AN EMPIRICAL STUDY ON THE VOLATILITY SPILLOVER EFFECT BETWEEN INDIAN AND WORLD LEADING STOCK MARKETS

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DECLARATION BY STUDENT

I hereby declare that the data presented in this Dissertation report entitled, "An Empirical Study on The Volatility Spillover Effect Between Indian and World Leading Stock Markets" is based on the results of investigations carried out by me in the Financial Services Discipline at the Goa Business School, Goa University under the Supervision/Mentorship of Mr. Jick Castanha and the same has not been submitted elsewhere for the award of a degree or diploma by me. Further, I understand that Goa University or its authorities will be not be responsible for the correctness of observations / experimental or other findings given the dissertation.

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COMPLETION CERTIFICATE

This is to certify that the dissertation **"An Empirical Study on The Volatility Spillover Effect Between Indian and World Leading Stock Markets"** is a bonafide work carried out by **Mr. Shawn Menezes** under my supervision/mentorship in partial fulfilment of the requirements for the award of the degree of **Master of Business Administration (Financial Services)** in the Financial Services Discipline at the Goa Business School, Goa University.

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LIST OF ABBREVIATIONS

SR.No	Abbreviations	Full Form
1	ADSE	Abu Dubai Stock Exchange
2	CEE	Central and Eastern Europe
3	DFM	Dubai Financial Market
4	DJIA	Dow Jones Industrial Average
5	EU	European Union
6	FTSE	Financial Times Stock Exchange 100
7	GCC	Gulf Cooperation Council
8	GDP	Gross Domestic Product
9	Nifty	Nifty 50
10	Nikkei	Nikkei 225
11	SMI	Swiss Market Index
12	SPTSX	S&P/TSX Composite
13	SSE	Shanghai Stock Exchange Composite Index
14	UAE	United Arab Emirates
15	UK	United Kingdom
16	USA	United States of America

CHAPTER 1: INTRODUCTION

1.1 INTRODUCTION

The world has now turned into one large global village, where various shocks and news affect one another, it seems to act like a domino effect when it comes to the stock market, wherein news from one country is likely to affect the other, hence the markets being well connected (Li, 2021). For instance, there appear to be strong linkages between the implied volatilities of gold and oil on the Indian Stock Market (Bouri et al., 2017).

Although it is a general notion that the International Financial Markets are closely connected, for instance in a study conducted by Narayan & Narayan, (2012), there were evidences of cointegration especially during the 'Pre-Crisis Period' of the 2008 Global Financial Crisis. However, some studies like Rajwani & Mukherjee, (2013), and Ahmad et al., (2005) which studied about the linkages between the Indian Stock Market with other Asian Markets, and interlinkages between the USA, Japan, and India respectively beg to differ. In a study conducted by Dhanaraj et al., (2013) it was revealed that the Stock Markets in Asia are not immune to the shocks originating in the USA, although the effects of the shocks vary considerably across the markets.

In terms of international portfolio diversification, it is advised to not select the sample countries that are positively correlated, as a positively correlated market would lead to higher risk of depreciation in the value of a portfolio (Dedi & Yavas, 2016). It is important for portfolio managers to identify markets that are not positively correlated so that it would assist them in creating a well-diversified portfolio. For international portfolio managers, it is important to understand the dynamic linkages between stock markets by evaluating the risks involved and constructing a portfolio by following a good hedging strategy (Aloui, 2011).

A rise in volatility in any security would lead to uncertainty prevailing, which would ultimately lead to a higher level of risk associated to it (Maitra, 2018). Therefore, to identify the dynamic linkages and shocks prevailing in the international financial markets, volatility would act as a good measure. Hence, this study analyzes the Volatility

Spillover Effect in Indian contexts. Volatility Spillover is the transmission of volatility among stock markets; hence volatility spillover tests are necessary for investors to support their investment decisions (Nghi & Kieu, 2021). The volatility spillovers may be unidirectional or bidirectional in nature, hence Diebold & Yilmaz., (2012) used a generalized vector autoregressive framework as the basis to build their model.

1.2 SCOPE OF THE STUDY

In this particular study, we hypothesize with the fact that a particular Country's Stock Market Index would behave as per the performance of another Country's Stock Market Index for which the trading period has ended or has opened before that particular country's Stock Market Index.

It is the short terms traders that look for ques like this that would serve as a basis for them to take a particular decision, and also for professional Portfolio Managers in order to hedge their client's position due to certain shocks. There also may arise possibilities that some countries may not have an effect on another country's stock market index, or in certain circumstances it may, therefore it is important to analyze such situations to have a clear understanding of this phenomenon. In this study we use the Volatility Spillover Effect to test the hypothesis.

1.3 LITERATURE REVIEW

There has been an increase in literature of the spillover effect from 2019 onwards, and the studies have been based on the spillover effect over returns and volatility across geographies. It is hypnotically quite evident that performance of a country's stock market may have an impact on another country's stock market performance on that particular day. The reasons could be due to foreign investments, imports & exports, or major business deals taking place. This paper has reviewed 36 research papers relating to the Volatility Spillover Effect on the stock markets across the globe.

To study the spillovers in terms of volatility due to the monetary policy uncertainty on the stock markets of consisting of 21 countries which comprises of emerging and developed countries. It was revealed that there was a negative correlation between the stock returns and US Equity Market Volatility, this study found out that an increase in uncertainty in the US Monetary Policy will result in an adverse effect on the stock returns (Chiang, 2021). Similarly, in a study conducted by Valadkhani & Chen., (2014) which considered the Gross Domestic Product (GDP) and the volatility spillovers of Australia, Canada, and the United Kingdom (UK) with that of the USA revealed that the USA exerts a far significant output volatility to Australia, Canada, and the UK. To understand the impact of the volatility spillover effect even further, a study conducted by Kirkulak Uludag & Khurshid., (2019) indicated that the impact of the volatility spillovers from the Chinese Stock Market to the stock markets of the G7 Countries was far more obvious compared to the volatility spillovers to the stock markets of the E7 Countries. The same result was observed in the opposite direction as well, the volatility spillovers were far stronger from the G7 Countries to China as compared from the E7 Countries to China. When considering comparing spillovers from one country or region to another, studies show that the volatility transmission between the Indian and Asian Stock Markets were significantly higher as compared to the volatility transmission between the USA and the UK (Mishra et al., 2022). The results also indicated that the Indian Stock Market Index tends to move in line with the US and Hong Kong Stock Market Indices. When considering the volatility spillovers from stock market indices from the major countries from the Subcontinent and South-East Asia, it is observed that there is a significant follow of market information to India from Stock Market Indices like Hong Kong, Korea Republic, and Thailand (Mukherjee & Mishra, 2010). The same can be said when compared to the samples of the Japanese and Vietnamese Stock Market Indices, where there was a significant volatility spillover from USA to Vietnam, but no evidence whatsoever of volatility spillovers from Japan to Vietnam (Nghi & Kieu, 2021). Analysis in another study also found that there have been a one-way returns spillover from the Chinese Stock Market to the Japanese Stock Market but the Chinese Stock Market does not seem to react from the Japanese Stock Market, however there have been no volatility spillovers between the Chinese Stock Market and the Japanese Stock Market (Nishimura et al., 2016). This similar result can also be seen in a study conducted by Olbrys., (2013), wherein there was no volatility spillovers found between USA Poland, and Hungary, but there were evidences of returns spillovers between the selected samples. On the contrary, Poland and Hungary being located in the Central and Eastern Europe (CEE), in a different study there was a strong conditional correlation in the CEE Emerging Markets which are tightly integrated (Hung, 2020). To understand the nature of spillover between a particular country's stock markets, Choudhry., (2004) has studied the spillovers between countries having Geo-Political tensions, the pairs include; ‘Greece – Turkey – USA’, ‘India – Pakistan – USA’, and ‘Israel – Jordan – USA’. As per the results, there existed spillovers from USA to Greece, and news from Turkey had a significant impact on the returns and volatility of the Greece Stock Market Index. Also, news from India had an impact on Pakistan’s stock market index in terms of returns and volatility, however news from Pakistan only had impact on the Indian stock market index in terms of returns, and the USA seemed to have a larger impact on terms of volatility spillovers on Pakistan as compared to India. Lastly, spillovers were found in terms of volatility and returns from the Israeli stock market index to the Jordanian stock market index and not the other way around. There were spillovers found from the USA to Israel, and Israel had no impact on the stock market index of the USA whatsoever. However, the results also showed that there was a bidirectional volatility spillover between Jordan’s stock market index and USA’s stock market index. In terms of the African Continent, Bonga-Bonga & Phume., (2022) considered studying the returns and volatility spillovers between Nigeria and South Africa which has the highest GDP and Market Capitalization in the African Continent respectively. It was found that the South African stock market index had a volatility spillover to the Nigerian stock market index, and the Nigerian Stock Market is more vulnerable to shocks as compared to the South African stock market. The volatility Spillover Effect can also occur with the same country as well by taking two or more indices to check the impact. In a study conducted by Maghyereh & Awartani., (2012), the index of Dubai Financial Market (DFM) and Abu Dhabi Stock Exchange (ADSE) was used, wherein the returns and volatility of the DFM are important in predicting the dynamics of the ADSE, however the ADSE does not have a significant impact on the future dynamics of the DFM.

When analyzing the spillover effect, it is usually studied taking samples of emerging and developed markets. The reason for selecting such samples could be due to the notion of a developed market having a significant impact on an emerging market. In order to test this hypothesis, researchers prefer have a combination of emerging as well as developed markets in their sample study. Gulzar et al., (2019) studied the spillover effect with a sample containing six emerging Asian Stock Market Indices and one developed Stock Market Index being the US Stock Market Index. The study tried to analyze the spillover effect before, during and after the 2008 Global Financial Crisis. It was found that there was a significant spillover effect from the US Stock Market to the selected samples of six emerging Asian Stock Markets in all three sample periods. Similarly, a study conducted by Alfreedi., (2019) indicated a positive correlation between all five emerging stock markets of the Gulf Cooperation Council (GCC) Countries and the three developed stock markets of USA, UK, and China. The highest correlation among the Stock Markets of the GCC Countries was recorded between Oman and Qatar, and followed by Oman and Bahrain, whereas the lowest correlation was between Saudi Arabia and Bahrain. All in all, the US Stock Market had a major influence on the volatility spillover of the stock markets of the United Arab Emirates (UAE) and Oman. It is evident that the stock market indices of the GCC Countries are highly correlated, and the reason for this is due to the setup and policies of the GCC, and in turn facilitates the spillovers due to such integration (Al-Deehani & Moosa, 2006). In the European Context, Dedi & Yavas., (2016) studied the returns and volatility spillovers between the stock markets of stable European Countries and Emerging Countries. The results indicated that the UK and Turkey did not experience any volatility spillovers, however, the Russian Stock Market had volatility spillovers from China and Turkey but not from other markets. In the selected samples, most of the volatility spillovers are unidirectional in nature.

When it comes to analyzing the spillover effect, it is also important to understand if the spillover effect is unidirectional or bidirectional in nature. As the research conducted on the spillover effect has been conducted to merely understand if there exist spillovers between countries, however it is also important to understand the nature of those spillover that exist between countries. In terms of the Asia-Pacific region, there existed a cross-mean spillover effect except for the pairs of 'Hong-Kong – China', 'Japan – Hong Kong', 'Taiwan – Jakarta', and 'Korea Republic – New Zealand' (Panda et al., 2021). In the same study, during the full sample period consisting of the 2008 Global Financial Crisis, it was found that the highest pair wise directional spillovers were from Hong Kong to Singapore, Singapore to The Philippians, and Indonesia to Thailand. It was observed that the spillovers were more evident during the Post-Crisis Period of the sample study period. We also see similar results with the study conducted by Hung., (2019) where the volatility spillovers are significantly unidirectional in nature, from China to Vietnam, Thailand, Singapore, and Malaysia. In terms of the volatility spillovers from the stock market indices of USA to Turkey during the 2008 Global Financial Crisis, there was a bidirectional volatility spillover, wherein Turkey was impacted the most since it is an emerging country (Özdemir & Vurur, 2019). Along with the 2008 Global Financial

Crisis, when the Chinese Stock Market Crash is considered in the study period, the results in a study conducted by Yousaf et al., (2020) reveal that there were unidirectional returns spillovers from the stock market indices of the USA to the Latin American Countries during the full sample period, whereas there were bidirectional volatility spillovers between the stock market indices of the USA and the Latin American Countries. When considering the 2008 Global Financial Crisis with the COVID-19 Pandemic, it was observed that the Volatility Spillovers exceeded that of the 2008 Global Financial Crisis. There was a bidirectional volatility spillover between stock market indices of Saudi Arabia, Bahrain, Qatar, and Oman (Yousaf et al., 2022). In a study conducted by Erdoğan et al., (2020) which analyzed the volatility spillover effect between the Islamic Stock Market Indices of major emerging Asian countries such as India, Malaysia, and Turkey, and the foreign exchange rate. It was found that there existed a volatility spillover from the Islamic Stock Market to the Exchange Rates in Turkey. Hence, the study proved that there was a bidirectional volatility spillover between the Islamic Stock Market Indices of India, Malaysia, and Turkey, and the Foreign Exchange Market after 2018.

It has been observed that the volatility spillovers have been significantly higher during shocks and times of uncertainty in the stock market. Hence, having a study period which includes particular shocks or events would be beneficial in understanding the impact caused by that particular event. According to Fang & Su., (2021), uncertainty plays a major role in US Financial Volatility Spillovers, stock market volatility spills over the foreign exchange and bond markets through economic policy uncertainty and financial uncertainty. In the 1997 Asian Financial Crisis, there were strong evidences of reactions among six stock markets in South-East Asia (Chancharoenchai & Dibooglu, 2006). In a study conducted by Engle et al., (2012) revealed that there was a buildup period in terms of volatility transmission before the 1997 Asian Financial Crisis and the 9/11 Attack. Similar results were found in a study conducted by Diebold & Yilmaz., (2009), wherein there were gentle increases in trends and clear signs of volatility spillovers at the time of crisis events happening in the economy. In another study taking the sample period which includes both the 1997 Asian Financial Crisis and the 2008 Global Financial Crisis, the volatility spillovers were evident during the periods of crisis from the stock market index of Brazil to Turkey, however, in the post crisis period the volatility spillover effect was from Turkey to Brazil (Taşdemir & Yalama, 2014). The 2008 Global Financial Crisis was a significant event, and the effects were seen all over the world. In Asian contexts, significant returns spillovers were found from the stock market indices of USA and prominent Asian stock markets, however the volatility spillovers were much higher during the Chinese Stock Market Crash as compared to the 2008 Global Financial Crisis (Yousaf et al., 2020b). Before the onset of the COVID-19 Pandemic, the Returns Spillovers had a decline with a drop in frequencies, whereas the volatility spillovers increased with the drop in frequencies among the stock market indices of the BRICS Countries (Shi, 2021). Within the same context, the BRICS Countries have exhibited volatility spillover effects due to the COVID-19 Pandemic (Malik et al., 2022). The increase in the volatility spillover effect during a major shock event like the COVID-19 Pandemic revealed that the spillovers are quite evident, however, after the Pandemic in its recovery period, the Total Volatility Spillover decreased (Choi, 2022).

While studying the Spillover Effect, it is also important to understand who are the major transmitters and receivers of the spillovers. This plays an important role for the investors to identify potential markets to hedge their positions. In a study conducted by Mensi et al., (2021), the volatility spillovers are studies with samples of developed and emerging countries in North America, South America, Europe, and Asia. The results of the study revealed that the East Asian Markets were the largest net receivers of volatility, and the USA, Canada, the Netherlands, and France were the largest net transmitters of volatility to other markets. Similar results can be seen in Li., (2021), wherein in the selected sample, the stock markets of Japan and China (East Asian Markets), along with India and Brazil were risk receivers, and stock markets of the USA, Germany, the UK, France, Italy, and Canada were risk transmitters. The stock markets of the USA can also be regarded as a risk enhancer. Since the spillover effect can be evident during a particular shock or event, the impact would also be noticed in the countries which emit and receive the spillovers. In the study conducted by Charfeddine & al Refai., (2019), which studied the volatility spillovers in the GCC Markets during the Political Tensions that took place in March 2014 and June 2017. The results indicated that Qatar was the net shock receiver along with Saudi Arabia, and the UAE, and Saudi Arabia was the net shock transmitter to the other markets in the GCC.

1.4 RESEARCH GAP

In lieu of the empirical literature which has been devoted towards studying the Volatility Spillover Effect between major world indices, this study aims towards contributing the following to the existing literature: -

1. Comparison of Volatility Spillovers- In this study we compare the volatility spillovers between the Indian Stock Market Index with the foreign stock market indices where Indian Investors invest, such as Asia, Europe, and North America. In this study we create pairs such as; 'India-Asia', 'India-Europe', and 'India-North America' and analyze the Volatility Spillovers.
2. Study Period covering the COVID-19 Pandemic- This study would provide insights as to the magnitude of the Volatility Spillovers caused due to this sudden shock due to a global pandemic. As per the previously studied literature indicated that the magnitude of spillovers were evident due to sudden shocks such as the Global Financial Crisis, Chinese Stock Market Crash, GCC Political Crisis, etc. Therefore, we use the COVID-19 Pandemic which was far more devastating compared to any other global economic event as a basis to analyze the spillovers.

1.5 OBJECTIVES AND HYPOTHESIS

The following are the objectives to the study: -

1. To study the volatility spillover effect between the Indian Stock Market Index with the selected samples of the Asian, European, and North American Stock Market Indices
2. To study the volatility spillover effect on the basis of Pre- and During the COVID-19 Pandemic

Hypothesis for Augmented Dickey-Fuller Test: -

H_{Oa}: Nifty has a unit root

H_{Ob}: SSE has a unit root

H_{Oc}: Nikkei has a unit root

H_{Od}: FTSE has a unit root

H_{Oe}: SMI has a unit root

H_{Of}: DJIA has a unit root

H_{Og}: SPTSX has a unit root

Hypothesis for BEKK-GARCH: -

H_{O1}: There are no significant volatility spillovers between Nifty 50, and SSE Composite Index

H_{O2}: There are no significant volatility spillovers between Nifty 50, and Nikkei 225

H_{O3}: There are no significant volatility spillovers between Nifty 50 and FTSE 100

H_{O4}: There is no significant volatility spillovers between Nifty 50 and the Swiss Market Index

H_{O5}: There is no significant volatility spillovers between Nifty 50 and the Dow Jones Industrial Average

H_{O6}: There is no significant volatility spillovers between Nifty 50 and S&P/TSX Composite

1.6 METHODOLOGY

1. Data- The purpose of this study is to examine the volatility spillover effect on Asia, Europe and North America region. In order to determine the sample countries from each region the following selection criteria was designed. The top 2 stock market from each region having highest market capitalization as on October 2022 were selected for this study (Statista, 2023). As per the data provided, the Euronext will not qualify for selection in the European sample since it represents companies spanning across the European Union (EU), and the EU does not qualify as a country. The data can be visualized in 'Table 1.1.'

Table 1.1: Largest Stock Exchange Operators Worldwide as of October 2022, by Market Capitalization of Listed Companies

Region	Country	Stock Market (Main Index)	Market Capitalization
Asia	China	Shanghai Stock Exchange (SSE Composite Index)	$5.98 Trillion
	Japan	Japan Exchange Group (Nikkei 225)	$4.91 Trillion
	China	Shenzhen Stock Exchange (SZSE Composite Index)	$4.23 Trillion

	Hong Kong	Hong Kong Exchanges (Hang Seng)	$3.36 Trillion
	India	National Stock Exchange of India (Nifty 50)	$3.28 Trillion
	Saudi Arabia	Saudi Stock Exchange (Tadawul All Share Index)	$2.86 Trillion
	Australia	ASX Australian Securities Exchange (S&P/ASX 200)	$1.55 Trillion
	South Korea	Korea Exchange (KOSPI)	$1.49 Trillion
	Taiwan	Taiwan Stock Exchange (Taiwan Stock Exchange Weighted Index)	$1.26 Trillion
	Iran	Tehran Stock Exchange (TEDPIX)	$1.05 Trillion
Europe	European Union	Euronext (Euro Stoxx 50)	$5.52 Trillion
	United Kingdom	LSE Group (FTSE 100)	$2.82 Trillion
	Switzerland	SIX Swiss Exchange (Swiss Market Index)	$1.71 Trillion
	Germany	Deutche Boerse AG (DAX)	$1.7 Trillion
North America	United States of America	New York Stock Exchange (Dow Jones Industrial Average)	$22.11 Trillion
	United States of America	NASDAQ (NASDAQ Composite)	$17.23 Trillion
	Canada	TMX Group (S&P/TSX Composite)	$2.76 Trillion

Source: [*www.statista.com*](http://www.statista.com)

As per ‘Table 1.1’, the selected samples of Asia would comprise of; China (SSE Composite Index) and Japan (Nikkei 225), the selected samples of Europe would comprise of; the United Kingdom (FTSE 100) and Switzerland (Swiss Market Index), and the selected samples of North America would comprise of; the United States of America (Dow Jones Industrial Average) and Canada (S&P/TSX Composite). The index that would represent India would be Nifty 50 as the National Stock Exchange of India has the 5th largest market capitalization in Asia which is higher than the BSE, hence the S&P BSE Sensex would not be considered. The selected sample stock market indices which are denominated in their local currency have been converted to the dollar-denominated currency by using daily exchange rate data for each applicable currency pair. By converting the locally-denominated stock market indices to dollar-denominated stock market indices, the study takes into account the effects of exchange rate risk. The dataset for all the selected indices has been collected from www.investing.com and filtered for valid trading days.

In terms of the sample period, this study considers the Full Sample Period to be ranging from 8th January 2001 to 30th December 2022. Furthermore, to investigate the volatility spillover effect due to the effects of the COVID-19 Pandemic, the Pre-COVID-19 sample period would be from 2nd January 2017 to 31st December 2019, and the During COVID-19 sample period would be from 1st January 2020 to 30th December 2022. In total, the Full Sample Period contain 5,713 observations, the Pre-COVID-19 Pandemic Period contain 777 observations, and the During COVID-19 Pandemic Period contain 784 observations.

The raw data of the sample indices represent the local currency of that particular country, for the purpose of this study in order to get a meaningful result, the selected sample indices have been adjusted to the US Dollar currency to maintain uniformity, hence this study considers a common currency for all selected indices. However, there are no adjustments made for the Dow Jones Industrial Average as its index point is in US Dollar terms. After the data has been adjusted for the common currency, it is then computed for daily logarithmic returns multiplied by 100.

$$Ln = \left(\frac{P_t}{P_{t_0}}\right) \times 100$$

2. Augmented Dickey-Fuller Test- After the data has been converted to the daily logarithmic returns, it is important to test the data for stationarity or to examine if the data has the presence of a unit root. Hence to conduct the Unit Root Test, the Augmented Dickey-Fuller Test is used. The Augmented Dickey-Fuller Test was put forth by Dickey & Fuller., (1981).

$$y_t = c + \beta t + \alpha y_{t-1} + \emptyset_1 \Delta Y_{t-1} + \emptyset_2 \Delta Y_{t-2} .. + \emptyset_p \Delta Y_{t-p} + e_t$$

3. Correlation- To understand the results of the econometric models in an efficient manner, this study uses the Correlation Matrix. The Correlation Matrix is used to understand the relationship between the selected sample indices, whether there exist negative or positive correlation.

$$r = \frac{N \sum xy - \sum x \sum y}{\sqrt{(N \sum x^2 - (\sum x)^2)(N \sum y^2 - (\sum y)^2)}}$$

4. Vector Autoregression- Before examining the Volatility Spillover Effect, the interactions between the sample indices need to be examined. To examine the interlinkages, this study uses a Vector Autoregression Model developed by Sims, C. A., (1980). For the purpose of this study, the Vector Autoregression Model's Impulse Response Function is examined.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \epsilon_t$$

5. Granger-Causality Test- The Granger-Causality Test is used as an auxiliary test to Vector Autoregression. This test is used to examine the causation of returns from one market to another (Granger, 1969).

6. BEKK-GARCH- The BEKK-GARCH Model is used to examine the volatility spillover effect between Nifty 50 and the six selected sample world leading stock market indices. The BEKK-GARCH Model was put forth by Engle & Kroner., (1995).

$$H(t) = CC' + A'u(t-1)u(t-1)'A + B'H(t-1)B + D'v(t-1)v(t-1)'D$$

1.7 MOTIVATION FOR THE STUDY

The reason for conducting this study to help Portfolio Managers to identify opportunities of hedging their client's position and assist them in creating an optimal portfolio that can withstand sudden shocks. Due to the availability of parking funds in foreign markets, Portfolio Managers need to understand if certain markets are highly correlated or not, accordingly they can formulate investment strategies to meet their client's investment needs and protect it against shocks.

The Spillover Effect provides a clear picture of how one country's shocks would affect another country. The Spillover Effect would also test if there are unidirectional or bidirectional spillovers between the selected country's/region's indices, and which country's stock market indices are major transmitters and receivers of spillovers. We consider using the Volatility Spillover Effect for our study since volatility would likely serve as a clear sign to determine the outcome in another country's Stock Market Index. As per the reviewed literature, we have identified that the spillovers are evident when the world goes through a major shock or a major event. Hence, we study the impact of the volatility spillover effect by taking the COVID-19 period into consideration.

1.8 LIMITATIONS OF THE STUDY

1. Overlapping of Stock Market Timings- When studying the Volatility Spillover Effect between the selected samples, they occur a limitation of the overlapping of Stock Market Timings. Ideally, to have a clear result while testing the Spillover Effect, there should not be any overlapping in terms of the time a country's Stock Market is open for trading on that particular day.
2. Time Period- Since this study has been conducted during the aftermath of the COVID-19 Pandemic, there arises a limitation in terms of determining the pre-COVID-19 Pandemic period and the During-COVID-19 Pandemic period. Ideally, a larger time period in both phases would provide more insight into the results of the study.
3. Limited Data- The initial methodology would be formed on the basis of the top two countries from Asia, Europe, and North America where the Indian investors have invested the most capital, however, to support this, no relevant sources were

available. Moreover, data related to market capitalization of most of the indices were not available, hence it is one of the limitations of the study.

1.9 CHAPTERISATION

1. Chapter 1: Introduction- This chapter contains the Introduction to the volatility spillover effect, Scope of the study, Literature Review, Research Gaps, Objectives and Hypothesis, Methodology, Motivation for the study, and Limitations of the study.
2. Chapter 2: Empirical Results- This chapter includes testing the data for normality, and for the econometric models to test the volatility spillover effect between the selected samples. This chapter contains graphs and charts to represent the results.
3. Chapter 3: Summary, Findings, and Conclusion- This particular chapter includes the summary of the results, findings of the study, conclusions, theoretical and practical implications, and scope for further research.

CHAPTER 2: DATA ANALYSIS AND DISCUSSION

2.1 INTRODUCTION

This chapter consists of the empirical results of the econometric models used to fulfill the objectives of this study. The econometric models used in this study are; Vector Autoregression, Granger-Causality Test, and BEKK-GARCH. Before analyzing the results of the above-mentioned models, the data shall be tested for outliers by using a Box Plot graph, followed by Descriptive Statistics, and a Unit Root Test to test the data for stationarity. The selected sample variables in this study are; Nifty 50 Returns (Nifty), SSE Composite Index Returns (SSE), Nikkei 225 Returns (Nikkei), FTSE 100 Returns (FTSE), Swiss Market Index Returns (SMI), Dow Jones Industrial Average Returns (DJIA), and S&P/TSX Composite Returns (SPTSX).

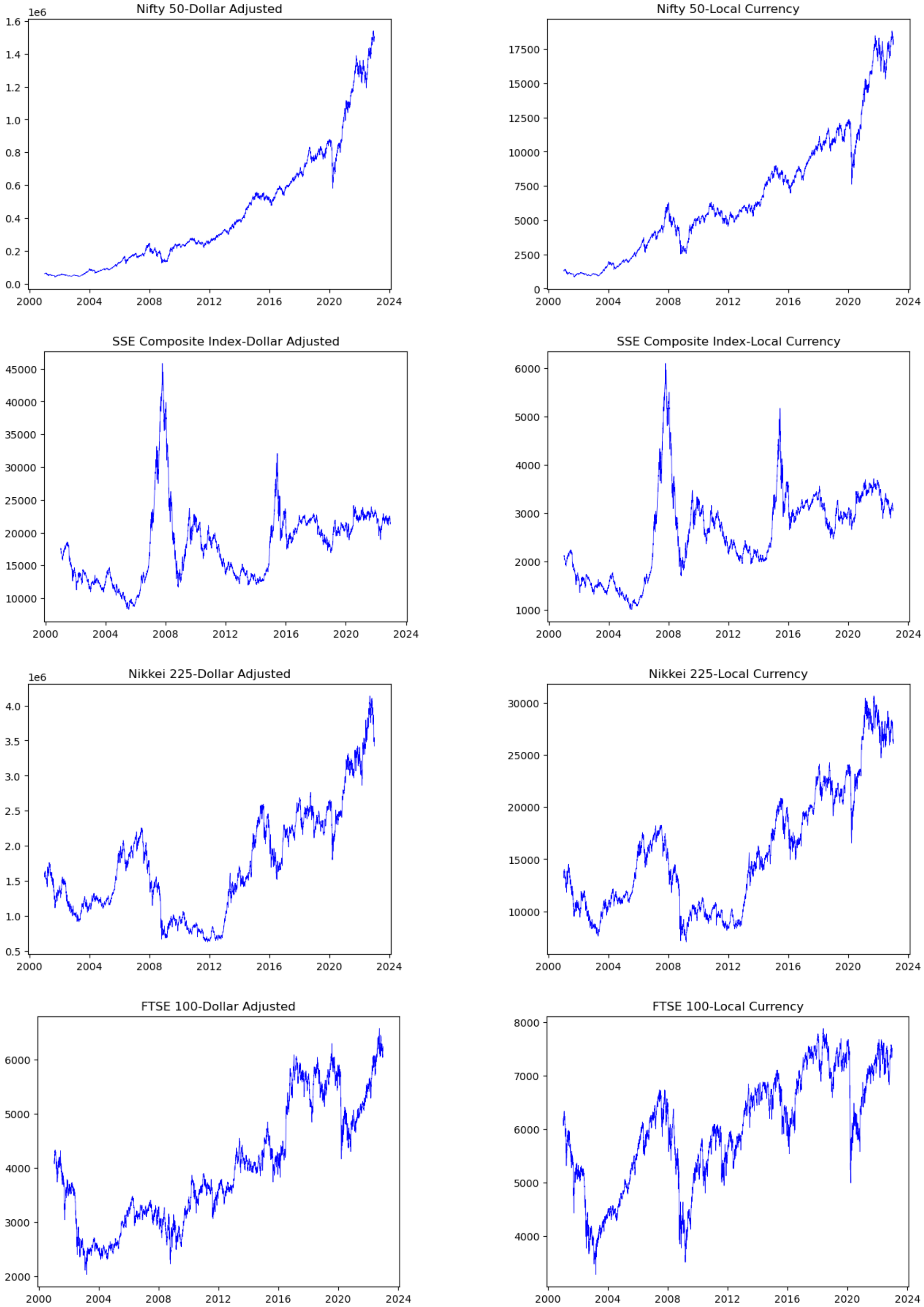
2.2 GRAPHS

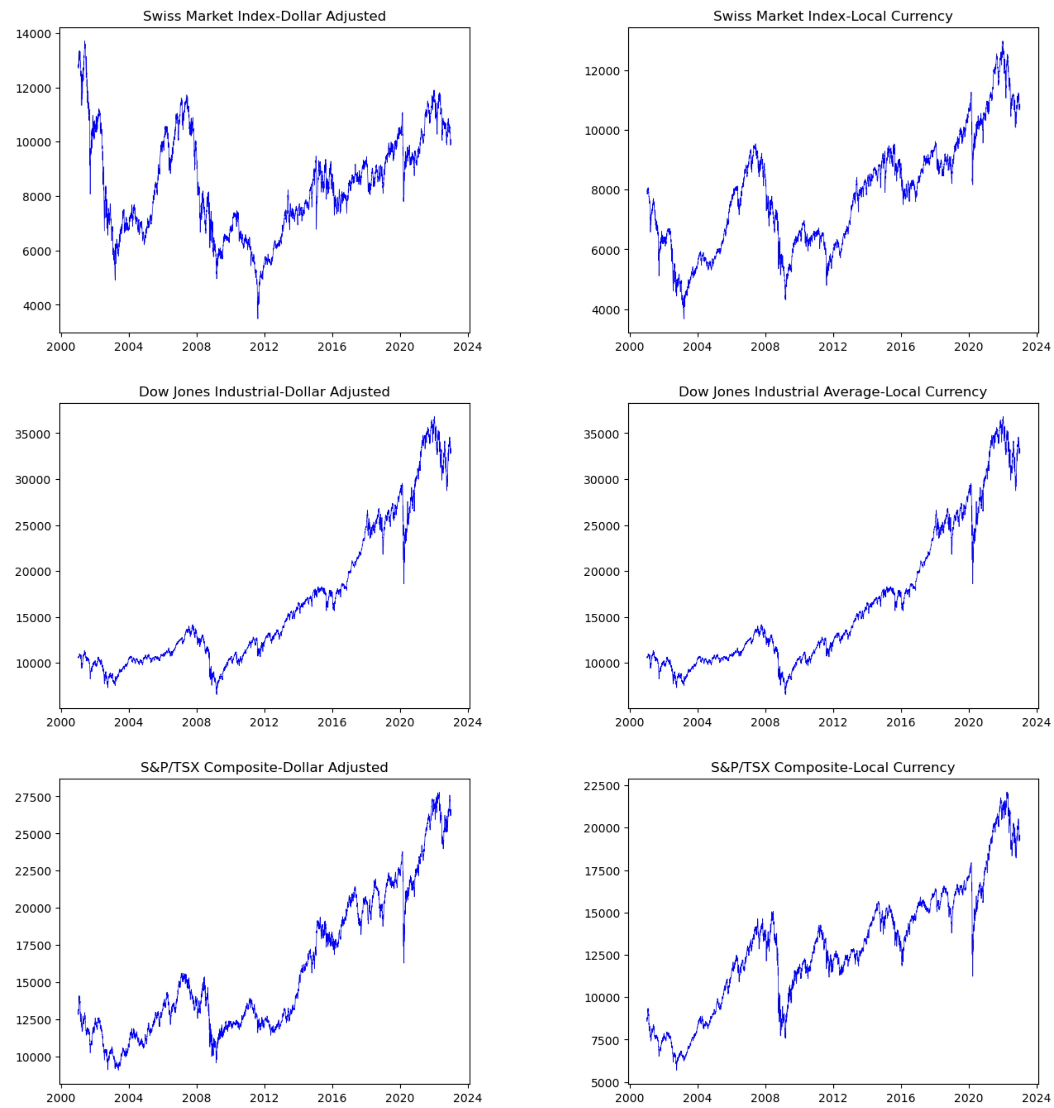
1. Indices Points (Dollar Adjusted and Local Currency)- In order to maintain uniformity in the data set, this study has adjusted the sample indices in dollar terms. 'Figure 2.1' depicts the slight variation in the trends of the selected sample indices after making the adjustment for the common currency. It is to be noted that the trend for the Dow Jones Industrial Average in terms of the Dollar Adjusted trend and the Local Currency adjusted trend remain the same, as the currency for the Dow Jones Industrial Average is the US Dollar. It is noticed that both the Dollar Adjusted and the Local Currency Indices are following a similar trend, however, the variations are notices in terms of sudden dips and rise in the trend. The reason for this is due to the constant appreciation or depreciation in the currency pairs that cause such variations in the trends. Major variations in the trends can be identified around the 2008 Global Financial Crises period.

2. Indices Returns- 'Figure 2.2' represents the Returns Graph of the selected sample in Dollar terms. As per 'Figure 2.2,' it is noticed that a high volatility surge can be noticed for all selected sample indices during the 2008 Global Financial Crisis for a long period. It is quite evident that the SSE Composite Index observed a huge volatility for most of the 2008 Global Financial Crisis period. Whereas, the

volatility during the onset of the COVID-19 Pandemic was for a brief duration for all the selected sample indices. Visually, the SSE Composite Index seems to be the most volatile in comparison to the other selected sample indices, whereas the Swiss Market Index seem to be the least volatile.

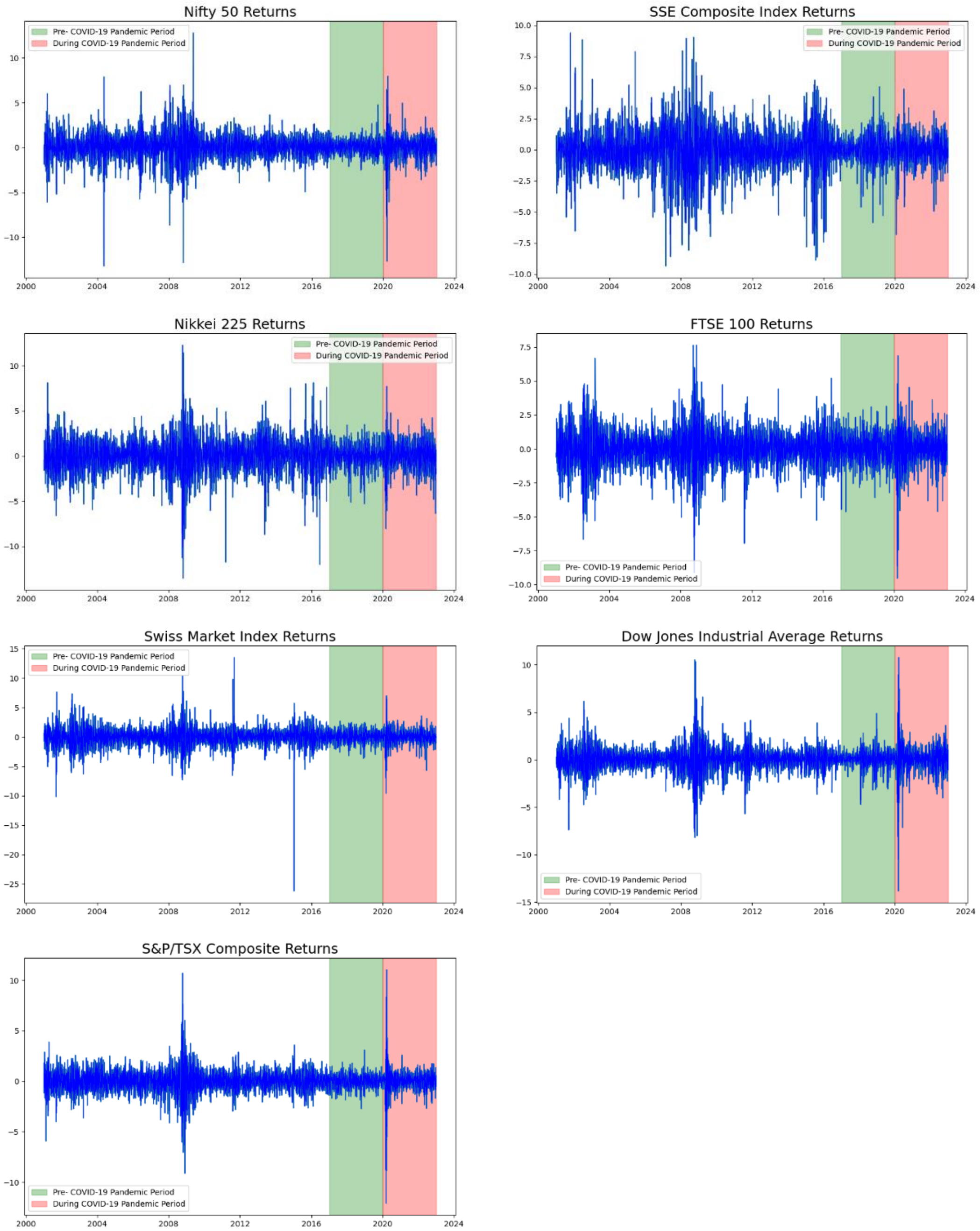
Figure 2.1: Dollar Adjusted V/S Local Currency Indices Graphs





Source: Computed using Python

Figure 2.2: Selected Sample Indices Returns Graph

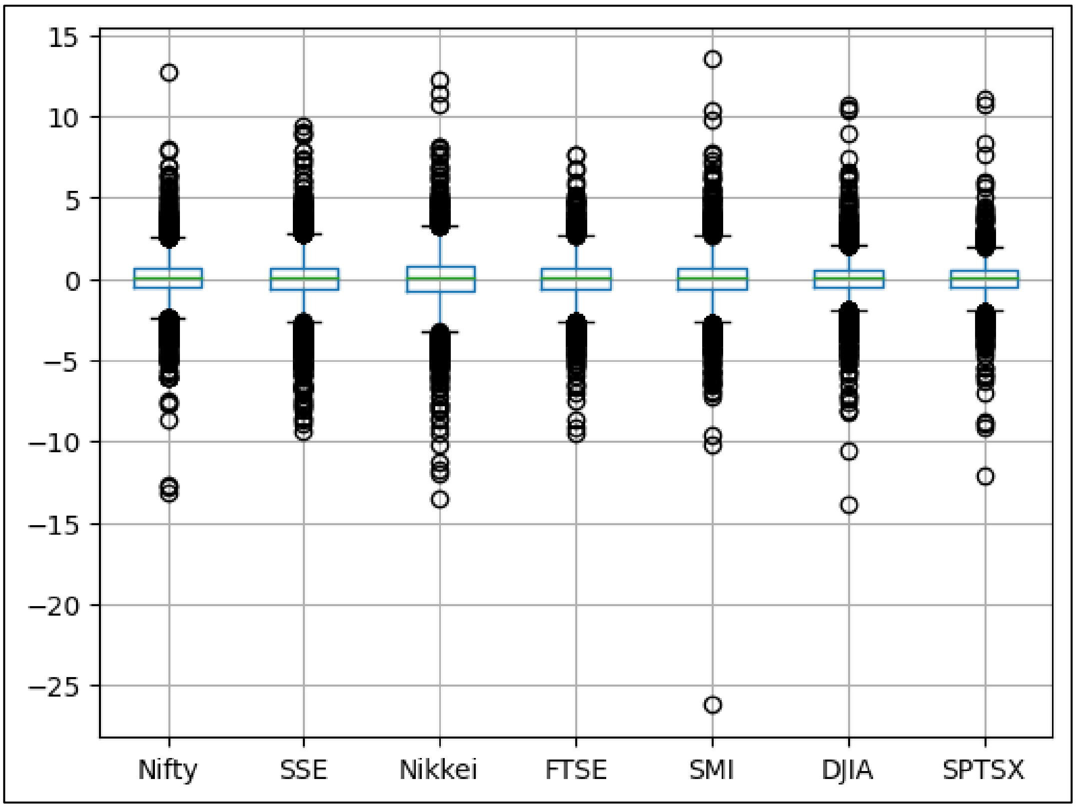


Source: Computed using Python

2.3 BOX PLOTS

‘Figure 2.3’ depicts the Box Plots of the selected sample data set. The Box Plot is a representation of the data set and to identify the possible outliers. As per the box plot, there appears to be an outlier in SMI, whereas all data points of the other sample indices are within range. To attain a fair result for this study, the outlier of SMI is considered.

Figure 2.3: Box Plot of the Selected Sample Indices to Identify Outliers



Source: Computed using Python

2.4 DESCRIPTIVE STATISTICS

Table 2.1: Descriptive Statistics of the Selected Sample Indices

	Nifty	SSE	Nikkei	FTSE	SMI	DJIA	SPTSX
Mean	0.0557	0.0184	0.0082	0.0036	-0.0076	0.0197	0.0122
Standard Deviation	1.2839	1.4795	1.6307	1.2498	1.4122	1.1768	0.9913
Minimum	-13.2078	-9.3465	-13.5488	-9.5440	-26.2149	-13.8418	-12.0932
25%	-0.5121	-0.6343	-0.7944	-0.6512	-0.6626	-0.4519	-0.4806
50%	0.0667	0.0381	0.0519	0.0280	0.0319	0.0497	0.0432
75%	0.7101	0.7212	0.8464	0.6922	0.6909	0.5468	0.5212
Maximum	12.7839	9.3984	12.2742	7.6412	13.5067	10.7643	11.0389
Skewness	-0.5706	-0.4176	-0.4103	-0.2952	-1.0874	-0.3886	-0.3718
Kurtosis	10.9241	5.3342	6.1050	4.4261	26.2514	13.3361	16.9603

Source: Computed using Python

'Table 2.1' represents the Descriptive Statistics of the data set, as per the table it is observed that Nifty had the highest mean indicating that Nifty had the highest daily average returns, and SMI had the lowest daily average returns among the selected sample indices. Nifty being the highest in terms of daily average returns, it also tops the charts in terms of having the highest daily maximum returns, whereas SSE has the lowest daily maximum returns. The SSE has the highest Minimum daily returns, whereas The SMI had the lowest Minimum daily returns. The Standard Deviation represents the degree of variation from the mean, ideally the Standard Deviation of a particular variable should be lower in comparison. The SPTSX has the lowest Standard Deviation, and Nikkei has the highest standard deviation in the selected sample indices. The Skewness levels of all the selected sample indices are in negative figures; hence all indices are negatively skewed. The Kurtosis levels of all the selected sample indices are higher than 3, hence all indices are Leptokurtic.

2.5 UNIT ROOT TEST

Table 2.2: Results of Augmented Dickey-Fuller Test

Index	Test Statistic	Probability
Nifty	-22.4368	0.0000*
SSE	-15.3618	0.0000*
Nikkei	-38.4994	0.0000*
FTSE	-15.8346	0.0000*
SMI	-31.0282	0.0000*
DJIA	-17.8021	0.0000*
SPTSX	-14.3729	0.0000*

*Note: * 5% level of significance*

Source: Computed using Python

In order to examine the stationarity of the data set, the Augmented Dickey-Fuller Test is used. ‘Table 2.2’ present the results of the Augmented Dickey-Fuller Test. The Augmented Dickey-Fuller Test results indicate that the P-Value of all the selected sample indices is 0. Which means that P-Value of all the indices is less than 0.05 at 5% level of significance, this the null hypothesis (from H_{Oa} to H_{og}) gets rejected. Hence, we arrive to a conclusion that the returns of all the indices in the selected sample are stationary and do not have a unit root.

2.6 CORRELATION

Table 2.3: Correlation Matrix

	Nifty	SSE	Nikkei	FTSE	SMI	DJIA	SPTSX
Nifty	1						
SSE	0.1670	1					
Nikkei	0.3162	0.2199	1				
FTSE	0.2673	0.0984	0.3229	1			
SMI	0.2565	0.0702	0.3561	0.6763	1		
DJIA	0.2006	0.0727	0.2507	0.4158	0.4350	1	
SPTSX	0.1940	0.0848	0.2375	0.3936	0.3863	0.5369	1

Source: Computed using Python

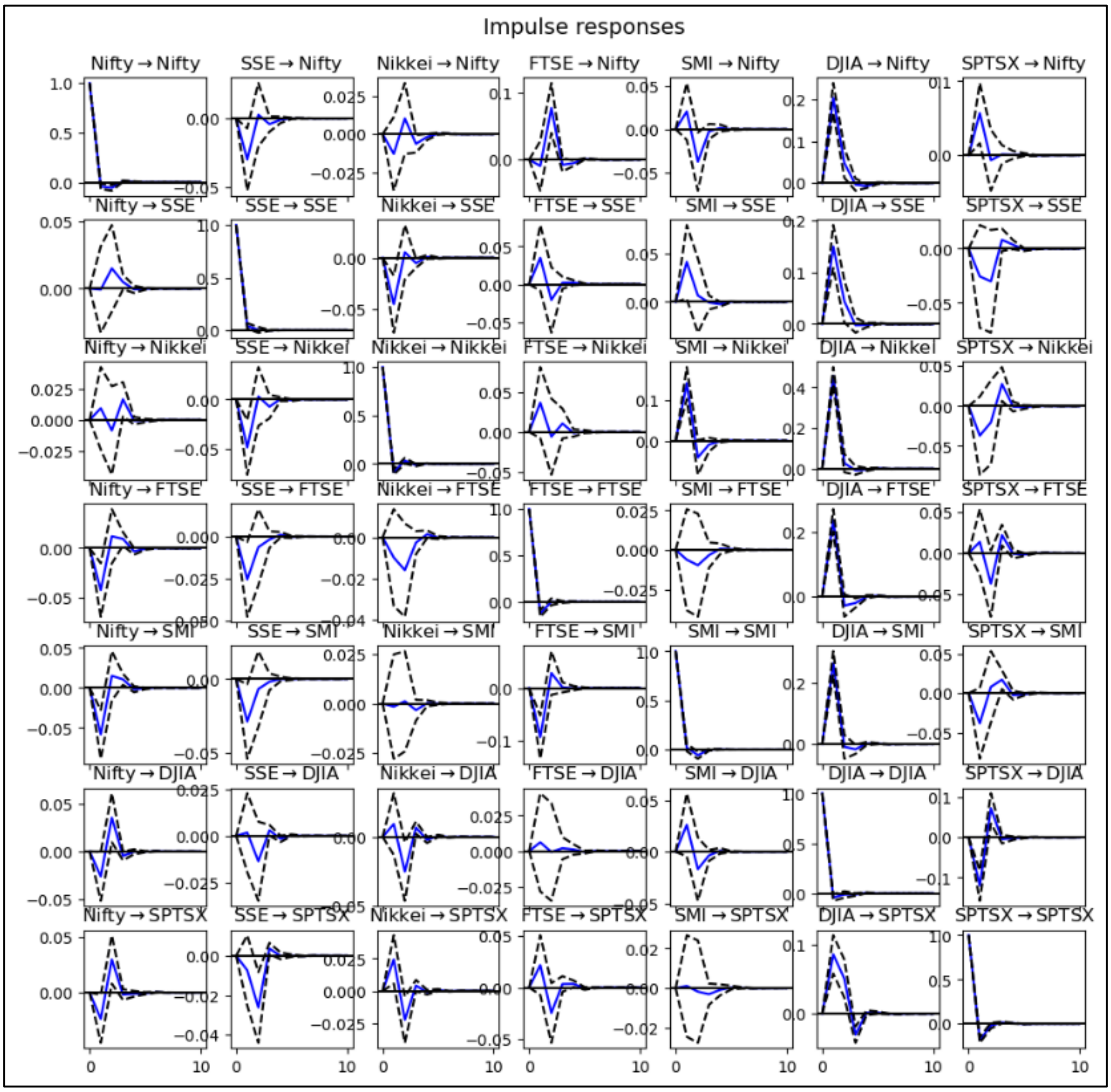
'Table 2.3' represents the Correlation Matrix of the selected sample indices. As per 'Table 2.3', we notice that SMI and FTSE have the highest correlation, i.e., 0.6763, and SMI and SSE have the lowest correlation, i.e., 0.0727. It is noticed that Nifty has the highest correlation with Nikkei, and the lowest correlation with SSE in the selected sample indices. The results of the Correlation Matrix can be used as a basis to form a more meaning full interpretation in terms of examining the Volatility Spillover Effect with the Vector Autoregression, Granger-Causality Test, and BEKK-GARCH.

2.7 VECTOR AUTOREGRESSION

'Figure 2.4', 'Figure 2.5', and 'Figure 2.6' represent the Vector Autoregression's Impulse Response Function of the Full Sample Period, Pre-COVID-19 Pandemic Period, and During COVID-19 Pandemic Period respectively. In all the above-mentioned figures, the responses received and sent by Nifty are analyzed. In terms of the Asian samples, it is noticed that Nifty had significant impact on the SSE and Nikkei, however we notice that impact fading away from the Pre-COVID-19 Pandemic Period to During COVID-19 Pandemic Period. In terms of the European Samples, Nifty was having a visible impact on the FTSE in the Pre-COVID-19 Pandemic Period, however there is not much variation seen During the COVID-19 Pandemic Period. In terms of the impact on the SMI, there is little impact for all sample periods. In terms of the North American Samples, Nifty shows very little impact in the full sample period and during the COVID-

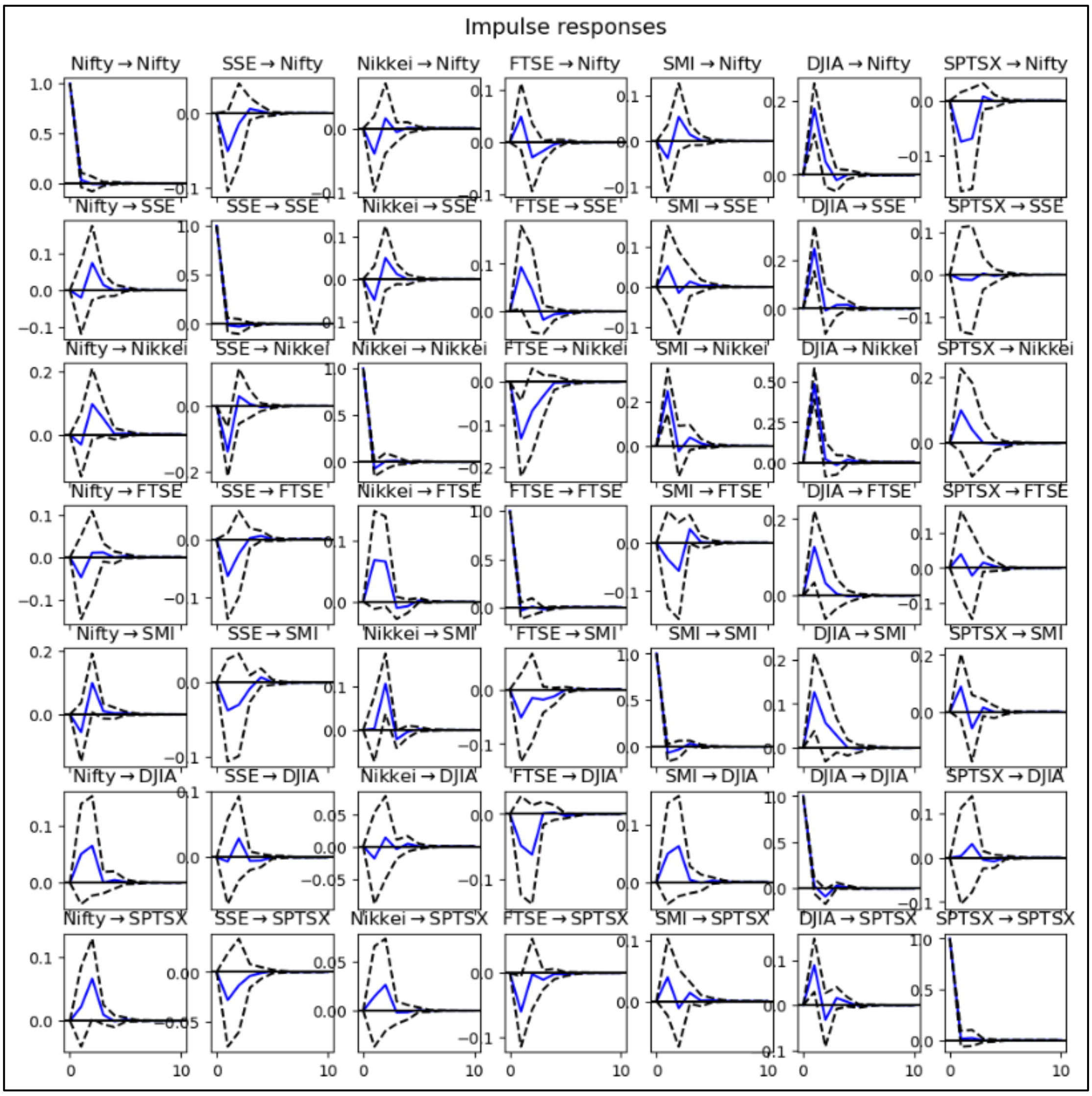
19 Pandemic period for both DJIA and SPTSX, however, there appears to be a significant impact on both DJIA and SPTSX in the Pre-COVID-19 Sample Period.

Figure 2.4: Vector Autoregression Impulse Response Function for the Full Sample Period



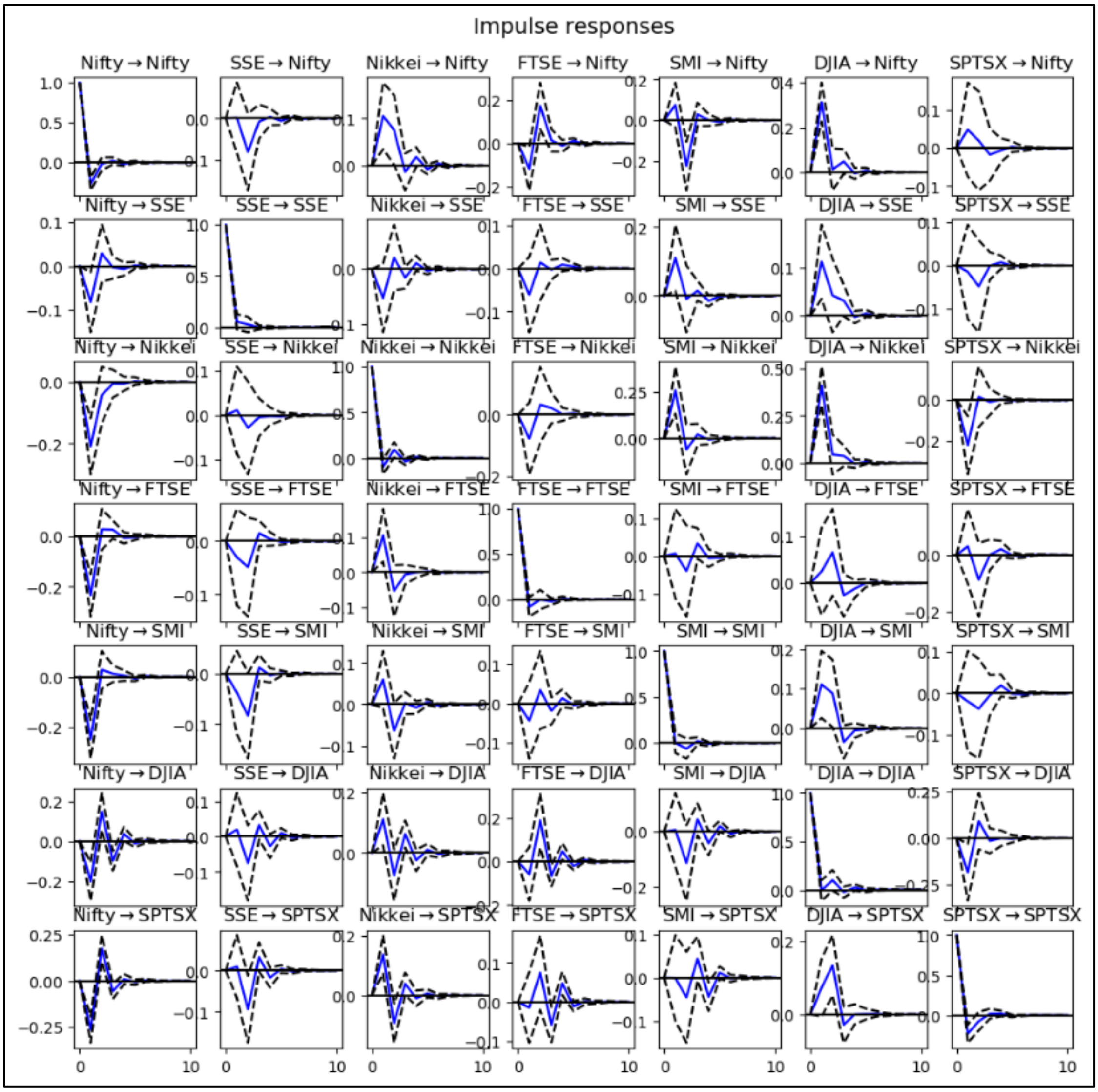
Source: Computed using Python

Figure 2.5: Vector Autoregression Impulse Response Function for the Pre-COVID-19 Pandemic Period



Source: Computed using Python

Figure 2.6: Vector Autoregression Impulse Response Function for the During COVID-19 Pandemic Period



Source: Computed using Python

In the Asian Pair, the impact received by Nifty from SSE and Nikkei is significant across all sample periods. Whereas in terms of the European Pair, there is very little impact in the Full Service Period and During COVID-19 Pandemic Period, but a noticeable impact in the Pre-COVID-19 Pandemic Period from FTSE and SMI. In terms of the North American Pair, there appears to be not a significant impact in all the sample periods for the DJIA. The impact received by SPTSX on Nifty is significant in the full sample period, however, there was a huge impact seen on Nifty from SPTSX in the Pre-COVID-19 Pandemic Period and During COVID-19 Pandemic Period.

2.8 GRANGER-CAUSALITY TEST

‘Table 2.4’ contain the results of the Granger-Causality Test for the Full Sample Period. In the Asian Pair, it was observed that there was no causality between Nifty and the SSE, however, there was a bi-directional causality between Nifty and Nikkei. In the European Pair, it was observed that there was a unidirectional causality from FTSE to Nifty, whereas there was a bi-directional causality between Nifty and SMI. In the North American pair, it was observed that there was a bi-directional causality between Nifty and DJIA, whereas there was a unidirectional causality from SPTSX to Nifty.

‘Table 2.5’ contains the results of the Granger-Causality Test for the Pre-COVID-19 Pandemic Period. In the Asian Pair there was no causality detected. In the European pair, there was no causality between Nifty and FTSE, however, there was a unidirectional causality from SMI to Nifty. In the North American pair, there was a unidirectional causality from DJIA to Nifty, and no causality detected between Nifty and SPTSX.

‘Table 2.6’ contains the results of the Granger-Causality Test for During COVID-19 Pandemic Period. In the Asian Pair, there appears to be no causality between Nifty and SSE, whereas there is a unidirectional causality from Nikkei to Nifty. In the European Pair, there appears to be a bi-directional causality between Nifty and FTSE, and between Nifty and SMI. In the North American Pair, there appears to be a bi-directional causality between Nifty and DJIA, and between Nifty and SPTSX.

Table 2.4: Results of Granger-Causality Test for the Full Sample Period

Region	Null Hypothesis (H_o)	F-Statistic	Probability	Conclusion	Causality
Asia	SSE does not Granger-Cause Nifty	1.2129	0.2974	Failed to reject H_o	No Causality
	Nifty does not Ganger-Cause SSE	2.6923	0.0678	Failed to reject H_o	
	Nikkei does not Ganger-Cause Nifty	10.3386	0.0000*	Rejected H_o	Bi-Directional Causality
	Nifty does not Granger-Cause Nikkei	14.0841	0.0000*	Rejected H_o	
Europe	FTSE does not Granger-Cause Nifty	37.1578	0.0000*	Rejected H_o	Unidirectional Causality
	Nifty does not Ganger-Cause FTSE	1.8148	0.1630	Failed to reject H_o	
	SMI does not Granger-Cause Nifty	33.9067	0.0000*	Rejected H_o	Bi-directional causality
	Nifty does not Ganger-Cause SMI	5.0430	0.0065*	Rejected H_o	
North America	DJIA does not Granger-Cause Nifty	130.5672	0.0000*	Rejected H_o	Bi-directional causality
	Nifty does not Ganger-Cause DJIA	3.5878	0.0277*	Rejected H_o	
	SPTSX does not Granger-Cause Nifty	59.0766	0.0000*	Rejected H_o	Unidirectional causality
	Nifty does not Ganger-Cause SPTSX	1.1851	0.3058	Failed to reject H_o	

*Note: * 5% level of significance*

Source: Computed using Python

Table 2.5: Results of Granger-Causality Test for Pre-COVID-19 Pandemic Period

Region	Null Hypothesis (H_o)	F-Statistic	Probability	Conclusion	Causality
Asia	SSE does not Granger-Cause Nifty	1.3218	0.2673	Failed to reject H_o	No Causality
	Nifty does not Ganger-Cause SSE	1.6260	0.1974	Failed to reject H_o	
	Nikkei does not Ganger-Cause Nifty	0.2405	0.7863	Failed to reject H_o	No Causality
	Nifty does not Granger-Cause Nikkei	1.2214	0.2954	Failed to reject H_o	
Europe	FTSE does not Granger-Cause Nifty	1.2841	0.2775	Failed to reject H_o	No Causality
	Nifty does not Ganger-Cause FTSE	0.1699	0.8438	Failed to reject H_o	
	SMI does not Granger-Cause Nifty	1.1039	0.3321	Failed to reject H_o	Unidirectional causality
	Nifty does not Ganger-Cause SMI	3.6194	0.0273*	Rejected H_o	
North America	DJIA does not Granger-Cause Nifty	10.8964	0.0000*	Rejected H_o	Unidirectional causality
	Nifty does not Ganger-Cause DJIA	1.9472	0.1434	Failed to reject H_o	
	SPTSX does not Granger-Cause Nifty	0.2976	0.7427	Failed to reject H_o	No Causality
	Nifty does not Ganger-Cause SPTSX	2.4656	0.0856	Failed to reject H_o	

*Note: * 5% level of significance*

Source: Computed using Python

Table 2.6: Results of Granger-Causality Test for During COVID-19 Pandemic Period

Region	Null Hypothesis (H_o)	F-Statistic	Probability	Conclusion	Causality
Asia	SSE does not Granger-Cause Nifty	0.8671	0.4206	Failed to reject H_o	No Causality
	Nifty does not Ganger-Cause SSE	1.4860	0.2269	Failed to reject H_o	
	Nikkei does not Ganger-Cause Nifty	17.1117	0.0000***	Rejected H_o	Unidirectional causality
	Nifty does not Granger-Cause Nikkei	1.8394	0.1596	Failed to reject H_o	
Europe	FTSE does not Granger-Cause Nifty	7.5206	0.0006***	Rejected H_o	Bi-directional causality
	Nifty does not Ganger-Cause FTSE	11.4282	0.0000***	Rejected H_o	
	SMI does not Granger-Cause Nifty	15.1194	0.0000***	Rejected H_o	Bi-directional causality
	Nifty does not Ganger-Cause SMI	13.7227	0.0000***	Rejected H_o	
North America	DJIA does not Granger-Cause Nifty	65.7744	0.0000***	Rejected H_o	Bi-directional causality
	Nifty does not Ganger-Cause DJIA	15.0357	0.0000***	Rejected H_o	
	SPTSX does not Granger-Cause Nifty	37.3953	0.0000***	Rejected H_o	Bi-directional causality
	Nifty does not Ganger-Cause SPTSX	19.5968	0.0000***	Rejected H_o	

*Note: 2 lags used, * 5% level of significance*

Source: Computed using Python

2.9 BEKK-GARCH

Table 2.7: Estimates of BEKK-GARCH Model for the Full Sample Period

	Asia		**Europe**		**North America**	
	Nifty-SSE	**Nifty-Nikkei**	**Nifty-FTSE**	**Nifty-SMI**	**Nifty-DJIA**	**Nifty-SPTSX**
Conditional Mean						
μ_1	1.0646*	1.0846*	1.0872*	1.0870*	1.0871*	1.0379*
μ_2	1.0150*	1.0408*	1.0297*	1.0219*	1.0558*	1.0302*
Conditional Variance						
c_{11}	0.2568*	0.2568*	0.2568*	0.2568*	0.2568*	0.9997*
c_{21}	0.0780*	0.4909	0.3080*	0.1156*	0.0472*	0.2115*
c_{22}	0.2917*	0.9218	0.6169*	0.2730*	0.2306*	0.1945*
α_{11}	0.3281*	0.3563*	0.3208*	0.3451*	0.3246*	0.5172*
α_{21}	0.0043	0.2202	-0.0020	-0.0115	0.0313*	0.1592*
α_{12}	0.0304*	0.0034	0.0383	0.0194	-0.0279	0.2982*
α_{22}	0.3268*	0.4082*	0.5205*	0.3826*	0.3815*	0.3768*
β_{11}	0.9196*	0.9178*	0.9280*	0.9184*	0.9215*	0.0000
β_{21}	-0.0096	-0.0241	0.0163	-0.0014	-0.0146*	-0.2378*
β_{12}	-0.0080	-0.0158	-0.0305	-0.0112	0.0148	-0.3673
β_{22}	0.9252	0.6222	0.6645*	0.9066*	0.8994*	0.8317
Diagnostic Test						
Log-Ih	-18085.92	-18827.63	-17282.58	-17654.86	-16155.93	-16105.79
Q(m)	42.6298 (0.000)	19.1999 (0.0378)	17.3265 (0.0674)	8.9782 (0.5342)	23.6562 (0.0086)	36.5354 (0.0001)

*Note: Variable order is Nifty (1) and the other selected sample indices (2). In the mean equation, 'μ' denotes the constant terms. In the variance equation, 'c' denotes the constant term, 'α' denotes the ARCH term, and 'β' denotes the GARCH terms. Log-Ih = Log-likelihood. Q(m) denotes the Portmanteau Test. * 5% level of significance*

Source: Computed using R

'Table 2.7' represents the results of the BEKK-GARCH Model for the Full Sample Period. In the BEKK-GARCH Model output, 'α' represents the shock spillovers, and the 'β' represents the volatility spillovers. As per the results, in the Asian Pair, it is observed that the SSE observes the shock spillovers from Nifty (α_{12}), and there are no significant shock spillovers between Nifty and Nikkei (α_{12}). In terms of the European Pair, there are no significant shock spillovers observed in either FTSE or SMI. In the North American Pair, it is observed that the DJIA has a significant shock spillover to Nifty (α_{21},) whereas there is a bi-directional shock spillover between Nifty and SPTSX (α_{12} and α_{21}). In terms of the volatility spillover effect, there appears to be no volatility spillovers in the Asian and European pair, however, there appears to be a unidirectional volatility spillover from the DJIA to Nifty (β_{21}), and from SPTSX to Nifty (β_{21}). Hence, H_{O5} and H_{O6} get rejected for the Full Sample Period.

Table 2.8: Estimates of BEKK-GARCH Model for the Pre-COVID-19 Pandemic Sample Period

	Asia		**Europe**		**North America**	
	Nifty-SSE	**Nifty-Nikkei**	**Nifty-FTSE**	**Nifty-SMI**	**Nifty-DJIA**	**Nifty-SPTSX**
Conditional Mean						
μ_1	1.0913*	1.0005*	1.0830*	1.0236*	1.0893*	1.0832*
μ_2	0.9855*	1.0577*	0.9929*	1.0549*	1.1045*	1.0009*
Conditional Variance						
c_{11}	0.1470	0.1978	0.1425*	0.8680	0.6593*	0.1425
c_{21}	0.0600	0.4059	0.1466	0.5691*	0.0493	0.0755
c_{22}	0.2682	0.4890	0.9332	0.4489*	0.1672*	0.6004*
α_{11}	0.2142*	0.2352*	0.2958*	0.0000	0.1948*	0.2920*
α_{21}	-0.2598	-0.1456*	0.1889*	0.1700*	0.1563*	0.0999
α_{12}	0.0384	0.0487	-0.0642	0.3740*	0.2427*	-0.1861*
α_{22}	0.3068	0.4316*	0.0000	0.2352*	0.4165*	0.0000
β_{11}	0.9470	0.9653*	0.9423*	0.2527	0.0000	0.9323*
β_{21}	0.4655	0.0652	0.0911	-0.5000	-0.0106	0.0465
β_{12}	-0.2455	-0.0558	-0.0669	-0.0056	-0.0957	-0.1126
β_{22}	0.7815	0.6935*	0.0237	0.1247	0.8697*	0.0000
Diagnostic Test						
Log-Ih	-1854.142	-2130.803	-1868.313	-1929.59	-1627.819	-1514.717
Q(m)	8.4211 (0.5878)	13.5173 (0.1962)	5.3191 (0.8689)	5.9047 (0.8232)	11.9351 (0.2894)	6.3336 (0.7865)

*Note: Variable order is Nifty (1) and the other selected sample indices (2). In the mean equation, 'μ' denotes the constant terms. In the variance equation, 'c' denotes the constant term, 'α' denotes the ARCH term, and 'β' denotes the GARCH terms. Log-Ih = Log-likelihood. Q(m) denotes the Portmanteau Test. * 5% level of significance*

Source: Computed using R

'Table 2.8' represents the results of the BEKK-GARCH Model for the Pre-COVID-19 Pandemic Period. As per the Asian Pair, there appears to be no shock spillovers between

Nifty and SSE (α_{12}), however, there appears to be a shock spillover from Nikkei to Nifty (α_{21}). In terms of the European Pair, there appears to be a shock spillover from the FTSE to Nifty (α_{21}), whereas there appears to be a bi-directional shock spillover between Nifty and SMI (α_{12} and α_{21}). In terms of the North American pair, there appears to be a bi-directional shock spillover between the DJIA and Nifty (α_{12} and α_{21}), whereas the SPTSX receives the shock spillover from Nifty (α_{12}). In term of the volatility spillovers, there appears to be no volatility spillovers for all sample pairs.

Table 2.9: Estimates of BEKK-GARCH Model for During COVID-19 Pandemic Period

	Asia		Europe		North America	
	Nifty-SSE	**Nifty-Nikkei**	**Nifty-FTSE**	**Nifty-SMI**	**Nifty-DJIA**	**Nifty-SPTSX**
Conditional Mean						
μ_1	1.1042*	1.0988*	1.1046*	1.1284*	1.1016*	1.1125*
μ_2	1.0013*	1.0095*	1.0190*	1.0361*	1.0316*	1.0311*
Conditional Variance						
c_{11}	0.9235	0.2662*	0.2662*	0.2662*	0.7125*	0.5540*
c_{21}	0.3070*	0.5774	0.0994	0.0872	0.5093	0.4669*
c_{22}	0.2076	1.1218*	0.2459*	0.4652*	0.6757	0.2243
α_{11}	0.5418*	0.3268*	0.1997*	0.1683*	0.3618*	0.3947*
α_{21}	0.2977*	-0.4118*	0.1699*	0.2895*	0.4510*	0.4737*
α_{12}	0.1661*	-0.2312*	-0.1359	0.0053	-0.0888*	0.0037
α_{22}	0.3644*	0.0000	0.2808*	0.4160*	0.5635*	0.5450*
β_{11}	0.0000	0.9528*	0.8095*	0.9055	0.4691	0.7520
β_{21}	-0.5000	0.4550*	-0.2591*	-0.0633	-0.5000	-0.3107
β_{12}	-0.5000	-0.1154	0.2666*	0.1177	-0.5000*	-0.5000
β_{22}	0.6659*	0.0000	0.9653*	0.7591*	0.0000	0.0000
Diagnostic Test						
Log-Ih	-2364.568	-2501.353	-2338.229	-2282.777	-2475.37	-2117.5
Q(m)	14.2822 (0.1605)	21.5099 (0.0178)	9.9459 (0.4453)	9.5507 (0.4808)	18.4057 (0.0485)	11.9041 (0.2915)

*Note: Variable order is Nifty (1) and the other selected sample indices (2). In the mean equation, 'μ' denotes the constant terms. In the variance equation, 'c' denotes the constant term, 'α' denotes the ARCH term, and 'β' denotes the GARCH terms. Log-Ih = Log-likelihood. Q(m) denotes the Portmanteau Test. * 5% level of significance*

Source: Computed using R

‘Table 2.9’ represents the BEKK-GARCH Model for the During COVID-19 Pandemic Period. As per the Asian Pair, there appears to be a bi-directional shock spillover between Nifty and SSE, and Nifty and Nikkei (α_{12} and α_{21}). As per the European Pair, there appears to be a shock spillover from FTSE to Nifty, and from SMI to Nifty (α_{21}). For the North American Pair there appears to a bi-directional shock spillover between Nifty and DJIA (α_{12} and α_{21}), and a unidirectional shock spillover from SPTSX to Nifty (α_{21}). As per the Volatility Spillover Effect, there appears to be a volatility spillover from Nikkei to Nifty in the Asian Pair (β_{21}), and a bi-directional volatility spillover between FTSE and Nifty in the European Pair (β_{12} and β_{21}). In terms of the North American Pair, there appears to be a volatility spillover from Nifty to DJIA (β_{12}) Hence, H_{O2}, H_{O3}, and H_{O5} get rejected for the During COVID-19 Pandemic Period.

2.10 SUMMARY

In this chapter, the results of the econometric models used are presented. The models used in this chapter are Vector Autoregression, Granger-Causality Test, and BEKK-GARCH. It has been observed that the results for each model during each selected sample period were noticeable and can be drawn significant conclusions from.

The subsequent chapter would present the conclusions and interpretation of the results found in this chapter.

CHAPTER 3: SUMMARY, FINDINGS, AND CONCLUSION

3.1 INTRODUCTION

This Chapter provides a brief insight to the finds of the study. The purpose of this study was to analyze the volatility spillover effect between the Indian Stock Market Index with the leading stock market index of the world, and to study the volatility spillover effect based on the Pre-COVID-19 Pandemic Period and During COVID-19 Pandemic Period. Before conducting the necessary test to identify the volatility spillover effect, Vector Autoregression had to be used in order to examine the responses or impact the Nifty 50 Index sends and receives. Further, the Granger-Causality Test was used to examine the causations caused in the sample periods of the study. After examining the impact and causation of the index, the BEKK-GARCH model was used to help fulfill the objectives of studying the Volatility Spillover Effect.

3.2 FINDINGS OF THE STUDY

After conducting the necessary tests, this study provides evidences of a volatility spillover taking place for the full sample period. There is evidence of shocks transmitted from Nifty 50 to the SSE Composite Index, the Dow Jones Industrial Average to Nifty 50, and the S&P/TSX Composite and Nifty 50 transmitting shocks to each other. Ultimately, there is strong evidence of the Volatility Spillover Effect from the Dow Jones Industrial Average to Nifty 50, and the S&P/TSX Composite to Nifty 50. Hence, with the above-mentioned evidences, the first objective of the study is achieved.

In the Pre-COVID-19 Pandemic Period, there were strong evidences of shock transmission from all samples except the SSE Composite Index, however, there was no evidence of Volatility Spillovers during this period. During the COVID-19 Pandemic Period, the shock transmission was evident from one index to the other, and there is strong evidence of the volatility spillover effect taking place from Nikkei 225 to Nifty 50, bi-directional volatility spillover effect taking place between Nifty 50 and FTSE 100, and Nifty 50 to the Dow Jones Industrial Average. Hence, the above-mentioned evidences fulfill the second objective of the study, due to the constant shocks taking place due to the COVID-19 Pandemic, the volatility spillover effect was evident.

To support the evidences of the results of the volatility spillover effect, the Impulse Response Function of the Vector Autoregression reveals that the impact received by the Nifty 50 Index were more significant compared to Nifty 50 towards the other sample indices. The impact response received by Nifty 50 intensified during the COVID-19 period, especially from the Asian samples. The impact response is also notable from the S&P/TSX Composite to Nifty 50 during the COVID-19 Pandemic Period. Since there was evidence of a volatility spillover from Nikkei 225 to Nifty 50 during the COVID-19 Pandemic Period, the Granger-Causality Test also indicated significant causality in the full sample and during COVID-19 Pandemic Period. Also, it is observed that the Nifty 50 has the highest correlation with Nikkei 225 in the Correlation Matrix.

3.3 IMPLICATIONS OF THE STUDY

The evidences drawn from this study can be used for fund managers to construct portfolios for their clients and to facilitate hedging in terms of shock events that could potentially take place in the future. The type of impact that has been observed due to the COVID-19 Pandemic has triggered the spillovers to take place, if at all another event of a huge magnitude would take place, the fund managers or portfolio managers would be prepared to hedge their portfolios against sudden shocks.

3.4 CONCLUSION

The results of this study concludes that there exists a significant volatility spillover from the Dow Jones Industrial Average to Nifty 50, and from S&P/TSX Composite to Nifty 50 in the full sample period. Whereas, it was observed that during the COVID-19 Pandemic Period there were volatility spillovers from Nikkei 225 to Nifty 50, Nifty 50 to the Dow Jones Industrial Average, and a bi-directional spillover between Nifty 50 and FTSE 100. In comparison to the Pre-COVID-19 Pandemic Period, where there were no Volatility Spillovers seen, hence, the COVID-19 Pandemic may have caused significant volatility spillovers to take place.

After drawing results from this study, a peculiar observation would be that during the COVID-19 Pandemic Period, the Nifty 50 and FTSE 100 having a bi-directional volatility spillover, and Nifty 50 having a volatility spillover to the Dow Jones Industrial

Average. The possible reason for Nifty 50 and FTSE 100 to have a bi-directional volatility spillover would be due to the fact that India surpassing the United Kingdom's economy in 2022 (World Economic Forum, 2022). The possible reason for Nifty 50 to have a volatility spillover to the Dow Jones Industrial Average could be due to the performance of the Information Technology sector. In 2021, the stock market saw a surge in technology companies stock prices, however, that trend did not last long, and as a result technology companies started underperforming (CNBC, 2022). Also, Indian Technology Companies contribute to $198 Billion to the US Economy (CNBC TV 18, 2022), all these factors could potentially be the reason for a unidirectional volatility spillover effect from Nifty 50 to the Dow Jones Industrial Average.

3.5 SCOPE FOR FURTHER RESEARCH

Despite of having a significant amount of research conducted on the topic of the volatility spillover effect, there are still more areas that can be explored. Even though investors would look out for interconnectedness or interactions between various stock markets, it is also important to take volatility into consideration. The dominance of India in the past decade is a sign itself that the Indian Stock Markets would serve as a good destination for more inflows of foreign portfolio investments at least in the next twenty years. Hence, there also could arise further scope in examining the volatility spillover effect with India's allies. There arose a new wave of uncertainty in the geopolitical environment on the onset of the war between Russia and Ukraine, and in investments terms, if the volatility spillover effect would be studies between India and its allies, it would form as a new beginning for Indian investors to invest into the stock markets of their allies.

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