideration in a generalised variance decomposition framework. The Diebold and Yilmaz (DY) spillover index provides additional and concrete information on the direction and extent of return and volatility transmission. Mathematically, the assumption is of a covariance stationary N-variable VAR of order p, that is, $x_t = \Sigma_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, where the innovations ε_t are independence and identically distributed (i.i.d.) and $\varepsilon \sim N\ (0, \Sigma)$. They can also be represented in a moving average framework as $x_t = \Sigma_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where A is an N X N matrix and obeys the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots \Phi_p A_{i-p}$. and $A_0 = I_N$ an N X N identity matrix and $A_i = 0$ for $i < 0$. The generalised VAR decomposition methodology produces variance decomposition invariant to the variable ordering. This framework allows for the innovation correlation, which accounts appropriately using the historically observed distribution of the errors. Equation (1) provides P-step-ahead forecast error variance decomposition based on this framework.

$$S_{i,j}(P) = \frac{\sigma_{jj}^{-1} \Sigma_{p=0}^{P-1} (e_i' A_p \Sigma e_j)^2}{\Sigma_{p=0}^{P-1} (e_i' A_p \Sigma A_p' e_j)} \quad (1)$$

Where Σ is the variance-covariance matrix of the residuals $\boldsymbol{\varepsilon_t}$, σ_{jj} is the standard deviation of the error term for the j^th asset, and e_i is the selection vector, with one as the i^th element and zeros otherwise. By construction, the sum of the rows of the $S_{ij}(P)$ matrix need not be equal to 1, i.e., $\Sigma_{j=1}^{N} S_{ij}(P) \neq 1$. Hence, for the spillover index calculation, each entry of this variance decomposition matrix is normalised through the row sum in the variance decomposition matrix, that is:

$$\widetilde{S_{ij}}(P) = \frac{S_{ij}(P)}{\Sigma_{j=1}^{N} S_{ij}(P)} \quad (2),$$

where $\Sigma_{j=1}^{N} \widetilde{S_{ij}}(P) = 1$ and $\Sigma_{i,j=1}^{N} \widetilde{S_{ij}}(P) = N$

Using the volatility contributions from the variance decomposition, the total volatility spillover index, which measures the contribution of volatility shocks across all variables to the total forecast error variance, is estimated as:

$$\tilde{S}(P) = \frac{\Sigma_{i,j=1, i\neq j}^{N} \widetilde{S_{ij}}(P)}{\Sigma_{i,j=1}^{N} \widetilde{S_{ij}}(P)} * 100 = \frac{\Sigma_{i,j=1, i\neq j}^{N} \widetilde{S_{ij}}(P)}{N} * 100$$

Next, the directional volatility spillovers to market i from all other markets j are defined as

$$\tilde{S}_{i.}(P) = \frac{\Sigma_{j=1,i\neq j}^{N} \widetilde{S_{\iota J}}(P)}{\Sigma_{i,j=1}^{N} \widetilde{S_{\iota J}}(P)} * 100 = \frac{\Sigma_{j=1,i\neq j}^{N} \widetilde{S_{\iota J}}(P)}{N} * 100$$

and the volatility spillovers from market i to all other markets j are estimated as:

$$\tilde{S}_{.i}(P) = \frac{\Sigma_{j=1,i\neq j}^{N} \widetilde{S_{J\iota}}(P)}{\Sigma_{i,j=1}^{N} \widetilde{S_{J\iota}}(P)} * 100 = \frac{\Sigma_{j=1,i\neq j}^{N} \widetilde{S_{J\iota}}(P)}{N} * 100$$

The difference between $\tilde{S}_{.i}(P)$ and $\tilde{S}_{i.}(P)$ is net volatility spillover from market i to all other markets j, that is:

$$\tilde{S}_{i}(P) = \tilde{S}_{.i}(P) - \tilde{S}_{i.}(P)$$

If the net volatility spillover $\tilde{S}_{i}(P)$ is positive, it infers that market i is the net transmitter of volatility, whereas if the net volatility spillover $\tilde{S}_{i}(P)$ is negative, it indicates that market i is a net receiver of volatility.

4. Empirical Results

This section presents the volatility spillover index results so as to find out the sectors that are volatility transmitters and volatility receivers.

Table 8 presents volatility spillover for the USA. Besides the directional volatility spillover, the cross-volatility spillover between the sectors ranges from 2.99% to 14.25%. The net volatility spillover is 82.60% in the pre-COVID-19 period and 85.80% in the COVID-19 period. In the pre-COVID-19 period, net volatility transmitter sectors are the USA market index, consumer goods, finance, healthcare, industrial goods, IT, and material goods. Among these sectors, the USA market index is the highest (36.2%), and the consumer goods sector is the lowest (4.6%) net volatility transmitter. The net volatility receiver sectors are communication, energy, real estate, and utility, in which the utility is the highest (-32.3%), followed by communication (-29%), and the real estate sector is the lowest net volatility receiver (-1.9%).

During COVID-19, the net volatility transmitter sectors are the USA market index, consumer goods, finance, industrial goods, and basic materials. Among the net volatility transmitters, the USA index is the highest net transmitter (33.1%), and basic material is the lowest (6%). The net volatility receiver sectors are communication, energy, healthcare, IT, real estate, and utility, in which the utility sector is the highest net volatility receiver (-33.2%), followed by real estate (-31.6%), and the communication sector is the lowest (-1.4%).

The USA market index is the largest volatility transmitter before and during COVID-19. Most sectors were volatility transmitters before the pandemic and became volatility receivers during COVID-19. Hence, overall net volatility transmission is high across the sectors in the USA during the pandemic.

Table No.-8: Volatility Spillover Index for USA

Pre COVID-19

	USA	UCgoods	UCommunication	Uenergy	Ufinan	Uhealth	Industrial	UIT	Materials	Urestate	Utility	From Others	NET
USA	14.33	8.17	4.95	7.82	10.15	10.08	11.52	11.28	10.37	7.6	3.72	85.7	36.2
UCgoods	12	17.19	6.39	5.99	7.78	10.33	8.59	9.19	7.25	7.97	7.31	82.8	2.4
UCommunication	10.52	11.42	20.47	5.5	7.16	8.55	8.04	9.91	6.32	6.65	5.48	79.5	-29
Uenergy	11.99	7.47	4.47	17.99	9.2	8.44	9.94	8.76	11.12	6.56	4.07	82	-11.6
Ufinan	13.14	7.02	4.48	7.87	15.08	8.54	11.65	8.9	10.76	8.85	3.71	84.9	4.9
Uhealth	13.46	9.43	4.96	6.55	8.61	17.2	9.66	10.35	8.36	6.71	4.71	82.8	6.4
Industrial	13.61	7.28	4.69	7.81	10.56	9.04	14.34	10.5	11.06	7.8	3.29	85.7	12.4
UIT	14.25	7.73	5.93	7.05	9.1	9.61	11.12	16.61	9.57	5.92	3.1	83.4	7.9
Materials	12.96	6.81	4.24	9.75	10.48	8.27	11.93	9.43	15.51	7.64	2.99	84.5	4.6
Urestate	10.77	7.71	4.66	6.57	10.15	7.22	9.28	6.67	8.6	20.88	7.49	79.1	-1.9
Utility	9.23	12.2	5.69	5.5	6.61	9.15	6.33	6.36	5.64	11.5	21.81	78.2	-32.3
To Others	121.9	85.2	50.5	70.4	89.8	89.2	98.1	91.3	89.1	77.2	45.9	908.6	
Including Own	136.3	102.4	70.9	88.4	104.9	106.4	112.4	108	104.6	98.1	67.7	Total	82.60%

During COVID-19													
	USA	UCgoods	UCommunication	Uenergy	Ufinan	Uhealth	Industrial	UIT	Materials	Urestate	Utility	From Others	NET
USA	13.71	12.69	9.71	3.95	8.84	8.54	11.2	10	9.69	5.74	5.95	86.3	33.1
UCgoods	12.89	15.91	9.88	4.54	9.51	7.86	10.35	9.3	8.76	5.26	5.72	84.1	30.4
UCommunication	13.57	14.2	15.09	2.95	7.18	9.03	9.37	10.1	8.42	4.44	5.64	84.9	-1.4
Uenergy	7.84	7.18	4.46	23	17.48	5.95	12.7	3.89	9.38	4.6	3.52	77	-28.9
Ufinan	10.79	9.91	6.76	8.72	15.67	6.33	13.81	6.15	10.27	6.47	5.12	84.3	17.6
Uhealth	12.73	12.87	9.45	3.8	8.28	11.28	10.7	9.03	9.9	5.93	6.03	88.7	-13.3
Industrial	11.45	10.28	6.51	6.71	12.54	6.37	16.08	6.61	10.4	6.94	6.1	83.9	27.4
UIT	14.18	14.39	10.85	2.43	7.07	8.74	9.68	13.4	9.37	4.19	5.68	86.6	-6
Materials	12.24	10.44	8.38	5.14	10.19	8.51	11.87	8.44	11.86	6.68	6.24	88.1	6
Urestate	11.96	10.48	8.14	5.09	11	6.82	11.62	8.26	9.3	10.51	6.81	89.5	-31.6
Utility	11.72	12.08	9.38	4.78	9.77	7.29	10.02	8.77	8.61	7.59	10	90	-33.2
To Others	119.4	114.5	83.5	48.1	101.9	75.4	111.3	80.6	94.1	57.9	56.8	943.5	
Including Own	133.1	130.5	98.6	71.1	117.5	86.7	127.4	94	106	68.4	66.8	Total	85.80%

Table No.-9: Volatility Spillover Index for India													
Pre COVID-19													
	India	Inenergy	Infinan	InFMCG	Inhealth	Ininds	InIT	Inmaterials	Incomuni	Inrestate	Inutility	From Others	Net
India	24.78	10.1	16.19	4.78	2.47	10.62	2.1	11.2	2.28	4.6	10.89	75.2	19.3
Inenergy	14.1	36.5	7	2.6	3.71	8.75	1.83	7.45	2.37	4.45	11.23	63.5	-6.3
Infinan	19.81	6.58	26.11	4.16	1.48	12.41	0.94	9.92	1.73	5.19	11.67	73.9	-7.7
InFMCG	10.9	4.14	7.42	53.64	3.73	5.3	1.54	5.35	0.76	1.98	5.24	46.4	-20.9
Inhealth	4.97	6.78	2.29	5.25	67.56	2.53	0.91	3.11	2.3	2.11	2.18	32.4	-12.1
Ininds	7.19	4.64	7.04	1.53	0.64	34.29	0.4	12.31	0.9	4.24	26.82	65.7	33.1
InIT	7.11	3	2.55	1.38	1.52	2.46	75.26	2.84	0.15	1.09	2.64	24.7	-14.8
Inmaterials	9.12	4.96	6.03	1.5	1.31	15.19	0.33	40.92	1.47	4.98	14.19	59.1	18.3
Incomuni	5.93	5.89	3.62	0.91	2.48	3.49	0.25	3.94	66.2	4.52	2.77	33.8	-19.2
Inrestate	8.01	5.19	7.58	1.89	2.13	11.8	0.98	8.87	1.85	39.3	12.4	60.7	-23.2
Inutility	7.38	5.93	6.44	1.52	0.87	26.24	0.63	12.38	0.8	4.34	33.47	66.5	33.5
To Others	94.5	57.2	66.2	25.5	20.3	98.8	9.9	77.4	14.6	37.5	100	602	
Including Own	119.3	93.7	92.3	79.2	87.9	133.1	85.2	118.3	80.8	76.8	133.5	Total	54.70%

During COVID-19													
	India	Inenergy	Infinan	InFMCG	Inhealth	Ininds	InIT	Inmaterials	Incomuni	Inrestate	Inutility	From Others	Net
India	11.32	12.58	6.99	4.85	4.19	11.51	6.34	13.66	6.96	5.4	16.2	88.7	3.1
Inenergy	9.33	16.99	4.96	5.34	3.65	10.29	6.94	12.19	7.58	5.7	17.02	83	35.4
Infinan	11.87	11.68	11.51	3.16	3.37	12.44	5.34	12.49	7.38	5.86	14.9	88.5	-39
InFMCG	9.38	12.89	4.04	10.75	5.47	10.02	6.65	14.1	5.68	5.78	15.24	89.2	-41.5
Inhealth	7.33	10.88	3.1	5.77	29.43	4.48	4.26	9.97	6.19	4.87	13.72	70.6	-28.9
Ininds	9.3	10.88	5.62	4.31	2.71	18.74	5.89	14.38	5.42	5.66	17.1	81.3	22.6
InIT	8.01	13.53	3.12	6.06	3.92	9.57	17.42	12.07	6.99	3.26	16.04	82.6	-28.4
Inmaterials	9.39	11.92	4.51	4.99	3.8	12.84	6.05	17.86	5.99	5.42	17.23	82.1	39.1
Incomuni	8.74	10.33	5.74	3.39	6.69	8.77	2.34	8.83	22.1	10.31	12.75	77.9	-8.6
Inrestate	9.32	11.18	6.76	5.06	4.34	10.51	4.28	9.28	10.54	16.18	12.56	83.8	-25.6
Inutility	9.09	12.51	4.65	4.76	3.6	13.46	6.15	14.21	6.6	5.98	18.98	81	71.8
To Others	91.8	118.4	49.5	47.7	41.7	103.9	54.2	121.2	69.3	58.2	152.8	908.7	
Including Own	103.1	135.4	61	58.4	71.2	122.6	71.7	139.1	91.4	74.4	171.7	Total	82.60%

Note- The transmission of volatility "from others" column indicates total volatility transmitted to a sector from the rest of the sectors. Similarly, the "to other" row means total volatility transmission from one sector to the rest of the sectors. This table shows how much volatility transmits from others and to others for individual sectors. Net volatility spillover is a difference between others and others for a particular sector. If net volatility spillover is positive, the market/the sector is said to be a volatility transmitter. If net volatility spillover is negative, the market/sector is said to be a volatility receiver.

Table 9 presents the volatility spillovers across sectors for India. Each sector has a higher own directional volatility spillover than their cross-volatility spillover. The cross-volatility spillover between the sectors ranges from 0.25% to 19.81%. The net volatility spillover was 82.60% during COVID-19, which is extensively higher than the net volatility spillover before the pandemic (54.70%). Before COVID-19, the net volatility transmitter sectors are the Indian market, industrial goods, basic materials, and utility. Among these sectors, utility is the highest volatility transmitter (33.5%), followed by industrial goods, and basic material is the lowest transmitter (18.3%). The net volatility receiver sectors are energy, finance, FMCG, healthcare, IT, communication, and real estate, in which real estate is the highest net volatility receiver (-23.2%), and energy is the lowest (-6.3%) sector.

During COVID-19, the net volatility transmitter sectors are the Indian market index, energy, industrial goods, basic materials, and utilities. Among the net volatility transmitters, the utility market index is the highest net transmitter (71.8%), and the Indian market index is the lowest (3.1%). However, the net volatility receivers are finance, FMCG, healthcare, IT, communication, and real estate, in which the FMCG sector is the highest net volatility receiver (-41.5%) and the communication sector is the lowest (-8.6%).

Hence, the Indian stock market index is a volatility transmitter in both periods. However, 60% of the sectors are net volatility receivers, whereas 40% are volatility transmitters during COVID-19. The utility sector is the highest net volatility transmitter among all the sectors before and during COVID-19. In the pre-pandemic period, the energy sector was a low net volatility receiver but became a high volatility transmitter during COVID-19.

Table 10 presents the volatility transmitters and receivers for France. The own directional volatility spillovers are higher than cross-volatility spillovers. The cross-volatility spillover between the sectors ranges from 0.15% to 14.88%. The net volatility spillover is 79.50% during COVID-19, slightly higher than before the pandemic (79%). Before COVID-19, the net volatility spillover transmitter sectors are the French market index, consumer goods, healthcare, finance, and industrial. The French market index is the highest (40.5%), and the healthcare sector is the lowest (0.4%) volatility transmitter. The net volatility receiver sectors are basic materials, oil and gas, communication, IT, real estate, and utility sectors, in which the utility sector is the highest net volatility receiver (-37.1%) and the real estate sector is the lowest (-4.7%).

During COVID-19, the net volatility transmitter sectors are the French market index, basic materials, consumer goods, healthcare, and utilities. The French market index is the highest net volatility transmitter (38.2%), and the utility sector is the lowest (2.5%). However, the net volatility receivers are communication, finance, industrial goods, oil and gas, technology, and real estate sectors, in which the real estate sector is the highest net volatility receiver (-43.1%) and the industrial goods sector is the lowest (-5.5%).

In the French stock market, 60% of the sectors are net volatility receivers, while 40% are volatility transmitters before and during COVID-19. The French stock market is the highest net volatility transmitter pre- and during COVID-19. The basic material sector is a low net volatility receiver in the pre-pandemic period but a high volatility transmitter during the pandemic. In contrast to the net volatility spillover of basic material, the utility sector alone is the highest volatility receiver before the pandemic but the lowest volatility transmitter during the pandemic. Therefore, France's market index influences the market by transmitting volatility to other sectors to a high degree.

Table No.-10: Volatility Spillover Index for France

Pre COVID-19

	France	Franbasic	FraCgoods	Fracomuni	Frafinan	Frahealth	Frainds	Fraginds	Frarestate	FraTechnology	Frautilities	From Others	Net
France	15.76	9.29	11.44	5.3	9.34	8.55	14.2	8.18	5.84	7.57	4.51	84.2	40.5
Franbasic	14.38	16.23	10.5	4.41	9.51	7.98	13.37	7.88	4.18	8.16	3.4	83.8	-7.8
FraCgoods	14.63	8.58	23	3.65	5.14	7.8	12.43	6.32	5.67	9.15	3.62	77	7.3
Fracomuni	9.4	4.55	4.3	30.98	8.51	8.21	9.83	8.27	8.52	3.54	3.89	69	-11.7
Frafinan	13.79	8.84	6.18	6.3	18.51	7.59	12.23	8.55	7.5	5.68	4.84	81.5	2.4
Frahealth	13.04	6.81	9.18	5.99	8.38	20.49	12.36	6.02	7.34	5.5	4.88	79.5	0.4
Frainds	14.65	9.07	10.91	5.92	8.37	8.32	16.53	6.53	6.96	8.54	4.2	83.5	36
Fraginds	12.7	8.3	8.34	6.18	8.86	7.66	10.91	19.7	7.19	4.57	5.59	80.3	-8.1
Frarestate	9.37	5.31	5.24	7.66	9.65	7.91	9.92	8.13	27.45	4.3	5.06	72.6	-4.7
FraTechnology	12.57	9.65	12.42	3.64	6.26	5.94	13.78	5.13	5.48	22.34	2.79	77.7	-17.2
Frautilities	10.12	5.56	5.79	8.23	9.84	9.97	10.48	7.22	9.25	3.46	20.08	79.9	-37.1
To others	124.7	76	84.3	57.3	83.9	79.9	119.5	72.2	67.9	60.5	42.8	868.9	
Including own	140.4	92.2	107.3	88.3	102.4	100.4	136	91.9	95.4	82.8	62.9	Total	79.00%

During COVID-19													
	France	Franbasic	FraCgoods	Fracomuni	Frafinan	Frahealth	Frainds	Fragínds	Frarestate	FraTechnology	Frautilities	From Others	Net
France	15.03	13.02	11.57	4.57	10.13	10.87	10.45	7.34	2.97	5.71	8.35	85	38.2
Franbasic	13.21	19.71	10.66	6.78	7.37	12.37	7.19	5.72	0.78	5.28	10.92	80.3	36.1
FraCgoods	14.88	13.17	15.68	4.08	9.29	11.06	8.9	5.71	2.79	6.46	7.99	84.3	3.9
Fracomuni	8.19	8.42	6.02	37.41	4.06	11.15	3.51	2.03	1.82	6.61	10.78	62.6	-15.2
Frafinan	13.78	11.21	10	3.38	14.81	10.59	9.56	8.53	6.04	4.55	7.55	85.2	-2.2
Frahealth	12.17	11.87	9.51	4.68	6.18	27.45	6.66	4.15	0.15	9.16	8.01	72.5	35.4
Frainds	14.49	12.69	10.2	4.33	9.41	10.37	12.89	7.64	4.2	5.64	8.12	87.1	-5.5
Fraoil and Gas	12.74	11	6.88	3.46	12.47	7.33	10.98	18.22	8.15	4.56	4.23	81.8	-22.5
Frarestate	10.45	7.6	7.36	2.43	11.98	9.8	8.41	7.38	27.62	2.04	4.95	72.4	-43.1
FraTechnology	11.13	14.07	7	7.54	4.71	13.39	8.31	5.57	0.82	16.22	11.24	83.8	-27.7
Frautilities	12.18	13.32	9.03	6.21	7.36	10.96	7.59	5.24	1.59	6.07	20.43	79.6	2.5
To Others	123.2	116.4	88.2	47.4	83	107.9	81.6	59.3	29.3	56.1	82.1	87.45	
Including Own	138.2	136.1	103.9	84.9	97.8	135.3	94.4	77.5	56.9	72.3	102.6	Total	79.50%

Note- The transmission of volatility "from others" column indicates total volatility transmitted to a sector from the rest of the sectors. Similarly, the "to other" row means total volatility transmission from one sector to the rest of the sectors. This table shows how much volatility transmits from others and to others for individual sectors. Net volatility spillover is a difference between others and others for a particular sector. If net volatility spillover is positive, the market/the sector is said to be a volatility transmitter. If net volatility spillover is negative, the market/sector is said to be a volatility receiver.

For Germany, the own directional volatility spillover is high in the case of each sector for both periods, as presented in Table 11. Besides the directional volatility spillover, the cross-volatility spillover between the sectors ranges from 0.04% to 18.17%. The net volatility spillover is 68.00% in the period before COVID-19. However, during COVID-19, the net volatility spillover increased to 78.70%. Before COVID-19, the net volatility transmitter sectors were the German market index, consumer goods, communication, finance, industrial goods, and materials. Among these indices, the German market index is the highest volatility transmitter (35.8%), followed by industrial goods (35.4%), and the consumer goods sector is the lowest transmitter (4.00%). The net volatility receiver sectors are basic resources, healthcare, real estate, technology, and utility, in which the real estate sector is the highest net volatility receiver (-42.2%) and the technology sector is the lowest (-22.1%).

Similarly, during COVID-19, the net volatility transmitter sectors were the German stock market, communication, financial, healthcare, material, and utilities. Among the net volatility transmitters, the utility sector is the highest net transmitter (29.6%), and the material sector is the lowest (6.9%). However, the net volatility receivers are basic resources, industrial goods, and technology, in which the technology sector is the highest net volatility receiver (-27.6%) and the consumer goods sector is the lowest (-15.3%).

The German market and its different sectors are higher net volatility transmitters during COVID-19 than before COVID-19. The net volatility of the German market index was the highest net transmitter before the pandemic but is a low volatility transmitter during the pandemic. Moreover, the utility sector has the highest volatility receiver in the pre-pandemic period and the highest volatility transmitter during the pandemic. Therefore, it can be concluded that the degree of volatility transmission was high among the German sectors during the pandemic.

Table 12 presents the volatility transmitters and receivers for Russia. The cross-volatility spillover between the sectors ranges from 5.3% to 20.89%. The net volatility spillover is 73.40% during COVID-19, a little higher than the net volatility spillover (72.60%) before COVID-19. Before COVID-19, the net volatility transmitter sectors were the Russian market index, finance, and industrial goods. Among these sectors, the finance sector has the highest net volatility transmitter (8.9%), followed by industrial goods (7.7%), and the Russian market index has the lowest net volatility transmitter (2.3%). The net volatility receiver sectors are consumer goods, utility, basic materials, and FMCG, in which the basic material sector is the highest net volatility receiver (-15%) and the utility sector is the lowest (-1%).

During COVID-19, the net volatility transmitter sectors were the Russian market index, consumer goods, utilities, and finance. Among the net volatility transmitters, the utility sector has the highest net transmitters (35.4%), and the Russian market index has the lowest (4.8%). However, the net volatility receiver sectors are basic material, FMCG, and industrial goods, in which the basic material sector is the highest net volatility receiver (-38.9%), followed by the industrial goods sector, and FMCG is the lowest (-23.4%).

Table No.-11: Volatility Spillover Index for Germany

Pre COVID-19

	Germany	Bresources	GraCgoods	Gracomuni	Grafinan	Grahealth	Grainds	Gramaterials	Grarestate	GraTechnology	Grautility	From Others	Net
Germany	18.72	3.33	8.67	8.65	18.17	6.6	15.69	12.01	1.43	5.14	1.57	81.3	35.8
Bresources	10.57	34.63	3.42	5.93	10.37	4.68	11.46	10.06	1.04	7.57	0.28	65.4	-42.2
GraCgoods	12.42	1.65	30.96	7.09	12.64	5.34	11.5	8.96	1.76	4.57	3.1	69	4
Gracomuni	10.14	2.06	5	41.72	9.87	2.96	10.04	9.65	3.6	3.01	1.95	58.3	18
Grafinan	17.95	3.37	8.78	8.35	18.2	6.95	15.65	12.44	1.3	5.69	1.32	81.8	35.1
Grahealth	13.82	2.63	8.54	6.79	14.24	22.12	12.46	10.18	2.77	5.32	1.13	77.9	-26.2
Grainds	16.31	3.47	7.98	7.61	16.4	6.37	21.3	11.41	1.46	6.58	1.1	78.7	35.4
Gramaterials	11.86	3.34	6.63	9.19	11.92	4.91	12.35	31.04	2.82	5.29	0.64	69	28.4
Grarestate	6.25	0.27	4.37	8.14	5.28	5.52	5.55	10.05	51.09	1.65	1.82	48.9	-28.8
GraTechnology	11.26	2.79	6.52	4.76	12.54	5.9	13.84	9.38	0.57	32.42	0.04	67.6	-22.1
Grautility	6.51	0.32	13.12	9.78	5.52	2.47	5.6	3.23	3.39	0.69	49.39	50.6	-37.6
To Others	117.1	23.2	73	76.3	116.9	51.7	114.1	97.4	20.1	45.5	13	748.4	
Including Own	135.8	57.9	104	118	135.1	73.8	135.4	128.4	71.2	77.9	62.4	Total	68.00%

During COVID-19													
	Germany	Bresources	GraCgoods	Gracomuni	Grafinan	Grahealth	Grainds	Gramaterials	Grarestate	GraTechnology	Grautility	From Others	Net
Germany	13.86	5.29	8.7	8.92	14.5	10.4	8.99	10.1	4.32	5.24	9.68	86.1	10.2
Bresources	7.63	29.24	8.43	5.04	8.58	5.92	4.62	10.16	4.32	5.61	10.47	70.8	-21
GraCgoods	12.08	6.04	14.23	6.85	12.67	8.5	9.4	10.02	6.44	5.34	8.44	85.8	-15.3
Gracomuni	8.09	4.84	3.68	26.91	10.06	13.44	4.63	7.35	4.63	5.08	11.28	73.1	8.6
Grafinan	13.29	5.57	8.46	9.26	14.68	10.77	8.63	9.99	3.59	5.73	10.03	85.3	24.6
Grahealth	10.17	4.14	7.59	11.15	12.17	20.97	5.78	7.23	4.66	6.02	10.13	79	21.9
Grainds	11.37	5.17	7.39	7.5	12.54	9.59	14.53	9.63	6.37	6.55	9.37	85.5	-19.5
Gramaterials	10.1	5.02	7.68	8.25	11.42	10.9	7.26	22.47	4.88	3.81	8.21	77.5	6.9
Grarestate	5.64	2.61	4.74	10.43	6.72	10.37	4.54	8.93	30.33	3.64	12.07	69.7	-18.4
GraTechnology	9.33	6.47	6.83	7.9	11.16	10.14	7.54	5.49	4.85	18.92	11.38	81.1	-27.6
Grautility	8.66	4.7	6.98	6.41	10.08	10.89	4.64	5.48	7.19	6.48	28.49	71.5	29.6
To Others	96.3	49.8	70.5	81.7	109.9	100.9	66	84.4	51.3	53.5	101.1	865.4	
Including Own	110.2	79.1	84.7	108.6	124.6	121.9	80.5	106.8	81.6	72.4	129.5	Total	78.70%

Note- The transmission of volatility "from others" column indicates total volatility transmitted to a sector from the rest of the sectors. Similarly, the "to other" row means total volatility transmission from one sector to the rest of the sectors. This table shows how much volatility transmits from others and to others for individual sectors. Net volatility spillover is a difference between others and others for a particular sector. If net volatility spillover is positive, the market/the sector is said to be a volatility transmitter. If net volatility spillover is negative, the market/sector is said to be a volatility receiver.

The Russian market index is the lowest net volatility transmitter in both periods. Moreover, most Russian sectors are volatility receivers before COVID-19. However, during COVID-19, the majority of sectors are volatility transmitters. In the pre-COVID-19 period, the consumer goods and utility sectors were net volatility receivers, but they were net volatility transmitters during COVID-19. In contrast to the net volatility spillover of these two sectors, the industrial goods sector was a net volatility transmitter before the pandemic. Still, it was a net volatility receiver during the pandemic. Therefore, the Russian market index influences the market by transmitting volatility to other sectors. Hence, it can be concluded that the degree of volatility transmission was high among Russia's sectors during the pandemic.

Table No.-12: Volatility Spillover Index for Russia

Pre COVID-19									
	Russia	Incgood	Rsutil	Rsfinan	Rsmat	RsFMCG	Rsinds	From Others	Net
Russia	26.27	10.81	9.82	15.47	10.44	10.46	16.73	73.7	2.3
Incgood	11.16	27.11	15.42	13.82	6.33	10.57	15.58	72.9	-1.2
Rsutil	10.14	15.41	27.1	13.4	6.25	13.36	14.34	72.9	-1
Rsfinan	14.38	12.45	12.08	24.42	8.76	11.32	16.59	75.6	8.9
Rsmat	13.54	7.96	7.85	12.22	34.07	15.15	9.22	65.9	-15
RsFMCG	11.14	10.91	13.79	12.97	12.44	27.98	10.76	72	-1.7
Rsinds	15.63	14.1	12.98	16.67	6.64	9.44	24.54	75.5	7.7
To Others	76	71.7	71.9	84.5	50.9	70.3	83.2	508.5	
Including Own	102.3	98.8	99	109	84.9	98.3	107.8	Total	72.60%
During COVID-19									
	Russia	Incgood	Rsutil	Rsfinan	Rsmat	RsFMCG	Rsinds	From Others	Net
Russia	23.38	15.08	17.85	15.44	8.28	14.67	5.3	76.6	4.8
Incgood	9.28	37.05	16.34	14.05	5.49	7.84	9.94	62.9	28.8
Rsutil	13.42	15.37	27.28	16.07	6.34	9.22	12.28	72.7	35.4
Rsfinan	12.9	19.1	18.18	25.91	5.12	9.87	8.93	74.1	16.8
Rsmat	14.43	15.28	17.68	14.3	23.64	7.89	6.78	76.4	-38.9
RsFMCG	20.89	14.28	15.9	17.39	5.4	20.84	5.3	79.2	-23.4
Rsinds	10.44	12.63	22.1	13.65	6.84	6.34	27.99	72	-23.5
To Others	81.4	91.7	108.1	90.9	37.5	55.8	48.5	513.9	
Including Own	104.7	128.8	135.3	116.8	61.1	76.7	76.5	Total	73.40%

Note- The transmission of volatility "from others" column indicates total volatility transmitted to a sector from the rest of the sectors. Similarly, the "to other" row means total volatility transmission from one sector to the rest of the sectors. This table shows how much volatility transmits from others and to others for individual sectors. Net volatility spillover is a difference between others and others for a particular sector. If net volatility spillover is positive, the market/the sector is said to be a volatility transmitter. If net volatility spillover is negative, the market/sector is said to be a volatility receiver.

4. Conclusion and Implication of the Study

This study focused on the impact of the COVID-19 pandemic on sectoral indices in the countries most affected by COVID-19 in terms of the number of infected cases. Further, these countries contribute 53% to world market capitalisation and 28% to world-listed companies. The sectoral indices (such as basic material, consumer goods, industrial goods, healthcare, financial services, FMCG, Telecom, IT, real estate, energy, and utilities) and major market index of most affected countries such as the USA, India, France, Germany and Russia were considered for the analysis. The study attempted to observe the interrelationship between sectors before and during the pandemic. Data in the form of returns of indices are used for generating time-varying volatility series that acts as an input for the application of the Diebold and Yilmaz volatility spillover index developed in 2012. The descriptive statistics demonstrate that average returns and standard deviation increased during the pandemic compared to the pre-pandemic period. All data are found to be stationary based on the ADF test.

We applied a spillover index developed by Diebold and Yilmaz to estimate the directional volatility spillover and net volatility spillover effect among the sectors. The analysis was conducted for two periods, before and after the pandemic, to find the connectedness among the sectors of international markets. The study shows that the own directional volatility spillover is higher than the cross-volatility spillovers among the sectors. The volatility spillover from the broad market index to other sectors acted as a transmitter during the COVID-19. The volatility transmission across the sectors, including the broad market, demonstrated mixed results for net receivers and net transmitters. However, the transmission degree as a transmitter was higher than that as a receiver between the sectors during COVID-19. India's basic material, energy, industrial goods, and utility sectors are net volatility transmitters.

In contrast, India's communication, finance, IT, real estate and FMCG and healthcare sectors are net volatility receivers. This study's findings are aligned with Chowdhury (2021). The study findings of European countries such as Russia, Germany and France are almost similar to those of Lupu et al. (2021). In the case of the USA, basic materials, consumer goods, financial services, and industrial goods are net volatility transmitters. In contrast, communication, Energy, IT real estate, utility and healthcare are net volatility receivers. This study's findings are quite similar to those provided by Ngene (2021). The study also shows that the volatility spillover was high among the sectors during COVID-19 compared to the pre-COVID-19 period, which is relevant to the study by (Guru and Das, 2021). We conclude that the highest net volatility transmitters sectors are the Utility sector of India, the basic materials of France; the financial sector of Germany; the consumer goods sector of the USA, and the Utility sector of Russia and Germany. The highest net volatility receivers are the basic material sector of Russia, the IT sector of Germany, the Real estate sector of France, the Utility sector of the USA, and the FMCG sector of India. Finally, the study concludes that the degree of volatility spillover among the sectors is very high for all the countries during COVID-19. Hence, COVID-19 substantially impacts the relationship between sectoral indices of various countries.

These study findings guide investors in understanding the degree of volatility transmission between the sectors during pandemics. Also, they can identify sectors whose highest volatility receivers and transmitters are in each country. This study will help policymakers draft policies to immunise their economy and market from spillover contagions of international markets during varying pandemic scenarios. It will also guide potential local investors and foreign institutional investors in diversifying their portfolios by including and excluding each country's sectors in this study based on the net transmitters and receivers. Risk-averse investors may prefer to add stocks from the sectors with the highest net transmitters to their portfolios. In contrast, risk-taker investors may prefer to add the stocks to the portfolio from the highest net receivers' sector.

Future studies can consider region-wise and segment-wise factors, such as equity, debt, commodity, currency, and crude oil markets, to capture the volatility transmission during uncertainty.

References

Adekoya, O. B., Oliyide, J. A., & Tiwari, A. K. (2022). Risk transmissions between sectoral Islamic and conventional stock markets during COVID-19 pandemic: What matters more between actual COVID-19 occurrence and speculative and sentiment factors?. Borsa Istanbul Review, 22(2), 363-376.
https://doi.org/10.1016/j.bir.2021.06.002

Arouri, M. E. H., Jouini, J., & Nguyen, D. K. (2011). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. Journal of International money and finance, 30(7), 1387-1405.
https://doi.org/10.1016/j.jimonfin.2011.07.008

Arouri, M. E. H., Lahiani, A., & Nguyen, D. K. (2011). Return and volatility transmission between world oil prices and stock markets of the GCC countries. Economic Modelling, 28(4), 1815-1825.
https://doi.org/10.1016/j.econmod.2011.03.012

Baruník, J., Kočenda, E., & Vácha, L. (2016). Asymmetric connectedness on the US stock market: Bad and good volatility spillovers. Journal of Financial Markets, 27, 55-78.
https://doi.org/10.1016/j.finmar.2015.09.003

Bekaert, G., & Harvey, C. R. (2002). Research in emerging markets finance: looking to the future. Emerging markets review, 3(4), 429-448.
https://doi.org/10.1016/S1566-0141(02)00045-6

Belhassine, O. (2020). Volatility spillovers and hedging effectiveness between the oil market and Eurozone sectors: A tale of two crises. Research in International Business and Finance, 53, 101195.
https://doi.org/10.1016/j.ribaf.2020.101195

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. Journal of political economy, 81(3), 637-654.
https://doi.org/10.1086/260062

Caggiano, G., Castelnuovo, E., & Figueres, J. M. (2020). Economic policy uncertainty spillovers in booms and busts. Oxford Bulletin of Economics and Statistics, 82(1), 125-155.
https://doi.org/10.1111/obes.12323

Chiou-Wei, S. Z., Chen, S. H., & Zhu, Z. (2019). Energy and agricultural commodity markets interaction: an analysis of crude oil, natural gas, corn, soybean, and ethanol prices. The Energy Journal, 40(2).
https://doi.org/10.5547/01956574.40.2.schi

Choi, S. Y. (2022). Dynamic volatility spillovers between industries in the US stock market: Evidence from the COVID-19 pandemic and Black Monday. The North American Journal of Economics and Finance, 59, 101614. Available at https://www.sciencedirect.com/science/article/pii/S1062940821002102. Accessed on 17 February, 2022.
https://doi.org/10.1016/j.najef.2021.101614

Costola, M., & Lorusso, M. (2022). Spillovers among energy commodities and the Russian stock market. Journal of Commodity Markets, 100249.
https://doi.org/10.1016/j.jcomm.2022.100249

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal, 119(534), 158-171.
https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of forecasting, 28(1), 57-66.
https://doi.org/10.1016/j.ijforecast.2011.02.006

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Mea ring the connectedness of financial firms. Journal of econometrics, 182(1), 119-134.
https://doi.org/10.1016/j.jeconom.2014.04.012

Diebold, F. X., & Yilmaz, K. (2015). Trans-Atlantic equity volatility connectedness: US and European financial institutions, 2004-2014. Journal of Financial Econometrics, 14(1), 81-127.
https://doi.org/10.2139/ssrn.3680198

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. The journal of Finance, 25(2), 383-417.
https://doi.org/10.2307/2325486

Fama, E. F. (1991). Efficient capital markets: II. The journal of finance, 46(5), 1575-1617.
https://doi.org/10.1111/j.1540-6261.1991.tb04636.x

Fama, E. F., & French, K. R. (1995). Size and book-to-market factors in earnings and returns. The Journal of Finance, 50(1), 131-155.
https://doi.org/10.1111/j.1540-6261.1995.tb05169.x

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. The journal of finance, 51(1), 55-84.
https://doi.org/10.1111/j.1540-6261.1996.tb05202.x

Fama, E. F., & French, K. R. (2016). Dissecting anomalies with a five-factor model. The Review of Financial Studies, 29(1), 69-103
https://doi.org/10.1093/rfs/hhv043

Fama, E. F., & French, K. R. (2017). International tests of a five-factor asset pricing model. Journal of Financial Economics, 123(3), 441-463.
https://doi.org/10.1016/j.jfineco.2016.11.004

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market co-movements. The journal of Finance, 57(5), 2223-2261.
https://doi.org/10.1111/0022-1082.00494

Ghabri, Y., Huynh, T.L.D., Nasir, M.A., 2020. Volatility Spillovers, Hedging and Safe-havens Under Pandemics: All That Glitters Is Not Gold

Guru, B. K., & Das, A. (2021). COVID-19 and uncertainty spillovers in the Indian stock market. MethodsX, 8, 101199. Available at- https://www.sciencedirect.com/science/article/pii/S2215016120304192. Accessed on - 12 February 2022.
https://doi.org/10.1016/j.mex.2020.101199

Hanif, W., Mensi, W., & Vo, X. V. (2021). Impacts of COVID-19 outbreak on the spillovers between US and Chinese stock sectors. Finance Research Letters, 40, 101922.
https://doi.org/10.1016/j.frl.2021.101922

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID-19's impact on stock prices across different sectors-An event study based on the Chinese stock market. Emerging Markets Finance and Trade, 56(10), 2198-2212.
https://doi.org/10.1080/1540496X.2020.1785865

Kang, S. H., McIver, R., & Yoon, S. M. (2016). Modeling time-varying correlations in volatility between BRICS and commodity markets. Emerging Markets Finance and Trade, 52(7), 1698-1723.
https://doi.org/10.1080/1540496X.2016.1143248

Kouki, I., Harrathi, N., & Haque, M. (2011). A volatility spillover among sector index of international stock markets. Journal of money, investment and banking, 22(1), 32-45.

Laborda, R., & Olmo, J. (2021). Volatility spillover between economic sectors in financial crisis prediction: Evidence spanning the great financial crisis and COVID-19 pandemic. Research in International Business and Finance, 57, 101402.
https://doi.org/10.1016/j.ribaf.2021.101402

Lintner, J. (1965), "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets", Review of Economics and Statistics, Volume 47 (February), pp. 13-37.
https://doi.org/10.2307/1924119

Lupu, R., Călin, A. C., Zeldea, C. G., & Lupu, I. (2021). Systemic Risk Spillovers in the European Energy Sector. Energies, 14(19), 6410.
https://doi.org/10.3390/en14196410

Markowitz, H. (1952). Portfolio selection. The journal of finance, 7(1), 77-91.
https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Markwat, T., Kole, E., & Van Dijk, D. (2009). Contagion as a domino effect in global stock markets. Journal of Banking & Finance, 33(11), 1996-2012.
https://doi.org/10.1016/j.jbankfin.2009.05.008

Mensi, W., Beljid, M., Boubaker, A., Managi, S., 2013. Correlations and volatility spillovers across commodity and stock markets: linking energies, food, and gold. Econ. Modell. 32, 15-22.
https://doi.org/10.1016/j.econmod.2013.01.023

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Kang, S. H. (2016). Global financial crisis and spillover effects among the US and BRICS stock markets. International Review of Economics & Finance, 42, 257-276.
https://doi.org/10.1016/j.iref.2015.11.005

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. The Journal of finance, 29(2), 449-470.
https://doi.org/10.1111/j.1540-6261.1974.tb03058.x

Mossin, J. (1966). Equilibrium in a capital asset market. Econometrica: Journal of the econometric society, 768-783.
https://doi.org/10.2307/1910098

Nasir, M. A., & Du, M. (2018). Integration of financial markets in post global financial crises and implications for British financial sector: Analysis based on a panel VAR model. Journal of Quantitative Economics, 16(2), 363-388.
https://doi.org/10.1007/s40953-017-0087-2

Ngene, G. M. (2021). What drives dynamic connectedness of the US equity sectors during different business cycles?. The North American Journal of Economics and Finance, 58, 101493.
https://doi.org/10.1016/j.najef.2021.101493

Prabheesh, K. P., Padhan, R., & Garg, B. (2020). COVID-19 and the oil price-stock market nexus: Evidence from net oil-importing countries. Energy Research Letters, 1(2), 13745.
https://doi.org/10.46557/001c.13745

Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to COVID-19. The Review of Corporate Finance Studies, 9(3), 622-655.
https://doi.org/10.1093/rcfs/cfaa012

Roll, R., & Ross, S. A. (1980). An empirical investigation of the arbitrage pricing theory. The Journal of Finance, 35(5), 1073-1103.
https://doi.org/10.1111/j.1540-6261.1980.tb02197.x

Shahzad, S. J. H., Naeem, M. A., Peng, Z., & Bouri, E. (2021). Asymmetric volatility spillover among Chinese sectors during COVID-19. International Review of Financial Analysis, 75, 101754.
https://doi.org/10.1016/j.irfa.2021.101754

Sharma, S. S. (2020). A note on the Asian market volatility during the COVID-19 pandemic. Asian Economics Letters, 1(2), 17661.
https://doi.org/10.46557/001c.17661

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. The journal of finance, 19(3), 425-442.
https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Su, X., & Liu, Z. (2021). Sector Volatility Spillover and Economic Policy Uncertainty: Evidence from China's Stock Market. Mathematics, 9(12), 1411.
https://doi.org/10.3390/math9121411

Syriopoulos, T., Makram, B., & Boubaker, A. (2015). Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. International Review of Financial Analysis, 39, 7-18.
https://doi.org/10.1016/j.irfa.2015.01.015

Wu, F., Zhang, D., & Zhang, Z. (2019). Connectedness and risk spillovers in China's stock market: A sectoral analysis. Economic Systems, 43(3).
https://doi.org/10.1016/j.ecosys.2019.100718

Xiong, H., Wu, Z., Hou, F., & Zhang, J. (2020). Which firm-specific characteristics affect the market reaction of Chinese listed companies to the COVID-19 pandemic? Emerging Markets Finance and Trade, 56(10), 2231-2242.
https://doi.org/10.1080/1540496X.2020.1787151

Yavas, B. F., & Rezayat, F. (2016). Country ETF returns and volatility spillovers in emerging stock markets, Europe and USA. International Journal of Emerging Markets.
https://doi.org/10.1108/IJOEM-10-2014-0150

Zeng, S., Liu, X., Li, X., Wei, Q., & Shang, Y. (2019). Information dominance among hedging assets: Evidence from return and volatility directional spillovers in time and frequency domains. Physica A: Statistical Mechanics and its Applications, 536, 122565.
https://doi.org/10.1016/j.physa.2019.122565

Zhang, W., He, X., Nakajima, T., & Hamori, S. (2020). How does the spillover among natural gas, crude oil, and electricity utility stocks change over time? Evidence from North America and Europe. Energies, 13(3), 727.
https://doi.org/10.3390/en13030727

Zhang, W., Zhuang, X., & Wu, D. (2020). Spatial connectedness of volatility spillovers in G20 stock markets: Based on block models analysis. Finance Research Letters, 34, 101274.
https://doi.org/10.1016/j.frl.2019.08.022