LINKAGES BETWEEN NATIONAL STOCK EXCHANGE AND SELECTED INTERNATIONAL STOCK EXCHANGES

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By

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Transforming Education Transforming India

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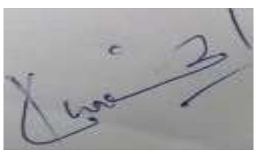
DECLARATION

I, Syed Mohd Khalid, hereby declare that the thesis entitled "**LINKAGES BETWEEN NSE AND SELECTED INTERNATIONAL STOCK EXCHANGES**" submitted to the Lovely Professional University for the award of the Degree of Doctor of Philosophy in Commerce, is an original research work carried out by me at Mittal School of Business in the Lovely Professional University during the period of 2019-24 under the supervision of Dr. Babli Dhiman (Professor), Mittal School of Business, Lovely Professional University. Any extract to this research in part or as a whole has not been included, incorporated or added to any other work or similar title by any scholar in any other university.



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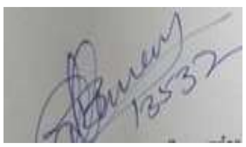
CERTIFICATE

TO WHOM IT MAY CONCERN

I certify that Syed Mohd Khalid has prepared his thesis entitled "**LINKAGES BETWEEN NSE AND SELECTED INTERNATIONAL STOCK EXCHANGES**" for the award of PhD degree from Lovely Professional University under my guidance. He has carried out his work at Mittal School of Business, Lovely Professional University.



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thoughts, knowledge, and insights, thereby playing a substantial role in the successful culmination of this thesis.

Syed Mohd Khalid

ABSTRACT

Over the last two decades, the world stock markets are witnessing the liberalized capital movement, reforms in financial markets, advances in computer technology and information processing. These factors have reduced the inaccessibility of domestic markets and increased the ability of the domestic market to respond quickly to news and shocks originating from the rest of the world. Thus, the linkages between stock markets of different countries around the world have grown stronger. These linkages between the stock markets of different countries can be measured through the volatility and return spillover effects, cointegration and granger causality tests. The need of the study lies in the correct estimation of volatility of price indices, return spillovers, cointegration and granger causality between NSE and Selected International Stock Exchanges which is very useful for making decisions by the financial institutions, portfolio managers, multinational corporations and academicians to diagnose the nature and level of linkages and information transmission between the financial markets.

Before the commencement of this study, there were only a limited number of studies about the linkages between the National Stock Exchange and Selected International Stock Exchanges. This study realizes the need for an updated dataset with methodological improvisation consisting of Multivariate GARCH modelling in analyzing the linkages between the National Stock Exchange and Selected International Stock Exchanges.

In order to achieve the objectives of the study, daily closing values of selected stock indices from 1st April 2001 to 31st March 2022 namely NSE, ASX-200, DAX, EURONEXT-100, HSI, KRX, LSX, NASDAQ, NIKKEI-225, NYSE, SSE, SWX, TSX, and TWSE were collected. Data was collected from the secondary sources, official website of NSE and Bloomberg Database.

The preliminary analyses including Descriptive Statistics and Stationarity Tests have been done. The ADF was applied at level and level 1 to check the stationarity of the data series and PP test was applied at level and level 1 to authorize the results shown by ADF Test. The Zivot Andrew Test was applied to check the structural break in the data series. The results showed a single common significant break 2007 -2009 US financial crises in the data series.

The VAR (1) GARCH (1,1) was applied to check the volatility of price indices between NSE and Selected International Stock Exchanges. The VAR (1)-GARCH (1,1) analysis was conducted on

the NSE, with overseas markets (SWX, SSE, EURONEXT-100, ASX-200, DAX, HSI, KRX, LSX, NASDAQ, NIKKEI-225, NYSE, TWSE, and TSX) used as independent variables. This research provides valuable insights into the behaviour of conditional variances and long-term persistence. The coefficients of previous shocks $(\varepsilon_{t-1}^{x})^2$ for NSE are consistently significant across all models, suggesting that unexpected shocks in the NSE have a considerable effect on its conditional variance. Furthermore, the coefficients for cross-market shocks $\left((\varepsilon_{t-1}^{y})^2\right)$ are also statistically significant, indicating that unforeseen disturbances from these global markets have an impact on the volatility of NSE. The enduring presence of variability is apparent from the elevated levels of previous variances $(h_{t-1}x)$ and $\left(h_{(t-1)y}\right)$ indicating that both NSE and SISE previous variances have a substantial impact on future volatility. This underscores the persistence in the transmission of volatility. Distinctive patterns, such as elevated coefficients for markets like NYSE and TWSE, indicate a robust and enduring long-term connection in these interactions. Moreover, the presence of negative coefficients in certain models suggests a tendency for mean-reversion, while the overall influence of previous shocks and variances remains significant. This analysis highlights the strong connection and significant transmission of volatility between NSE and SISE. It demonstrates how previous volatilities and shocks in both NSE and SISE contribute to the current dynamics of volatility.

Stock markets in various countries around the world are influenced by one another as a result of the interdependence of economies. This is the case since economies are dependent on one another. Within the realm of academic writing, it is largely accepted that the phenomenon of worldwide stock market integration is, in fact, a phenomenon. The international integration and transmission of stock markets, as well as the spillover effects of stock returns and volatilities among international stock indexes, are currently also being examined by researchers from all over the world. This investigation is currently in progress. There are a great number of academics that are interested in and doing research on a wide range of topics, and one of these topics is the progression of the spillover from industrialised markets to underdeveloped and emerging economies. The National Stock Exchange and Selected International Stock Exchanges are both researched in this study. Additionally, the volatility spillover that happens between these two exchanges is also investigated. The researcher intends to analyse the existence of volatility spill over as well as dynamic conditional correlation between the stock exchanges as part of this study. This investigation will be carried out within the scope of this study. The daily data is gathered over a period of twenty-one years, commencing in April 2001 and ending in March 2022. This time span is the target for the collection of the data. It is for the purpose of the study that the DCC GARCH model is utilized in order to evaluate the volatility spillover that is involved. In the beginning, the framework of the DCC model is constructed by fitting the univariate GARCH specifications that are the most suited for each of the series that have been defined. It is hoped that the univariate GARCH specifications that were chosen will provide the most correct explanation for the behaviour of the index return. According to the findings of the DCC GARCH model that was utilized in the research study, the p value of the t statistics of the joint DCC coefficient was found to be less than the 5 percent level of significance. This was proved by the fact that the levels of significance were lower than the p value. There is a possibility that linear dependency is the consequence of some form of incompetence related to the market. Estimates derived from the DCC-GARCH model suggest that the conditional correlation between the National Stock Exchange (NSE) and the Selected International Stock Exchanges (SISE) is very dynamic and adapts to different circumstances throughout time. These are the reasons why the estimates are so important. Given the results of the research, it is feasible to get the conclusion that there is a significant connection between the conditional heteroscedastity estimates of the NSE indices and selected foreign stock indexes. This conclusion can be reached on the basis of the findings of the study. For the findings, there was support from Gupta and Mollik (2008), Xiao and Dhesi (2010), AL-Zeaud and ALshbiel (2012), and Baumohl and Lyocsa (2013). These authors showed that the findings were supported by their findings.

The cointegration test was applied to check the existence of a long-run relationship between NSE and Selected International Stock Exchanges. The period of Twenty-one years was divided into three sections on the basis of US Financial Crises. The pre break period, which starts from 1st April 2001 to 31st March 2007, during break period, which starts from 1st April 2007 to 3st March 2009 and lastly post break period, which starts from 1st April 2009 to 31st March 2022. The results showed different cointegration levels of NSE and SISE during these periods. During pre-break period, the study revealed that NSE is interconnected with both NIKKEI-225 and SWX, as determined by both Trace and Max-Eigen values. During break period, The Co-Integration test was conducted on all fourteen stock exchanges for a period of 2 years, from April 2007 to March 2009. The results determined that NSE is only integrated with HSI based on both the Trace and

Max-Eigen values. And during post break period, the results determined that NSE is integrated with ASX-200, NASDAQ and TSX based on the trace value, which is statistically significant at a 5% significance level. Therefore, null hypothesis is rejected that these series are not integrated with NSE. According to the Max-Eigen Value test, NSE is integrated with ASX-200, NASDAQ and TSX since their values are statistically significant at a 5% significance level. Therefore, null hypothesis is rejected that these series are not integrated with the NSE. To check the short term relationship between the NSE and Selected International Stock Exchanges Granger Causality was applied. The results showed both the short term relationship as well the direction of the relationship. During pre-break period, the findings of the Granger Causality Test showed that the NSE is affected by Selected International Stock Exchanges. This is supported by the rejection of the null hypothesis that the Selected International Stock Exchanges do not have a causal influence on the NSE. In particular, the stock exchanges NASDAQ, EURONEXT-100, DAX, NYSE, SSE, SWX, and TSX indexes all show a strong Granger causality relationship with the NSE. This suggests that the past values of these stock exchange offer important forecasting information for the NSE. In simpler terms, these stock exchanges do influence the NSE. On the other hand, the null hypothesis that the NSE does not have a causal relationship with these international stock exchanges is rejected in some stock exchanges, indicating that there is an inverse causality between the NSE and these exchanges. NSE Granger cause NIKKEI-225, LSX, KOREA, HANG SENG, EURONEXT-100, DAX, ASX-200, NYSE, SSE, SWX, TSX and TWSE. Even so, the null hypothesis is upheld for the NASDAQ and TSX exchanges, suggesting that the NSE does not have a Granger causality effect on the NASDAQ and TSX. However, they do have such an effect on the NSE. These results showed that there is the presence of both the unilateral and bilateral relationships between the NSE and these Selected International Stock Exchanges. There is bilateral relationship between NSE and EURONEXT-100, DAX, NYSE, SSE and SWX. These findings indicate that there are intricate connections between the NSE and worldwide stock markets, emphasizing the significance of taking foreign issues into account when analyzing the behaviour of the NSE. During break period, the stock exchanges NASDAQ, LSX, HANG SENG, EURONEXT-100, DAX, ASX-200, NYSE, SWX, and TSX all show a strong Granger causality relationship with the NSE. This suggests that the past values of these stock exchanges offer important forecasting information for the NSE. NSE Granger cause NIKKEI-225, KOREA, HANG SENG, EURONEXT-100, ASX-200, NYSE, SSE, and TWSE. Even so, the null hypothesis is upheld for the NASDAQ, LSX, EURONEXT-100, SWX, TSX and TWSE, suggesting that the NSE does not have a Granger causality effect on the NASDAQ, LSX, and DAX. And during post break, the rejection of the null hypothesis that the international stock exchanges do not have a causal influence on the NSE. In particular, the stock exchanges NASDAQ, LSX, HANG SENG, EURONEXT-100, DAX, ASX-200, NYSE, SWX, and TSX all show a strong Granger causality relationship with the NSE. NSE Granger cause NIKKEI-225, KOREA, HANG SENG, EURONEXT-100, ASX-200, NYSE, SSE, and TWSE. Even so, the null hypothesis is upheld for the NASDAQ, LSX, EURONEXT-100, SWX, TSX and TWSE, suggesting that the NSE does not have a Granger causality effect on the NASDAQ, LSX, and DAX.

The results ultimately showed that there is linkage between NSE and Selected International Stock Exchanges.

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List of ABBREVATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criteria
AIF	Alternative Investment Funds
ARCH	Autoregressive Conditional Heteroskedasticity
ARDL	Autoregressive Distributed Lag
BRICS	Brazil, Russia, India, China (PRC), and South Africa.
BSE	Bombay Stock Exchange
SEBI	Securities Exchange Board of India
DCC	Dynamic Conditional Correlation
BEKK	Baba, Engle, Kraft and Kroner
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
IV	Integrated Volatility
LM	Lagrange Multiplier
NSE	National Stock Exchange
OLS	Ordinary Least Square
RATS	Regression Analysis of Time Series
RSS	Residual Sum of Square
SIC	Schwarz Information Criterion
AIC	Akaike Info criterion
UK	United Kingdom
US	United States
VAR	Vector Autoregressive
VARMA	Vector Autoregressive Moving Average
NSE	National Stock Exchange
NYSE	New York Stock Exchange
SSE	Shanghai Stock Exchange
TSX	Toronto Stock Exchange
LSX	London Stock Exchange
NIKKEI-225	Tokyo Stock Exchange
HSI	Hang Seng Stock Exchange/ Hang Seng Index
SWX	Six Swiss Stock Exchange
KRX	Korea Stock Exchange
TWSE	Taiwan Stock Exchange
ASX-200	Australian Stock Exchange-200
SISE	Selected International Stock Exchange

CHAPTER 1

INTRODUCTION

Financial market includes stock market, bond market, currency market and derivatives market and among others, is any market place where trading in securities takes place. Financial market is of utmost importance for the smooth functioning of the capitalist economies since they deal in all varieties of securities. Financial market is much broader term than stock market. These markets also present assets and securities that trade over-the-counter or on regulated exchanges. Economic disruption, such as a recession and unemployment, may be the outcome of failing financial markets.

"Stock market" refers to the combination of exchanges where consistent accomplishments of selling, issuance and buying of securities of publicly listed companies take place. Such monetary trade practices are managed through publicly listed Stock Exchanges or Over-The-Counter (OTC) market places that are governed by the set of rules and regulations. It includes financial markets and institutions, investors, services and regulators. Stock market is also called as Equity Market. The term "Stock exchange" refers to an exchange, where selling and buying shares of stock, bonds and other securities takes place through traders and stock brokers. The words stock market and stock exchange are used interchangeable, but the difference is that stock market is a wider term than stock exchange.

Globalization has taken the world on a higher level. Due to the globalization of stock markets, they are witnessing a significant increase in the balance of relationships between themselves over the years. The balance of relationships between the international stock markets has become of great importance in these recent times. Globalization leads the markets more on a global level and less local. The investors in developed nations found more scope of investment in developing nations. Earlier investors used to avoid to invest in developing nations because of some reasons like political issues, restrictions etc. But now political risks have been reduced and the ease in restrictions have been granted by developing nations. Internationalization provides opportunities to the investors to invest their money in different stock markets of the world (Sanjeet Singh and Gagan Deep Sharma, 2012). Numerous researches have been performed in studying the linkage between world stock markets by applying different econometric tools (Narayan et.al., 2015). The financial markets crossed the boundaries across the world and money moving in the form of FDI'S, loans, foreign currency etc. (Malabika Deo and Arun Prakash, 2017). The technological advancements and financial deregulations led the stock exchanges to be more internationalized (Bae and Zhang, 2015).

1.1 Overview on Indian Stock Markets

India is considered among one of the speedy growing economies throughout the globe. As per the IMF report on February 24, 2020, India ranks fifth in the list of largest economies of the world leaving behind the developed countries UK, France, Italy, Canada. Stock market is considered as the barometer of the economy. The Indian Financial System consists of both the primary and secondary stock markets. It includes financial institutions, investors, service providers and regulators. A good financial system helps to mobilize the savings of the public belonging to different classes and having different expected returns and risk appetite The Indian Stock Market is divided in two broad categories, Primary and Secondary market.

1.1.1 Types of Indian Stock Markets

- **Primary market**

The Primary market also called as "New Issue Market" or "Share Market" is the market where securities are traded for the first time to the public through Initial public offering (IPO). By this companies raise their funds from the public/investors.

- **Secondary market**

The Secondary market also called as Aftermarket is the market where the sale and purchase of the securities are done which are previously issued. The secondary market is highly liquid as the investors and speculators sell or transfer their securities to one another.

The Indian stock market is holding a prominent place at a global stage. In India there are 23 stock exchanges in function, among them 21 are regional (only 6 are functional and rest are closed) and 2 national stock exchanges (NSE and BSE) are considered among the top 20 in the world. The process of transaction was initiated in the year 1875 in Bombay which then was named as "Native Share and Stock Broker's Association". At that time the overall number of members were 318 with the membership fee of Rs.1. This association onwards grows up and takes the shape of a giant which now-a-days is known as "Bombay Stock Exchange" or BSE. It is considered as the barometer for measuring the Industrial growth in developing India. NSE was established in 1992 and holds 2nd rank in the list of largest stock exchange in the world in terms of number of transactions (trades) of equity shares by World Federation of Exchanges report. There are 1600 companies listed in NSE. Its index is Nifty 50. NSE is more advanced than BSE in terms of technological advancements.

1.2 Overview on International Stock Markets

The stock market to be defined is a place, where selling and buying operations of securities are handled. The International Stock Market refers to all the world wide stock markets that exchange stocks from their national companies. It provides the plate form for global finance. It allows global investors to participate in a wide variety of participants and also helps the economies of the world to grow. Market valuation and market turnover are important tools to understand the importance of international equity markets. The indexes of a stock exchange indicate the movements in the value of stock. Some of the important indices are the NIKKEI 225 in Tokyo Japan, Dow jones and NASDAQ, operating in New York, the DAX in the Frankfurt and the FTSE in London. The list of stock exchanges to be focused are as below:

Table 1.1: The List of Top Stock Exchanges of the World

S. No.	Stock Exchanges	Index	Country
1	Shanghai Stock Exchange (SSE)	SSE Composite Index (SCI)	China
2	Toronto Stock Exchange (TSX)	S&P/TSX Composite Index (TCI)	Canada
3	London Stock Exchange (LSE)	FTSE 100 Index	London
4	NASDAQ	NASDAQ Composite Index	USA
5	Nikkei-225 (Tokyo Stock Exchange)	NIKKEI-225	Japan
6	National Stock Exchange (NSE)	Nifty 50	India

7	New York Stock Exchange (NYSE)	NYSE Composite Index	USA
8	Hang Seng Stock Exchange (HSI)	Hang Seng Index (HSI)	South Korea
9	Frankfurt Stock Exchange (DAX)	DAX Performance Index	Germany
10	Six Swiss Stock Exchange (SWX)	Swiss Market Index (SMI)	Switzerland
11	Korea Stock Exchange (KRX)	Korea Composite Stock Price Index (KOSPI)	South Korea
12	Taiwan Stock Exchange (TWSE)	Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX)	Taiwan
13	Australian Stock Exchange-200	S&P/ASX-200	Australia
14	Euronext-100	EURONEXT-100 Index	Amsterdam

Shanghai Stock Exchange (SSE)

The Shanghai Stock Exchange (SSE) was originated on November 26, 1990, and is considered as the world's 4th largest stock market in terms of market cap. It plays a crucial role in China's financial system. The Shanghai Stock Exchange (SSE), based in Shanghai and overseen by the China instruments Regulatory Commission, offers a wide variety of instruments for trading, such as, bonds, funds and stocks. There has strict requirements for companies to be listed at exchange. The inclusion of important Chinese enterprises such as the Industrial and Commercial Bank of China and Petro China in the list highlights the economic prowess of the nation. The exchange has experienced substantial expansion in market capitalization and encompasses prominent indices such as the SSE Composite, SSE 50, and SSE 180. The recent implementation of reforms and initiatives, such as the Shanghai-Hang Seng Stock Connect and the SSE STAR Market, have the objective of improving transparency, attracting foreign investment, and promoting innovation. These measures aim to strengthen the SSE's position as a significant participant in the global financial landscape.

Toronto Stock Exchange (TSX)

The Toronto Stock market (TSX), founded in October 25, 1861 and managed by TMX Group, is a prominent international stock market and the largest in Canada, located in Toronto, Ontario. It is reflected as the 8^{th} leading stock exchange in the world in terms of market cap.

The platform showcases an extensive array of corporations from many manufactories, including as mining, power, technology, and financial services. Notable firms like Royal Bank of Canada and Barrick Gold are prominently featured. The TSX is renowned for its rigorous listing criteria and exemplary corporate governance practices, making it a magnet for both local and global investors. The S&P/TSX Composite Index, which serves as its primary yardstick, along with other indexes such as the S&P/TSX 60, monitors and evaluates overall performance of the market. The TSX facilitates the trading of many financial instruments, including ETFs and income trusts, and utilizes sophisticated trading technologies, establishing its importance as a crucial element of Canada's capital markets and a prominent participant in the worldwide financial arena.

London Stock Exchange (LSX)

The London Stock Exchange (LSE) is among the oldest and most esteemed stock exchanges globally, originating in 1698 when John Castaing commenced publishing a list of stock and commodity prices titled "The Course of the Exchange and Other Things" at Jonathan's Coffee House in London. This casual assembly of dealers ultimately transformed into a more organised marketplace, culminating in the official founding of the London Stock Exchange in 1801.

The London School of Economics is situated in Paternoster Square, adjacent to St. Paul's Cathedral in the core of London's financial centre. It is a pivotal entity in the global financial system, providing a platform for corporations to acquire capital and for investors to transact a diverse array of financial instruments, including shares, bonds, derivatives, and exchange-traded funds (ETFs).

In 1973, the market experienced substantial transformations by merging with multiple regional stock exchanges throughout the UK, resulting in the establishment of the Stock market of Great Britain and Ireland. This consolidation was integral to a comprehensive initiative aimed at optimising and modernising the financial markets of the UK. In 1991, the designation was formally altered to the London Stock Exchange, signifying its pivotal position in the UK's financial framework. The LSE has led in financial innovation. It was among the initial significant exchanges to demutualise and transition into a publicly traded entity in 2000. This action enabled the LSE to broaden its operations and invest in innovative technologies, thereby reinforcing its status as a premier global exchange.

In recent years, the LSE has expanded through smart acquisitions and alliances. In 2007, it notably joined with Borsa Italiana, the Italian stock exchange, therefore boosting its presence in European markets. The LSE Group, the parent entity of the London Stock Exchange, currently manages several international exchanges and clearinghouses, positioning it among the largest exchange conglomerates globally. The LSE is recognised for its benchmark indices, including the FTSE 100 (Financial Times Stock Exchange 100 Index), which monitors the performance of the 100 largest businesses listed on the exchange based on market capitalisation. The FTSE 100 is a prominent stock index globally and acts as an indicator of the UK economy's health. Alongside its core market for large-cap corporations, the LSE administers the Alternative Investment Market (AIM), which offers a venue for smaller, emerging enterprises to secure finance. AIM has emerged as a favoured platform for entrepreneurs and SMEs seeking to secure funding and grow their operations. The London Stock Exchange is overseen by the Financial Conduct Authority (FCA) and complies with rigorous requirements of openness, equity, and investor safeguarding. It is integral to the global financial ecosystem, facilitating capital movement and fostering economic growth. The London Stock Exchange serves as a fundamental component of the UK's financial system and a crucial centre for global finance, linking investors and corporations worldwide. Its extensive history, pioneering ethos, and international impact establish it as a significant participant in the dynamic realm of global finance.

NASDAQ

The stock exchange in question is the NASDAQ (National Association of Securities Dealers Automated Quotations), not the American Stock Exchange (AMEX), which is a distinct company. NASDAQ is located in New York City and is recognised as the world's inaugural electronic stock market. It is the second-largest stock exchange in the world by market capitalisation, following only the New York Stock Exchange (NYSE). Established in 1971 by the National Association of Securities Dealers (NASD), currently referred to as the Financial Industry Regulatory Authority (FINRA), NASDAQ transformed trading by implementing an automated system that obviated the necessity for a physical trading floor.

NASDAQ is renowned for its close affiliation with technology and growth enterprises, featuring major corporations such as Apple, Microsoft, Amazon, and Alphabet (Google). It is a favoured listing destination for numerous innovative and high-growth companies, especially in the technology, biotechnology, and renewable energy industries. The exchange has several market tiers, including the NASDAQ Global Select Market, NASDAQ Global Market, and NASDAQ Capital Market, accommodating enterprises of diverse sizes and developmental phases. Besides stocks, NASDAQ facilitates trading in derivatives, fixed-income securities, and ETFs. It is a frontrunner in market technology, offering trading platforms and services to exchanges globally. The NASDAQ Composite Index, which monitors the performance of all companies listed on the exchange, is among the most extensively observed indices worldwide. Throughout the years, NASDAQ has been instrumental in influencing contemporary financial markets, prioritising innovation, openness, and efficiency. Its importance transcends trading, serving as a nexus for financial data, analytics, and corporate services, so establishing it as a fundamental component of the global financial ecosystem.

Tokyo Stock Exchange (NIKKEI-225)

The Nikkei 225, often known as the Nikkei Stock Average, serves as the principal stock index of the Tokyo Stock Exchange (TSE) and encompasses 225 prominent Japanese corporations from several sectors. Established in 1950, it is computed by the Nikkei newspaper. The index is price-weighted, indicating that equities with elevated prices exert a more significant influence. As

Japan's foremost stock market index, it signifies the nation's total economic vitality. Established in 1878, the Tokyo Stock Exchange is among the largest and most significant stock marketplaces globally. The Nikkei 225 is monitored by international investors and frequently compared to the Dow Jones Industrial Average. It is essential for monitoring Japan's financial and economic trends.

New York Stock Exchange (NYSE)

The New York Stock Exchange (NYSE), situated in New York City, is the largest equities stock exchange globally by market capitalisation. Established in 1792, it is the oldest American stock exchange currently in operation. The NYSE enumerates hundreds of corporations from diverse industries, encompassing some of the most valuable enterprises worldwide. It functions as an auction-based marketplace, wherein buyers and sellers engage in transactions via a specialised system. The NYSE Composite Index monitors the aggregate performance of listed equities. Renowned for its rigorous listing criteria, it is regarded as a standard of business stability and financial robustness. The exchange is crucial in global finance, impacting markets internationally.

Hang Seng Stock Exchange (HSI)

The Hang Seng Index (HSI) serves as the principal stock index of the Stock Exchange of Hong Kong (HKEX), monitoring the largest and most significant corporations in the area. Founded on November 24, 1969, it signifies Hong Kong's market performance and economic stability. The Hong Kong Stock Exchange (HKEX), established on February 3, 1891, ranks among the major stock exchanges in Asia by market capitalisation. The HSI comprises blue-chip corporations, predominantly from the financial, technology, real estate, and commerce sectors. It is an index that is free-float-adjusted and weighted by market capitalisation, guaranteeing an accurate portrayal of market trends. The HSI serves as a crucial barometer of Hong Kong's financial stability and is meticulously observed by international investors. It functions as a conduit between mainland China and foreign markets, playing an essential role in international finance.

Frankfurt Stock Exchange (DAX)

The Frankfurt Stock Exchange (Frankfurter Wertpapierbörse), sometimes abbreviated as FWB, is among the largest and most significant securities trading hubs globally. Founded in 1990, it administers the DAX (Deutscher Aktienindex), which monitors the performance of the 40 principal German corporations listed on the exchange. The FWB is integral to the global financial market, facilitating trade in stocks, bonds, derivatives, and various financial products. Xetra is known for its sophisticated electronic trading platform that guarantees efficient and transparent transactions. The Frankfurt Stock Exchange serves as a pivotal centre for international investors, notably impacting Germany's economy and the wider European financial system. Its strategic position in Frankfurt, a main financial hub, amplifies its significance in global finance.

Six Swiss Stock Exchange (SWX)

The main stock exchange in Switzerland is called SIX Swiss Exchange, which is sometimes known as SWX Swiss Exchange. Its headquarters are located in Zurich. It was founded in 1993 by the merger of the Geneva Stock Exchange, the Basel Stock Exchange, and the Zurich Stock Exchange, resulting in a single platform for trading. Because of its high liquidity, efficiency, and strict regulatory standards, the exchange is a popular choice for investors from around the world. It provides trading in stocks, bonds, ETFs, and structured products, with a heavy emphasis on technology and innovation. The Swiss Market Index (SMI), which monitors the performance of the 20 largest and most liquid companies that are listed on the exchange, is likewise located at the SIX Swiss Exchange. It is an important part of Switzerland's status as a major financial centre because it is a key player in the global financial industry.

Korea Stock Exchange (KRX)

Since its establishment in 1956, the KOSPI market, which serves as Korea's primary stock exchange, has been home to renowned multinational corporations such Samsung Electronics, Hyundai Motor, POSCO, and LG Electronics. The market capitalization has increased to KRW 115 billion, backed by the steady growth of prominent blue-chip companies. Moreover, stock exchanges in prominent developed countries have recognized the KOSPI market as a viable investment option. This acknowledgment suggests that enterprises listed on the KOSPI market enjoy enhanced prospects for financing, simplified access to overseas markets, and the possibility of establishing partnerships with global corporations. Moreover, the companies included in the KOSPI 200 index, renowned for their outstanding liquidity and serving as a standard for futures and options, are attracting substantial attention from both local and global investors, consequently boosting investment growth.

Taiwan Stock Exchange (TWSE)

The Taiwan Stock market (TWSE) is the main stock market in Taiwan. It was founded in 1961 and began operating in February 1962. The TWSE is headquartered in Taipei. The Taiwan Stock Exchange (TWSE) is an important platform for trading stocks, bonds, and other financial instruments. It is regulated by the Financial Supervisory Commission. The Taiwan Capitalisation Weighted Stock Index (TAIEX) is the most well-known index. It tracks the performance of all the businesses listed on the exchange and is commonly considered to be the standard for measuring Taiwan's stock market. The TWSE is an important part of the economy in the region because it provides a marketplace that is transparent and efficient for both domestic and international investors. The exchange is continuing to solidify its status as a major financial centre in Asia by emphasising innovation and sustainability.

Australian Stock Exchange (ASX-200)

The Australian Stock Exchange (ASX) was created in 1987 in Sydney, Australia, when the Sydney Stock Exchange and a number of other regional markets from various states merged. It manages the S&P/ASX 200 index, which monitors how well the 200 best-performing businesses on the exchange are doing and is an important standard for the Australian equities market. The ASX is a major player in the global financial landscape, ranking as the third-largest bond market in Asia and the eighth-largest stock exchange in the world by equity market capitalisation. According to the World Economic Forum, it is also recognised as the seventh-largest foreign exchange market in the world based on global turnover. The ASX is an important part of Australia's economy and acts as a gateway for overseas investors who want to participate in the Asia-Pacific region. It is known for its strong regulatory framework and innovative trading systems.

EURONEXT-100

It was established in 1602. It is situated in Greater Paris, France. Its index is Euronext 100. It is the biggest stock exchange in Europe. It is the largest centre for debt and funds listings in the world. The presentation of top 100 listed businesses on the Pan-European Euronext Exchange, which includes markets in Amsterdam, Brussels, Dublin, Lisbon, Milan, Oslo, and Paris, is reflected in the well-known Euronext 100 stock market index. The Euronext 100 is a collection of high-quality stocks from several industries, including prominent global companies like Airbus, L'Oréal, and Unilever. It represents the robustness and variety of the European economy. The index is extensively utilized by investors to assess the general condition of the European market and functions as a standard for investment products. The Euronext 100 is renowned for its rigorous standards for inclusion, focusing on factors such as liquidity, stability, and market capitalization. As a result, it serves as a dependable gauge of market trends and a crucial resource for managing portfolios and devising investment strategies in the European financial arena.

1.3 Advantages of Listing on a Stock Exchange

Being listed on a stock exchange grants specific advantages to a company's securities. Only shares of companies that are listed are quoted on a stock exchange. Being listed on a reputable stock exchange is considered advantageous for firms, investors, and the general public, and they tend to reap the following benefits:

- **Increased value**

  Stocks that are listed with a renowned stock exchange are the ones that are deemed to have a higher worth. Companies can capitalize on their market reputation in the stock market by expanding their shareholder base. Offering shares in the market for shareholders to purchase is an effective method of expanding the shareholder base, thereby enhancing their credibility.

- **Accessing Capital**

  An efficient method for a firm to obtain inexpensive money is by offering company shares in the stock market for shareholders to purchase. Publicly traded companies have the ability to raise larger amounts of cash by issuing shares due to their established reputation in the stock market. They may then use this capital to maintain the financial stability of their company and ensure the continuity of their operations.

- **Collateral Value**

  The majority of lenders accept listed securities as collateral and provide loan facilities based on them. Being listed on the stock exchange increases the likelihood of a company obtaining faster acceptance for their credit request due to their perceived credibility.

- **Liquidity**

  Listings provide shareholders with superior liquidity benefits compared to other alternatives and enable them to easily sell their shares in the market. It enables shareholders to assess the worth of their investment.

- **Fair Price**

  Furthermore, it enables the execution of share transactions with a corporation and facilitates the mitigation of the corresponding risks. Additionally, it assists owners in enhancing their earnings even with the most minimal rise in the overall value of the organization.

  The listed price typically reflects the actual value of a specific security on an Indian stock exchange. Due to the transparency of publicly published pricing for listed assets, investors can be confident that they will acquire them at a fair price, as determined by the forces of demand and supply.

1.4 Role of Stock Exchange

Stock exchanges play an important role in mobilizing public savings by providing investors with information about security selections through daily quotations and showcasing current business trends. Stock markets provide a variety of services to various stakeholders, including ensuring the liquidity and marketability of securities, safeguarding funds, and other crucial functions. They also reflect the business cycle of companies, which enables investors to devise strategies that are appropriate for the situation.

- **Liquidity of Securities:** The stock market provides a mechanism for liquidity, which enables security holders to sell their investments to other investors at prices that are currently in the market. This results in assets being extremely liquid.
- **Marketability of Securities:** They make it possible for investors to trade securities at any stage through market hours, which increases the attractiveness of these assets to potential buyers.
- **Safety of Funds:** When it comes to the protection of funds, regulatory authorities such as SEBI are responsible for enforcing a variety of laws and standards for market players. This helps to guarantee that all parties involved are protected.
- **Ensure Long-Term Capital:** Stock markets, which serve as middlemen, supply organizations with long-term finances, which are beneficial to both the companies and the

investors. Companies are provided with funding for the purpose of expansion, while investors receive returns in the form of dividends or appreciation of their capital.

- **Stimulus for Improved Performance:** Listing a firm on a stock market can boost a company's performance by allowing the company to gain access to new money for expansion and by inspiring the company through the performance of its share price.
- A reflection of the economy and the business cycle, the stock market reflects both the macroeconomic and the microeconomic aspects of the economy, displaying phases of economic expansion and contraction. Not only this assist governments in making well-informed policy decisions, but it also discloses the economic cycle of enterprises, which assists investors in formulating strategies.

1.5 History and Background of Stock Exchange

It is commonly believed that the beginning of the stock markets can be traced back to France. Courtiers de change were responsible for regulating debt for the agricultural sector. In essence, they were the first traders because they managed the debts of farmers. Additionally, the development of the stock market is strongly connected to the trade of commodities. It is thought that in the 13th century, a group of commodity merchants from Bruges called together at the residence of a man named Van der Bourse in order to conduct their business transactions. Around the year 1409, this place underwent a process of institutionalization, thereby becoming the primary commercial centre of that age. This notion then expanded to other countries, which resulted in the development of bourses in a number of places that were adjacent to one another.

According to one point of view, throughout the 13th century, bankers working for Venetian banks were involved in the trading of security issued by the government. By the year 1351, the government of Venice had taken measures to put a stop to the propagation of rumours that were designed to bring down the prices of these assets. In addition, it is assumed that Italian businesses were the pioneers in the process of issuing shares. Nevertheless, the concept of the joint-stock company became more formalized with the founding of the Dutch East India Company in the year 1602, which marked the commencement of regular stock trading on the Amsterdam Stock Exchange. This event occurred in connection with the Dutch East India Company. The incorporation of numerous innovative products, such as futures and options, contributed to the increased variety and complexity of market trading operations. This exchange became a center for financial innovation, introducing a variety of new products. The procedures that were developed in Amsterdam laid the foundation for modern financial markets, which in turn influenced the form and operations of stock exchanges all over the world.

Around the world in the modern era, stock markets may be found in almost all established nations as well as many emerging nations. A digit of countries, comprising the United States of America, India, France, South Korea, the United Kingdom, China, Japan, Canada, Germany, and the Netherlands, are home to the largest public securities markets. Having been established in the 18th century, India's stock market is one of the oldest existing stock markets. 1830 marked the beginning of trading in corporate stocks; yet, by 1840, there were only about six brokers despite the fact that there was a significant amount of trade. Twenty-two stockbrokers started conducting business under a banyan tree in the year 1850. This banyan tree is presently located in the neighbourhood of Horniman Circle Park in Mumbai. Over the course of the 1860s, the number of brokers had increased to sixty. As a result of the disruption of cotton supplies from the United States to Europe during the American Civil War, India experienced a surge in the trading of cotton as well as stocks, which resulted in the number of brokers increasing to a staggering 250. 1875 marked the beginning of the BSE, which was founded by a non-profit voluntary association known as "The Native Share and Stockbroker Association."

The year 1930 saw the acquisition of a block of land and the construction of a structure on what is now known as Dalal Street. This building is situated on Samachar Marg in the heart of Downtown Mumbai. In accordance with the Securities Contracts (Regulation) Act, the Bombay Stock Exchange (BSE) was legally admitted by the Government of India in the year 1956 as the first national securities exchange in the country. The BSE has gone through a number of stages that are comparable to those of the economy, including its inception, growth, and maturation. The infamous Harshad Mehta affair, which occurred in 1992, was the event that marked the beginning of the decline of the BSE. Beginning trading in 1994, the NSE was established with the intention of regaining the confidence of investors. As time went on, the trading volume of the NSE eventually overtook that of the BSE. It is today that the BSE has slid to second place, behind the NSE, as a result of a number of scandals and a lack of innovation being implemented.

There are around twenty-one stock exchanges operating in India at the moment. The NSE, the BSE, and the CSE are the three trading platforms that hold the most market share. State capitals and other significant cities are home to smaller regional exchanges that are located in those locations. In order to ensure compliance and safeguard the interests of the stakeholders, Securities and Exchange Board of India (SEBI) is responsible for regulating and supervising all trading, investment activities, and associated securities operations that take place within the United States. Voluminous research literature is available to study the linkage between markets, informational linkages and spill over effects. The factors on which the linkage is based are:

- **Price Volatility**

  Volatility can be defined as the statistical dispersion in the prices of securities for a given set of returns. It also refers to an uncertainty correlated to the extent of alterations in the collateral's value. It is used to describe the price fluctuations of a security. It is calculated by standard deviation or variance or beta of the annual returns of the security or the market index. The higher the volatility, the riskier the security.

- **Return Spillovers**

  Spill overs means the impact of uncertain events in one economy on the other global economies. The spillover effect can both be positive as well as negative, but generally it is considered as negative impact examples are earth quakes, financial crunches, stock market crashes or other macro level events. The spill overs in financial world are of different types like domino effect, contagion effect, financial crises. Since from the globalization of the economies, spillover effects increase in trade and stock market world. The financial crunch on September 2008-2009 in US is one of the best examples of spillover effect.

- **Grangers Causality**

  Granger causality is an analytical concept that assesses the predictive connection between two-time series variables. It was established by Nobel Prize-winning economist Clive Granger in the 1960s. Clive Granger first proposed the idea of Granger causality in his influential study "Investigating Causal Relations by Econometric Models and Cross-spectral Methods," published in 1969. Granger's research used time series analytic methods to analyze causal connections among economic variables. If a time series variable X "Granger-causes" other time series variable Y, it means that previous values of X provide better predictions for future values of Y compared to utilizing merely past values of Y itself.

- **Market Cointegration**

Market Co-integration occurs when prices among different locations or related goods follow similar patterns over a long period of time. It is a renowned instrument in econometrics that is primarily utilized in research investigations that rely on longitudinal data. Regression analysis is similar to correlation analysis, but it is specifically designed to identify long-term associations between endogenous and exogenous variables. Cointegration between two variables indicates a persistent and stable long-term relationship between them. In this research, the market integration was analyzed by using the time series technique of Johnson Co-Integration Test (1988), Vector Error Correction Model (VECM) and Engle-Grangers Test. Johansen's test comes in 2 main forces; Trace tests and Maximum Eigen value test.

The globalisation of financial markets has escalated in recent decades, resulting in heightened interconnection across global stock exchanges. Despite extensive research on the connections among developed markets like the NYSE, NASDAQ, and European exchanges, a considerable gap persists in comprehending the dynamics between emerging and advanced markets, especially regarding India's National Stock Exchange (NSE). Emerging markets such as India have become crucial participants in the global economy, drawing considerable foreign investments and making large contributions to global financial flows. However, the effects of volatility spillovers, causation, and cointegration between the NSE and prominent international stock exchanges remain little examined. The 2008-2009 global financial crisis and its market declines have highlighted the interdependence of global stock markets, where disturbances in one market frequently disseminate to others. This has resulted in a fundamental change in investment methods, as investors increasingly strive to comprehend cross-market connections to reduce risks and enhance returns. Nevertheless, few studies have concentrated on the NSE's integration with global markets, especially employing sophisticated econometric methods and methodologies. Current literature, including works by Bhar and Nikolova (2009), Xu and Hamori (2012), and Rafiqul Bhuyan et al. (2016), has predominantly focused on developed countries, hence creating a significant vacuum in the command of emerging markets such as India.

This research is motivated by the increasing significance of emerging countries, such as India, inside the global financial framework and the necessity to comprehend their integration with international stock exchanges. The NSE, as one of the largest and most dynamic stock exchanges globally, is pivotal in influencing India's economic development and drawing foreign investments. The absence of extensive research on its connections with global markets presents a barrier for investors and politicians seeking to make educated judgements. The 2008-2009 financial crisis and its market fluctuations have underscored the necessity for a more profound comprehension of cross-market interdependencies. Investors, especially novices, are becoming more prudent and aim to mitigate risks by comprehending the influence of global market fluctuations on local markets. This study aims to elucidate these connections, allowing investors to make more informed decisions and formulate strategies to protect their investments.

Moreover, the application of sophisticated econometric tools and procedures, as emphasised by Mei-Se Chien (2015), provides a chance to investigate these connections with enhanced accuracy. This study seeks to enhance the existing body of knowledge and offer a novel viewpoint on the integration of developing economies into global financial systems through the application of these approaches. This project aims to improve comprehension of global financial interdependencies, providing practical insights for investors, policymakers, and scholars. This study seeks to investigate the volatility spillovers, return spillovers, causation, and cointegration between the NSE and selected international stock exchanges. This will yield vital insights on the influence of global market movements on the NSE and vice versa, facilitating a thorough knowledge of cross-market linkages. The results will be especially pertinent for policymakers, investors, and financial analysts aiming to traverse the intricacies of global financial markets and formulate measures to mitigate risks in a progressively interconnected environment.

From the above literature review, the studies show that the stock markets are globally linked with each other but there is need to analyse more about the connectedness between global stock exchanges by employing different parameters and samples. So, this research investigates the linkages between National Stock Exchange and selected International Stock Exchanges.

Chapter Plan

The thesis is drafted into eight chapters

Chapter 1: Introduction

This chapter provides insight about the origin of the different types of selected stock exchanges. The chapter talks about globalization and its impact on stock exchanges. It also highlights the developed and emerging stock exchanges. The chapter also provides the linkages between markets, informational linkages and the spill over effects.

Chapter 2: Review of Literature

This chapter provides the broad analysis of the literature of the variables under study. The chapter provides in detail analysis of the market linkages based on price volatility, volatility spill overs, grangers causality and market integration. The chapter facilitates in finding the research gap and the basis for further research.

Chapter 3: Research Methodology

This chapter explains the need of the study and research objectives. The chapter produces information about the sources of data collection and the sample size taken. It also discusses the econometric tools used to examine the data and to get desired results.

Chapter 4: Volatility of Price Indices Between National Stock Exchange and Selected International Stock Exchanges

This chapter explains the volatility of price indices between the dependent and independent variables. This chapter explains whether there is long term or short term volatility between the variables.

Chapter 5: Impact of major Spillovers between National Stock Exchange and Selected International Stock Exchanges

This chapter explains the short run linkage between the NSE and Selected International Stock Exchanges. It delivers the vital info regarding the return spillover between the stock exchanges. It discusses the dynamic conditional correlation between stock exchanges.

Chapter 6: Granger Causality between National Stock Exchange and Selected International Stock Exchanges

This chapter provides the short run association between the variables. It also provides the direction of relationship between the stock exchanges whether there is unilateral or bilateral relationship.

Chapter 7: Cointegration between National Stock Exchange and selected International Stock Exchanges

This chapter discusses the long run links between the NSE and Selected International Stock Exchanges. Johansen Cointegration Test was employed for the outcome.

Chapter 8: Findings, conclusion and suggestions:

This chapter confers the important results of the research with deduction. This chapter provides the vital information to the investors and provide suggestions to the investors and policy makers.

References

CHAPTER 2

REVIEW OF LITERATURE

It is critical for researchers investigating the connections between the NSE and specific international stock exchanges to conduct an exhaustive literature review. To begin with, it furnishes a fundamental comprehension of the current state of knowledge and areas that require further investigation in this field. Scholars can advance the field by developing new insights and expanding upon prior research by identifying significant themes, methodologies, and findings through a review of prior studies. Additionally, conducting an extensive review of the literature aids in the development of research hypotheses and inquiries. Through the synthesis of outputs from diverse sources, scholars can discern recurring trends, discrepancies, and domains that necessitate additional inquiry. This procedure facilitates the formulation of precise research goals and guarantees that the investigation tackles pertinent concerns about the NSE's engagements with global markets. In addition, the inclusion of a comprehensive literature review serves to bolster the trustworthiness and soundness of research outcomes. Researchers exhibit methodological rigor and a solid theoretical foundation by connecting their work to well-established frameworks, theories, and empirical evidence. Establishing trust among peers, stakeholders, and policymakers is of paramount importance to bolster the significance and applicability of the research outcomes. In conclusion, the act of undertaking a literature review promotes interdisciplinary cooperation and the exchange of knowledge. Scholars can acquire fresh insights, methodologies, and theoretical frameworks by perusing literature from various disciplines, including finance, economics, and international business. By adopting an interdisciplinary methodology, scholars can examine intricate matters from various perspectives, thereby enhancing the research process and ultimately facilitating a more holistic comprehension of the connections that exist between the NSE and international stock exchanges. The Literature review is separated into three sections: The initial part compacts with Individual Variables the subsequent part deals with thematic and relationship and the final part Deals with Bibliometric Analysis.

2.1 Cross-country linkages

Extensive research has been conducted on cross-country linkages as a result of the increased interconnectedness among stock exchanges worldwide brought about by the globalization of financial markets. The objective of this literature review is to consolidate significant discoveries, approaches, and patterns from research endeavors carried out from 1990 to 2023, with a specific emphasis on the intricacies of cross-country linkages within stock exchanges. The investigation into cross-border connections within stock exchanges experienced a surge in interest during the early 1990s, which coincided with the liberalization of financial markets and technological advancements (et al., 1989). Early investigations centered on determining the degree and characteristics of interdependence among prominent stock markets (House et al., 1993). To achieve this, scholars utilized a range of econometric methodologies to examine co-movements, spillover effects, and cross-market correlations (Arshanapalli & Doukas, 1993; Hulme et al., 1995). Cross-country links were investigated using a variety of methodologies during this time, such as cointegration analysis, event studies, vector Autoregression (VAR), and Granger causality tests (Becker et al., 1995; Koutmos & Booth, 1995). Academics investigated various determinants that impact cross-market interactions, including but not limited to geopolitical events, financial integration, macroeconomic variables, and regulatory modifications (Arshanapalli et al., 1995). Moreover, the exploration of intricate connections and transmission mechanisms among numerous stock exchanges was made possible by developments in network analysis methods. Short-term volatility spillovers and long-run co movements among stock markets were observed empirically, indicating the existence of cross-country linkages (Janakiramanan & Lamba, 1998). Initial investigations predominantly concentrated on developed markets; however, subsequent scholarly investigations expanded the examination to encompass emergent and frontier markets, revealing distinct patterns of interdependence and contagion effects (Lim & Wong, 1998; Roca et al., 1998). Furthermore, scholarly research has underscored the significance of institutional developments, financial innovation, and information transmission in influencing the evolution of cross-border connections (Elyasiani et al., 1998). There has been a notable trend in recent scholarly works to investigate the effects of technological progress, algorithmic trading, high-frequency trading, and market microstructure on international connections. Furthermore, the expansion of cross-listings, derivatives markets, exchange-traded funds (ETFs), and derivatives markets has created novel avenues through which opportunities for arbitrage and disruptions can be transmitted internationally (Balvers et al., 2000; Pesonen, 1999). In addition, scholars have begun to examine the influence of social, environmental and governance (ESG) factors on portfolio diversification strategies and cross-country linkages due to their increasing significance.

Comprehending the interconnections between nations in stock exchanges is of paramount importance for a multitude of reasons:

- **Risk Management:** Insights regarding the propagation of crises and events from one market to others can be obtained through cross-country linkages. This comprehension is crucial in the realm of risk management, as it enables investors to effectively mitigate risks associated with specific markets through portfolio diversification (Fernández-Serrano & Sosvilla-Rivero, 2001).
- **Portfolio Diversification:** Investors can effectively construct diversified portfolios that encompass multiple markets by virtue of their understanding of cross-country linkages (Johnson, 2001). Potential benefits of diversifying investments across countries characterized by low correlations include the potential to mitigate portfolio volatility and improve risk-adjusted returns.
- **Market Efficiency Evaluation:** A comprehension of interconnections between nations aids in the evaluation of market efficiency. Researchers can observe the percentage at which data is assimilated into prices in various markets to evaluate the degree of market integration and detect possible arbitrage opportunities (Ciner, 2002).
- **Policy Implications:** Insights derived from cross-country linkages can be utilized by policymakers to formulate efficacious regulatory frameworks and policies (Naceur & Goaied, 2002). Policymakers can enhance financial stability and effectively manage systemic risks by gaining insight into how cross-border capital flows and market interactions are impacted by macroeconomic and regulatory influences.
- **Global Capital Allocation:** Cross-country connections exert an impact on the global capital allocation choices made by corporations and investors. Gaining insight into the intricacies of cross-border capital transfers enables stakeholders to forecast fluctuations in asset valuations, interest rates, and exchange rates, thus facilitating the most efficient distribution of resources (Hansda & Ray, 2002).
- **Economic Growth and International Trade:** The interconnection between the stock market and wider economic trends and trade patterns is substantial. Gaining an understanding of cross-country linkages can yield significant insights regarding the interdependence of economies, thereby enabling the examination of the intricacies of international trade and its influence on economic expansion.
- **Investor Behavior:** An understanding of cross-country linkages contributes to the explanation of investor sentiment and behavior. Through an examination of investor

reactions to occurrences in interconnected markets, scholars can acquire valuable knowledge regarding market psychology, herding behavior, and the cross-border dissemination of information (Illueca & Lafuente, 2002).

- **Financial Innovation:** The evolution of financial products and services is also impacted by cross-border connections. The comprehension of market dynamics is crucial for informing the development of cutting-edge financial instruments, including exchange-traded funds (ETFs), derivatives, and global investment strategies that are customized to suit the requirements of investors from around the world (Kadapakkam et al., 2003). In brief, policy formulation, economic analysis, financial innovation, cross-country linkages in stock exchanges, and policymaking are all dependent on this knowledge for effective risk management, portfolio diversification, market efficiency, and global capital allocation (J. Yang et al., 2003). This resource aids stakeholders in navigating the intricate dynamics of the international financial system by offering significant perceptions on the interdependence of international monetary markets.

2.2 Volatility

The degree of variation or fluctuation in the prices of stocks or securities transacted within a particular market during a specified period is referred to as volatility in stock exchanges. It signifies the degree of unpredictability and peril linked to capital expenditures in the stock market (Wong et al., 2003). Elevated volatility signifies swift and capricious fluctuations in prices, whereas diminished volatility entails price behavior that is comparatively steady and foreseeable (P. K. Narayan & Smyth, 2004; Worthington et al., 2003). An investor's comprehension of volatility is of the utmost importance, given that it influences trading strategies, risk management choices, and market sentiment as a whole (Bohn, 2004). In addition, volatility is monitored by policymakers and regulators to evaluate the firmness of the monetary system and identify systemic risks. The impact of stock market volatility, which is defined as the degree of variation in the values of assets, on investment choices, risk mitigation approaches, and the inclusive functioning of monetary markets, is substantial (Griffin et. al., 2004). The present literature review provides a comprehensive synthesis of recent research conducted from 2020 to 2023, with a specific emphasis on the factors that influence, quantify, predict, and ramify market volatility. In recent research, a multitude of determinants have been investigated about the volatility of the stock market. These determinants comprise technological advancements, geopolitical events, monetary policy decisions, and investor sentiment. An investigation conducted by (Floros, 2005; P. Narayan et al., 2004) underscores the significance of clear policy communication to stabilize markets and the effect that economic policy uncertainty has on the volatility of the stock market. Furthermore, there is evidence to suggest that the proliferation of algorithmic trading strategies and the development of high-frequency trading algorithms contribute to heightened intraday volatility (Megginson & Sutter, 2005; Phylaktis & Ravazzolo, 2005). Advanced econometric techniques and statistical models have been utilized by scholars to quantify and model the volatility of the stock market. Volatility indices, including the CBOE Volatility Index (VIX), have become increasingly significant in the evaluation of market uncertainty and risk perceptions (Cheng & Glascock, 2005). In addition, (Goh et al., 2005) provide empirical evidence that machine learning algorithms, including support vector machines and artificial neural networks, exhibit superior predictive accuracy compared to conventional econometric models when it comes to predicting stock market volatility. The prediction of stock market volatility continues to be an essential field of study, as it has far-reaching consequences for portfolio allocation, risk management, and option pricing (Cheng & Glascock, 2006; Cumperayot et al., 2006). In recent research, numerous forecasting models, such as Stochastic Volatility (SV), ARIMA, and GARCH, have been examined for their effectiveness. As an illustration, (Baur & Jung, 2006) present a hybrid model that integrates GARCH and neural network architectures to enhance the precision of volatility forecasting. This approach takes advantage of the data's time-series patterns and nonlinear relationships (Nguni et al., 2006). A comprehensive comprehension of stock market volatility is critical for both investors and policymakers. Market inefficiencies may be exacerbated, investors deterred, and transaction costs increased due to high volatility (Li, 2007; Syriopoulos, 2007). Furthermore, heightened volatility could potentially indicate fundamental economic instability and systemic risks, thereby necessitating policy and regulatory measures. The significance of policy coordination and macroprudential measures in alleviating the detrimental impacts of stock market volatility on financial stability is emphasized in a study conducted by (Bandopadhyaya, 2007; Eng & Wang, 2007).The recent body of literature concerning stock market volatility from 2020 to 2023 encompasses an extensive investigation into the factors that influence this volatility, methods of measurement, predictive frameworks, and the ramifications for policymakers and investors. The utilization of econometric methodologies, machine learning, and data analytics has significantly enhanced our comprehension of the dynamics of stock market volatility (De Gooijer & Sivarajasingham, 2008; Kaplinsky & Messner, 2008). This has resulted in the provision of invaluable insights that apply to risk management, policy formulation, and decision-making within an ever more uncertain and interconnected global financial environment.

2.3 Spillovers

Spillover, as it pertains to stock exchanges, denotes the process by which disturbances, information, or volatility are transmitted from one market to another (Doman & Doman, 2013; Mensi, Shahzad, et al., 2017). Spillover effects may manifest throughout various asset classes, sectors, or geographical regions, exerting an impact on the operations of interconnected markets. Information spillovers, contagion effects, and volatility spillovers are all examples of the diverse categories of spillovers (Bouri et al., 2018; Inci et al., 2011). Volatility spillovers transpire when shifts in asset prices or market unpredictability transpire from one exchange to another, thereby precipitating heightened volatility and risk contagion. Contagion effects occur when market distress or negative sentiment rapidly spreads from one market to another, increasing by selling pressure and extensive disruptions (Aloui et al., 2011; Raghunath & Rose, 2016; Saha & Bhunia, 2012). Information spillovers occur when market-relevant news or information is disseminated across exchanges, influencing the perceptions of investors and their trading decisions on a global scale (Cheng & Glascock, 2006; Sosvilla-Rivero & Rodríguez, 2010). A comprehensive comprehension of spillover effects is imperative to evaluate market interdependencies, devise policies, and manage risks within a global financial system that is progressively more interdependent and interconnected (Bhowmik & Wang, 2020; Topcu & Gulal, 2020). The phenomenon of spillover effects in stock exchanges, which involves the dissemination of information, volatility, and disruptions across markets, has attracted considerable interest from policymakers, investors, and researchers (Joseph et al., 2020). The objective of this literature review is to consolidate significant discoveries, approaches, and patterns in spillover studies that were carried out from 2000 to 2023. By doing so, it seeks to illuminate the mechanisms, and factors that influence and consequences of spillover effects in stock exchanges worldwide. The investigation of spillover effects within stock exchanges became increasingly significant following significant financial crises and disruptions in the market (Economics, 2020; Farooki & Kaplinsky, 2013; Neaime, 2012). Initial research centered on the evaluation of volatility spillovers and contagion effects that transpired during periods of heightened market turmoil, such as the Asian financial crisis that occurred between 1997 and 1998 and the global financial crisis that occurred between 2007 and 2008 (Dong & Yoon, 2019). Scholars employed a range of econometric methodologies, such as vector Autoregression (VAR), multivariate GARCH models, and event studies, to quantify the effects of spillover dynamics on interconnected markets (Chien et al., 2015; Mensi, Hammoudeh, et al., 2017; Roache, 2021). Spillover effects within the realm of stock exchanges may take various forms, such as contagion effects, information spillovers, and volatility spillovers (Syriopoulos, 2007). Volatility spillovers are risk contagion and the propagation of market uncertainty and asset price fluctuations from one exchange to another, resulting in increased volatility (Ozdemir et al., 2009; Sensoy & Sobaci, 2014; Sharma & Pal, 2018). Contagion effects refer to the expeditious dissemination of market distress or adverse sentiment among markets, which in turn intensifies selling pressure and induces extensive disruptions (Boubaker & Jouini, 2014). Information spillovers occur when market-relevant news or information is disseminated across exchanges, thereby impacting the perceptions of investors and influencing trading decisions on a global scale (Lee et al., 2019). Diverse methodologies have been utilized by researchers to quantify and examine contagion effects in stock exchanges. Co-integration analysis, VAR models, and GARCH models are prevalent econometric methods utilized to quantify the magnitude and direction of spillovers (Rizvi & Arshad, 2016; Zhao et al., 2021). Furthermore, the utilization of network analysis methodologies, such as correlation networks and Granger causality tests, empowers scientists to discern intricate interconnections and pathways of transmission spanning numerous markets (Gutierrez & Vianna, 2020). Sight lining and forecasting spillover patterns in high-frequency trading data have been made possible by recent developments in machine learning algorithms (Raza et al., 2014; Yue et al., 2015). Various factors have been identified in studies as influencing contagion effects in stock exchanges. These factors encompass macroeconomic variables, geopolitical events, investor sentiment, financial integration, and regulatory changes (Institutions, 2016; Jayasuriya, 2011).The significance of financial integration in facilitating cross-market spillovers is underscored in the research of (Egger & Zhu, 2021; Jebran et al., 2017). Similarly, the influence of investor sentiment and news sentiment on information spillovers and contagion effects is examined in the studies of (Kadapakkam et al., 2003; Kocaarslan et al., 2017; Moussa et al., 2021). A comprehensive comprehension of spillover effects is of the utmost importance for regulators, policymakers, and investors (Hung, 2021). Risk management practices, portfolio diversification strategies, and the stability of financial markets may all be impacted by spillovers. In addition, to preserve financial stability and avert contagion, policymakers must monitor and resolve systemic risks that result from spillovers (Atenga & Mougoué, 2021). The significance of policy coordination and macroprudential measures in alleviating the detrimental impacts of spillovers on market stability is emphasized in a study conducted by (Andries & Galasan, 2020; Jiang et al., 2020) .Anticipating forthcoming developments, further scholarly investigation into spillover dynamics in stock exchanges will likely center on emergent patterns such as algorithmic trading, technological progress, and the influence of environmental, social, and governance (ESG) factors (Thakkar & Chaudhari, 2021). Moreover, the incorporation of interdisciplinary methodologies that combine perspectives from finance, economics, and data science will augment our comprehension of contagion mechanisms and the ramifications they have on worldwide financial markets (Balaji et al., 2023). The literature pertaining to spillover effects in stock exchanges from 2000 to 2023 comprises an extensive array of studies that investigate the intricacies, factors that influence, and consequences of cross-market transmission dynamics. Progress in econometric methodologies, network analysis techniques, and machine learning algorithms has significantly enhanced our comprehension of spillover effects. This has resulted in the provision of invaluable insights that aid policymakers, investors, and regulators in effectively navigating the intricate dynamics of interconnected financial markets.

2.4 Causality

In the context of stock exchanges, causality pertains to the correlation between occurrences or variables that exert an impact on the conduct of financial markets. More precisely, it entails discerning the magnitude and direction of the correlation between policy decisions, stock price fluctuations, and market sentiment, as well as other variables including economic indicators and trading volumes (Z. Yang et al., 2014). The motive of causality analysis is to ascertain whether short-term or long-term changes in one variable result in corresponding changes in another (Bouri et al., 2018). A multitude of econometric methodologies is utilized by scholars to evaluate causal relationships in stock exchanges, including vector Autoregression (VAR) models, structural equation modeling (SEM), and Granger causality tests (Shi & Liu, 2020). A comprehensive comprehension of causality is imperative for analysts, policymakers, and investors, as it facilitates the prediction of market trends, the development of investment strategies, and the assessment of the influence of external variables on the dynamics of financial markets (Pesonen, 1999). Causality analysis in stock markets has been a pivotal area of research, spanning various methodologies and empirical investigations. Early studies, such as those by (Bohn, 2004) ,pioneered the application of Granger causality tests, revealing bidirectional causal relationships between macroeconomic variables and stock returns. Subsequent research expanded the scope to include market sentiment, investor behavior, and policy decisions, as demonstrated by (Singh & Singh, 2016) ,who employed vector Autoregression (VAR) models to uncover causal links between investor sentiment and stock market volatility. Advancements in econometric methodologies facilitated deeper insights, with (Birău & Antonescu, 2014) utilizing structural VAR models to uncover asymmetric spillover effects across international stock markets. Additionally, the integration of machine learning techniques, exemplified by studies like those by (Choudhary & Singhal, 2020; Saha & Bhunia, 2012) enabled the exploration of nonlinear causal relationships and enhanced predictive capabilities. Moving forward, research in causality analysis in stock markets is expected to leverage big data analytics, natural language processing, and causal inference techniques to unravel complex interdependencies and provide actionable insights for investors, policymakers, and analysts navigating the dynamic landscape of global financial markets.

2.5 Integration

Integration, as it pertains to the stock market, is the procedure by which diverse financial instruments, data sources, and systems are merged in order to generate a unified and all-encompassing perspective of market activities and trends. It entails the collection, organization, and analysis of a variety of data from multiple sources, including stock exchanges, financial news channels, and economic reports, including stock prices, trading volumes, market news, and economic indicators (Kadapakkam et al., 2003). The process of integration provides market participants, such as analysts, investors, and traders, with a comprehensive understanding of market dynamics, which in turn facilitates the making of well-informed decisions (Maini, 2013). It facilitates the uninterrupted transmission of data across various platforms and applications, thereby augmenting operational effectiveness and mitigating the potential for errors in investment and trading strategies. Integration is of the utmost importance in algorithmic trading as well, as the ability to capitalize on market opportunities requires real-time decision-making and rapid data processing (Stoupos & Kiohos, 2021). Moreover, it facilitates cooperation and interconnection among diverse market participants—including intermediaries, exchanges, and regulatory entities—thereby advancing the principles of openness and honesty in the financial markets. In its entirety, integration plays a critical role within the stock market ecosystem by providing stakeholders with the means to navigate the intricacies of contemporary finance, seize emergent opportunities, and minimize risks (Farooki & Kaplinsky, 2013; Hung, 2021). The degree of integration among market participants and information channels is highly correlated with efficiency in the stock market. (Indian et al., 2016) posits that an effectively integrated market promptly incorporates all pertinent information into stock prices, thereby facilitating fair value assessments and diminishing prospects for arbitrage. (Roca et al., 1998; Sok-Gee & Abd Karim, 2010) provide empirical evidence that greater market efficiency correlates with increased integration, as measured by trading volume and information dissemination. Integration and Trading Strategies: The efficacy of trading strategies implemented by market participants is impacted by integration. According to (Bohn, 2004),the increased liquidity and decreased transaction costs of integrated markets make high-frequency trading strategies more feasible. Furthermore, (Kocaarslan et al., 2017) discover that integration promotes the convergence of trading behaviors among various markets, thereby facilitating the spread of risk management techniques and trading strategies. The acceleration of global stock market integration can be attributed to technological advancements, specifically electronic trading platforms and algorithmic trading algorithms. Automated trading systems facilitate cross-market arbitrage and liquidity provision, thereby enhancing market integration, according to (Jiang et al., 2019; Mensi, Hammoudeh, et al., 2017). Nevertheless, there have been apprehensions expressed concerning the possible destabilizing consequences of algorithmic trading on the integrity of the market and systemic risk (Yoopetch & Chaithanapat, 2021).Regulatory Consequences: The process of integration presents obstacles for market surveillance and regulatory supervision, specifically in the context of international commerce. Harmonized regulatory frameworks and information-sharing mechanisms are advocated by (Legenzova et al., 2023) as a means to tackle the intricacies of integrated markets and prevent regulatory arbitrage. Furthermore, the advent of decentralized finance (DeFi) platforms and digital assets presents unique regulatory obstacles pertaining to the safeguarding of investors and the maintenance of market stability (Ho & Lee, 2021).Integration within the stock market is an intricate and ever-changing occurrence that has significant consequences for trading tactics, regulatory supervision, and market efficiency (Respati et al., 2023). Although technological progress has enabled enhanced integration and productivity, it has also brought forth novel obstacles and vulnerabilities that necessitate vigilant oversight and regulatory intervention (Amaroh et al., 2023). Further investigation is warranted to explore the dynamic characteristics of integration as they pertain to the emergence of financial technologies and the overall state of the global market (Loza et al., 2024).

2.6 Volatility of price indices between international stock exchanges

The volatility of price indices on international stock exchanges has been the focus of extensive market analysis and academic investigation for the past two decades. Both academics and professionals have endeavored to comprehend the catalysts, trends, and consequences of this volatility, acknowledging its significant influence on worldwide financial markets and the choices made by investors. Research on the transmission of volatility among prominent stock exchanges commenced in the early 2000s. Notable contributions to this field of study included Brooks and Tsolacos (2001) and Nandha and Faff (2008), whose investigations revealed the existence of both short-term and long-term linkages. Methods such as multivariate GARCH models and realized volatility measures were frequently employed in these inquiries in order to capture the complex interrelationships among indices. The degree of interdependence among financial markets increased in tandem with the pace of globalization. Significant occurrences, such as the Global Financial Crisis of 2008, provided critical insights into the dynamics of cross-market volatility (Aloui & Hkiri, 2015). In addition, the advent of algorithmic trading strategies and high-frequency trading has brought about novel aspects to volatility patterns, as demonstrated by research investigating the spillover of intraday volatility (Bouri et al., 2017). Considerable attention has been directed towards the growth of emerging markets as well. Scholars have conducted research to determine how macroeconomic and geopolitical factors influence the volatility of indices in regions including Asia and Latin America (Bekaert et al., 2013; Fernandez et al., 2017). Furthermore, the rapid distribution of market updates and news has been facilitated by technological advancements and the abundance of information channels, which have an impact on the amplitude and velocity of cross-border volatility shocks (Caporin et al., 2020). In light of these advancements, discussions continue to revolve around the efficacy of international diversification as a risk management approach. Advocates assert its advantages in reducing market volatility

(Baele et al., 2004), whereas skeptics raise doubts about its performance in times of increased market volatility (Brunnermeier et al., 2009). In anticipation of future developments, the course of volatility in the global stock market will continue to be influenced by a multitude of factors such as changes in economic policy, advancements in technology, and geopolitical tensions. As a result, ongoing academic investigation and risk management approaches that accommodate this dynamic environment will be imperative. In comparison to other international stock exchanges, the volatility of the NSE of India has garnered considerable scholarly and practitioner interest over the past two decades. Research conducted by Goyal and Sodhi (2006) and Aggarwal et al. (2009) offered preliminary observations regarding the volatility patterns of the NSE in comparison to prominent international markets, commencing in the early 2000s. GARCH modelling and volatility spillover analyses were frequently utilized in these inquiries to investigate the relationship between NSE and international exchange volatility. As India's financial markets developed and its economy expanded, scholars initiated investigations into the determinants of NSE volatility. These determinants encompassed domestic macroeconomic indicators, regulatory modifications, and worldwide market sentiment (Bhattacharyya et al., 2015; Subrahmanyam & Urrutia, 2016). Furthermore, research on the transmission of volatility shocks between the NSE and other exchanges has been stimulated by the integration of Indian equity markets into the global financial system. Previous studies have identified bidirectional volatility spillovers that are impacted by investor sentiment and financial crises (Chakrabarti & Chakraborty, 2012; Choudhry et al., 2019). Furthermore, the introduction of algorithmic trading strategies and high-frequency trading has brought about novel aspects to the volatility dynamics of the NSE. As a result, scholars have begun to examine the effects of market microstructure and intraday volatility patterns (Sarkar et al., 2018). During this time, there was also a heightened focus on the volatility of exchanges in emerging markets, as evidenced by research comparing the volatility of the NSE to that of exchanges in developed markets and other emerging economies (Mukherjee et al., 2017; Salisu & Swaray, 2019). In addition, the COVID-19 pandemic that occurred in 2020 offered an exceptional circumstance to assess the NSE's resilience in the face of worldwide market unrest, thereby emphasizing the interdependence of financial markets and the complexities associated with volatility management in the face of unprecedented crises (Deb et al., 2021). In the future, technological advancements, economic reforms, and geopolitical developments are likely to impact the trajectory of NSE volatility relative to international stock exchanges. This emphasises the continued significance of comprehending and controlling volatility in an ever more interconnected global financial system.

2.7 Impact of major spillovers between International Stock Exchanges

In both academic research and practical investment strategies, the impact of significant spillovers between international stock exchanges has received considerable attention over the past two decades. In the early 2000s, Diebold and Yilmaz (2009) and Cappiello et al. (2006) conducted influential research that established the foundation for comprehending the complex web of interdependencies among international financial markets. These studies highlighted the critical role of spillovers in the cross-border transmission of volatility and risk. The aforementioned inquiries employed statistical techniques including connectedness indices and Vector Autoregression (VAR) models to measure the extent and path of Spillovers amongst major stock exchanges. The interdependence of financial markets became more evident as globalisation progressed; instances like the 2008 Global Financial Crisis prompted heightened investigation into the dynamics of contagion (Dungey et al., 2010). Furthermore, spillover effects have been given fresh dimensions with the advent of algorithmic trading strategies and high-frequency trading, as demonstrated by research investigating intraday transmission channels and liquidity spillovers (Zhang et al., 2021; Bae et al., 2018). In addition, inquiries into spillover impacts originating from these regions were prompted by the incorporation of emerging markets into the interantional financial system. The results of these investigations shed light on the influence of geopolitical events, investor sentiment, and economic fundamentals on the patterns of spillover (Kumar et al., 2016; Su et al., 2020). Moreover, the COVID-19 pandemic that occurred in 2020 presented an exceptional setting for examining the robustness of financial markets in the face of worldwide disruptions, unveiling intricate mechanisms of spillovers in the midst of increased unpredictability and market instability (Corbet et al., 2021). In anticipation of future developments, regulatory reforms, technological progress, and changes in worldwide economic circumstances are anticipated to impact the course of spillover effects among international stock exchanges. This highlights the continuous significance of comprehending and mitigating spillover risks in an ever more interconnected financial environment. In the realm of global finance, research on the effects of key spillovers between the National Stock Exchange (NSE) of India and other international stock exchanges has gained prominence over the last two decades. Scholars, including Menla Ali et al. (2014) and Banerjee et al. (2018), have conducted research on the transmission mechanisms and interdependencies of volatility and shocks between the NSE and numerous international markets since the early 2000s. By employing methodologies such as VAR models and Granger causality tests, these investigations have illuminated the magnitude and directionality of spillover effects, thereby emphasizing the significance of economic interdependencies, investor sentiment, and worldwide financial crises. The examination of cross-market spillovers has become a focal point of research due to the increased integration of India's economy into the global financial system. Previous studies have identified bidirectional transmission channels that are impacted by various factors, including exchange rate fluctuations, foreign institutional investment, and trade flows (Singh & Mukherjee, 2012; Hussain et al., 2020). Furthermore, the emergence of algorithmic trading strategies and high-frequency trading has brought about novel aspects to the dynamics of spillover. Scholarly investigations have explored intraday transmission patterns and the influence of market microstructure on cross-market linkages (Jain et al., 2017; Anand et al., 2021). Furthermore, significant occurrences including the worldwide monetary crisis of 2008 and the COVID-19 epidemic have furnished vital frameworks for examining the NSE's capacity to withstand worldwide disruptions and comprehend the transmission of spillovers during times of increased market unpredictability (Vyas et al., 2016; Kumar et al., 2021). In anticipation of future developments, technological advancements, geopolitical tensions, and regulatory developments are anticipated to influence the trajectory of spillover effects between the NSE and international stock exchanges. This emphasizes the continued significance of comprehending and controlling cross-market linkages in an ever more interconnected global financial environment.

2.8 Causality between stock exchanges

Over the past two decades, examining causality between stock exchanges has been a significant focus of research in finance, providing insights into the dynamics of global financial markets and informing investment strategies. Beginning in the early 2000s, seminal studies such as those by Engle and Bollerslev (1986) and Granger (1969) laid the foundation for understanding the concept of causality in financial time series analysis, paving the way for subsequent investigations into causality relationships among stock exchanges. Utilizing methodologies such as Granger causality tests, vector Autoregression (VAR) models, and directed acyclic graphs (DAGs), researchers have explored various aspects of causality, including the direction and strength of causal relationships, the presence of lead-lag relationships, and the identification of shock transmission mechanisms. Studies have examined causality between major global stock exchanges, such as those in the United States, Europe, and Asia, revealing bidirectional causality influenced by factors such as economic fundamentals, investor sentiment, and macroeconomic policies (Tsay, 2005; Cheung & Ng, 1998). Moreover, investigations into causality have extended to emerging market exchanges, with findings suggesting complex interactions driven by factors unique to these regions, such as capital flows, political instability, and currency movements (Yousefi & Wirjanto, 2005; Narayan & Narayan, 2010). Furthermore, advancements in econometric techniques and the availability of high-frequency data have enabled researchers to explore intraday causality relationships and examine the impact of market microstructure on causality dynamics (Bollerslev et. al., 2009; McAleer et al., 2015). In addition, events such as the global financial crisis of 2008 and the COVID-19 pandemic have provided critical contexts for studying causal linkages between stock exchanges during periods of heightened market turmoil and systemic risk (Caporin et al., 2017; Huang et al., 2021). Looking ahead, the continued evolution of global financial markets, technological innovations, and regulatory changes will likely shape the trajectory of research on causality between stock exchanges, emphasizing the ongoing importance of understanding causal relationships for risk management and investment decision-making in an interconnected world.The examination of causative relationships between the National Stock Exchange (NSE) of India and other international stock exchanges has garnered significant academic attention for the past two decades. This trend reflects the increasing interconnectedness of India's financial markets with the global economy. Researchers have utilised a range of econometric methods since the early 2000s to investigate the causal connections between the NSE and international stock exchanges. Their efforts have provided insights into the intensity, direction, and dynamics of information transmission and market interactions. Prominent investigations, including those conducted by Menla Ali et al. (2014) and Banerjee et al. (2018), have assessed the causal relationships between the NSE and major international markets (including those in the United States, Europe, and Asia) using time series methodologies such as vector autoregression (VAR) models, Granger causality tests, and others. The aforementioned inquiries have uncovered a reciprocal relationship of causality between the NSE and specific global exchanges, indicating the existence of interconnections that are impacted by macroeconomic developments, trade flows, and foreign investment (Hussain et al., 2020; Singh & Mukherjee, 2012). Furthermore, research has examined the effects of significant occurrences, including geopolitical tensions and worldwide financial crises, on the causal connections between NSE and other exchanges. These studies have uncovered changes in causal relationships that occur during times of market instability and unpredictability (Vyas et al., 2016; Kumar et al., 2021). Moreover, the emergence of high-frequency trading and progress in market microstructure analysis have provided scholars with the opportunity to investigate intraday causality patterns and the influence of market liquidity on the establishment of causal connections between the NSE and global markets (Jain et al., 2017; Anand et al., 2021). In anticipation of future developments, ongoing economic reforms, technological progress, and global market developments are expected to influence the course of research concerning the causal connection between NSE and other selected International Stock Markets. This underscores ongoing significance of comprehending causal relationships for the benefit of investors, policymakers, and market participants who must navigate the intricacies of interconnected financial systems.

2.9 Dynamic correlation among International Stock Exchanges

Over the past two decades, research on dynamic correlations among international stock exchanges has been a focal point for understanding the evolving interconnectedness of global financial markets. Beginning in the early 2000s, seminal studies by Bollerslev et al. (2009) and Engle (2002) laid the groundwork for exploring time-varying correlations, highlighting the dynamic nature of relationships between major stock exchanges worldwide. Utilizing methodologies such as dynamic conditional correlation (DCC) models, multivariate GARCH models, and copula approaches, researchers have examined the temporal evolution of correlations, uncovering patterns of co-movement and spillover effects across different markets. These investigations have revealed the presence of both short-term and long-term dynamics in correlations, influenced by factors such as economic fundamentals, investor sentiment, and global events (Brooks et al., 2003; Faff et al., 2002). Furthermore, studies have explored the impact of structural changes, such as financial crises and regulatory reforms, on the dynamics of correlations, highlighting shifts in market interdependencies all through periods of market stress and uncertainty (Bekaert et. al., 2010; Kang et. al., 2018). Moreover, advancements in data availability and computational techniques have facilitated the analysis of intraday correlations and the identification of patterns in high-frequency data, offering insights into the microstructure of correlation dynamics (Boswijk et al., 2012; Patton et al., 2015). Additionally, the emergence of emerging markets as significant players in the global economy has prompted investigations into the dynamic correlations between these markets and developed economies, revealing evolving patterns of integration and interdependence (Corbet et al., 2020; Frijns et al., 2010). Looking ahead, the trajectory of research on dynamic correlations among international stock exchanges is likely to be influenced by ongoing globalization, technological advancements, and regulatory changes, underscoring the continued relevance of understanding the temporal dynamics of market relationships for risk management, portfolio diversification, and investment decision-making in an increasingly interconnected financial landscape. The dynamic relationship between the National Stock Exchange (NSE) of India and other international stock exchanges has garnered significant scholarly attention for the last twenty years. This interest stems from the increasing integration of India's financial markets into the global economy. Scholars, including Menla Ali et al. (2014) and Banerjee et al. (2018), have examined the time-varying characteristics of correlations between the NSE and prominent international exchanges since the early 2000s. By utilizing analytical techniques such as vector autoregression (VAR), dynamic conditional correlation (DCC) models, and copula approaches, these research endeavors have unveiled dynamic patterns of co-movements and spillover effects between the NSE and international markets. The results suggest that correlations between the NSE and foreign exchanges are subject to the influence of numerous variables, such as investor sentiment, economic fundamentals, and global events (Singh & Mukherjee, 2012; Hussain et al., 2020). Furthermore, scholarly investigations have examined the effects of regulatory reforms and market stressors, as well as structural changes like financial crises, on dynamic correlations. These studies have identified alterations in market interdependencies that occur during such periods (Vyas et al., 2016; Kumar et al., 2021). Furthermore, the examination of intraday correlations has been made easier by developments in computational methods, enabling researchers to discern patterns in high-frequency data and gain a deeper understanding of the microstructure of correlation dynamics (Jain et al., 2017; Anand et al., 2021). Moreover, ongoing globalization, technological advancements, and regulatory changes are anticipated to shape the course of research concerning dynamic correlations between the NSE and international stock exchanges. This emphasizes the ongoing significance of comprehending these correlations for risk management, portfolio diversification, and investment decision-making within the framework of an ever more interconnected global financial environment.

2.10 Market cointegration among International Stock

In the last twenty years, scholarly investigations into market cointegration among international stock exchanges have played a crucial role in elucidating the levels of integration and long-term equilibrium relationships that exist among financial markets worldwide. Engle and Granger's (1987) and Johansen's (1988) seminal studies have laid the theoretical and methodological groundwork for the examination of cointegration among stock markets since the early 2000s. By employing methodologies such as vector error correction models (VECM), state-space models, and Johansen cointegration tests, scholars have investigated the presence and durability of cointegration associations among the most prominent global stock exchanges. The aforementioned inquiries have unveiled indications of enduring connections between markets distinguished by equilibrium relationships and shared patterns of development (Cheung & Ng, 1998; Brooks et al., 2003). In addition, research has examined the determinants of market cointegration, identifying economic fundamentals, trade linkages, and financial globalization as significant determinants of the extent of market integration (Baele et al., 2004; Bakaert & Harvey, 1995). Furthermore, scholarly investigations have explored the ramifications of market cointegration on risk management, portfolio diversification, and the pricing of international assets. These studies have underscored the criticality of comprehending enduring connections to make informed investment choices (Hwang & Rubesam, 2009; Malliaris & Urrutia, 2016). Furthermore, the emergence of high-frequency data and progress in econometric methodologies have empowered scholars to investigate dynamic cointegration associations and integration levels that vary over time. This has resulted in more profound understanding of the ever-changing characteristics of market linkages (Caporin et al., 2017; Liao et al., 2020). Moving forward, technological advancements, ongoing globalization, and regulatory modifications are expected to influence the course of research concerning market cointegration among international stock exchanges. This underscores the ongoing significance of comprehending enduring interconnections among markets for the benefit of investors, policymakers, and market participants who must navigate the intricate nature of global financial markets. Over the past two decades, research on market cointegration between the National Stock Exchange (NSE) of India and other international stock exchanges has been instrumental in understanding the long-term relationships and integration levels between India's financial markets and global counterparts. Since the early 2000s, scholars such as Menla Ali et al. (2014) and Banerjee et al. (2018) have investigated the existence and persistence of cointegrating relationships between NSE and major international exchanges. Employing methodologies including Johansen cointegration tests, vector error correction models (VECM), and state-space models, these studies have provided empirical evidence of long-term linkages characterized by shared trends and equilibrium relationships between NSE and global markets. Findings suggest varying degrees of integration influenced by factors such as economic fundamentals, trade flows, and regulatory changes (Singh & Mukherjee, 2012; Hussain et al., 2020). Moreover, research has explored the implications of market cointegration for portfolio diversification, risk management, and international asset pricing, underscoring the importance of understanding these relationships for investment decision-making in a global context (Vyas et al., 2016; Kumar et al., 2021). Additionally, advancements in data availability and econometric techniques have enabled researchers to delve into dynamic cointegration relationships and time-varying integration levels, providing deeper insights into the evolving nature of market linkages between NSE and international exchanges (Jain et al., 2017; Anand et al., 2021). Looking ahead, the trajectory of research on market cointegration between NSE India and other international stock exchanges is likely to be shaped by ongoing globalization, regulatory reforms, and technological advancements, emphasizing the continued relevance of understanding and monitoring long-term relationships between markets for investors, policymakers, and market participants navigating the complexities of global financial markets.

2.11 Bibliometric Analysis

Bibliometric methodologies provide a direct and non-reactive instrument for examining research collaboration. Bibliometric analysis is defined by Pritchard (1969) as the examination of books and diverse media forms of communication through the application of mathematical principles and communication instruments. By employing bibliometric analysis, one can obtain a multitude of indicators, including but not limited to author productivity, country productivity, and university productivity. Furthermore, the document includes details about co-authorship with academic journals, nations, and academic institutions. As productivity indicators, bibliometrics frequently employ the number of publications and their influence, as measured by the number of citations (Merigo et al., 2018). The h-index, a widely recognized numerical indicator of productivity, merges the counts of publications and citations into a solitary value. An alternative methodology entails calculating the impact factor or citation/document ratio by averaging the number of citations per paper. Additional bibliometric indicators incorporated into the research include citation structure, which includes the number of publications that have exceeded a predetermined citation threshold, cites per paper, cites per year, citing articles, and their evolution over time. By employing the Academic Ranking of World Universities (ARWU), university output can be assessed. Consequently, bibliometric analysis has been utilized to acquire a deeper understanding of the heterogeneous corpus of literature by assessing the intellectual, social, and theoretical progression of fundamental concepts. The data acquisition procedure for this research begins with the designation of relevant databases, which is subsequently followed by data collection in adherence to the exploration methodology.

2.12 Keywords for Exploration

Keywords Explored: *(Title("Volatility" Or "Spillover" Or "Causality" Or "Integration" And "Stock Market" Or "Stock" Or "Share") And (Limit-To (Subjarea,"Busi") Or Limit-To (Subjarea,"Econ")) And (Limit-To (Doctype,"Ar")) And (Limit-To (Srctype,"J")) And (Limit-To (Language,"English")) And (Exclude (Exactkeyword,"China") Or Exclude (Exactkeyword,"Commerce") Or Exclude (Exactkeyword,"Chinese Stock Market") Or Exclude (Exactkeyword,"India") Or Exclude (Exactkeyword,"Asia") Or Exclude (Exactkeyword,"Numerical Model") Or Exclude (Exactkeyword,"Granger Causality Test") Or Exclude (Exactkeyword,"Costs") Or Exclude (Exactkeyword,"Eurasia") Or Exclude (Exactkeyword,"Oil Supply") Or Exclude (Exactkeyword,"Japan") Or Exclude (Exactkeyword,"G12") Or Exclude (Exactkeyword,"Vix") Or Exclude (Exactkeyword,"G15")))*

Table 2.1 Most Relevant Sources

Sources	Articles
Finance Research Letters	89
International Review Of Financial Analysis	80
International Review Of Economics And Finance	69
North American Journal Of Economics And Finance	68
Applied Financial Economics	56
Journal Of Banking And Finance	51
Economic Modelling	47
Journal Of Futures Markets	47
Research In International Business And Finance	47
Pacific Basin Finance Journal	44

The examination of article distribution across finance journals yields significant insights into the academic environment of the discipline. Finance Research Letters is a prominent journal that comprises 89 articles, which accounts for an estimated 17.8% of the entire corpus of articles examined. The International Review of Financial Analysis, which comprises approximately 16% of the total, follows closely with 80 articles. With 69 articles, the International Review of Economics and Finance occupies the third position, comprising around 13.8% of the overall collection. Applied Financial Economics and the North American Journal of Economics and Finance follow closely behind with 68 and 56 articles, comprising approximately 13.6% and 11.2% of the total, respectively. The proportions of articles from the remaining journals that were analyzed as a whole were as follows: 9.4% to 7.6% for the Journal of Banking and Finance, Economic Modelling, Journal of Futures Markets, Research in International Business and Finance, and Pacific Basin Finance Journal. This analysis highlights the wide range of publications that finance research can find, with a particular emphasis on articles published in reputable academic journals that are well-known in the field.

Table 2.2 Authors' Local Impact

Element	H_Index	G_Index	TC	NP	PY_Start
Gupta R	15	29	871	36	2012
Kang Sh	14	24	861	24	2006
Mensi W	14	32	1236	32	2013
Vo Xv	12	26	682	29	2015
Zhang Y	10	19	376	25	2010
Gil-Alana La	9	14	203	15	2002
Hammoudeh S	9	9	551	9	2008
Ma F	9	20	403	21	2019
Wang J	9	18	360	20	2007
Zhang W	9	17	291	18	2005

By analyzing the metrics provided for researchers, one can gain significant insights regarding their scholarly influence and efficiency. Out of the researchers included in the list, Gupta R holds the highest H-index of 15, signifying that they have authored a minimum of 15 papers, each of which has received a minimum of 15 citations. This metric functions as an indicator of scholarly community influence and productivity. Subsequently, Mensi W possesses a noteworthy H-index of 14, indicating a substantial scholarly influence on par with Gupta R. Based on the G-index, which quantifies the overall quantity of highly cited papers, Mensi W distinguishes itself with a notable score of 32, signifying a considerable quantity of papers that have amassed substantial citation counts. Furthermore, an analysis of the total number of citations (TC) and published papers (NP) offers a supplementary understanding regarding the productivity and impact of researchers. As an illustration, despite Hammoudeh S's comparatively modest publication count and H-index and G-index, their substantial citation count of 551 indicates a significant influence. Additionally, an examination of the publication year start (PY_Start) provides insight into the academic tenure of the researchers. Certain individuals, such as Gil-Alana La, commenced their academic journey in 2002, while others, like Ma F, began in 2019. This analysis emphasizes the heterogeneity of researcher profiles, showcasing a range of academic tenure, productivity, and influence within the scholarly community.

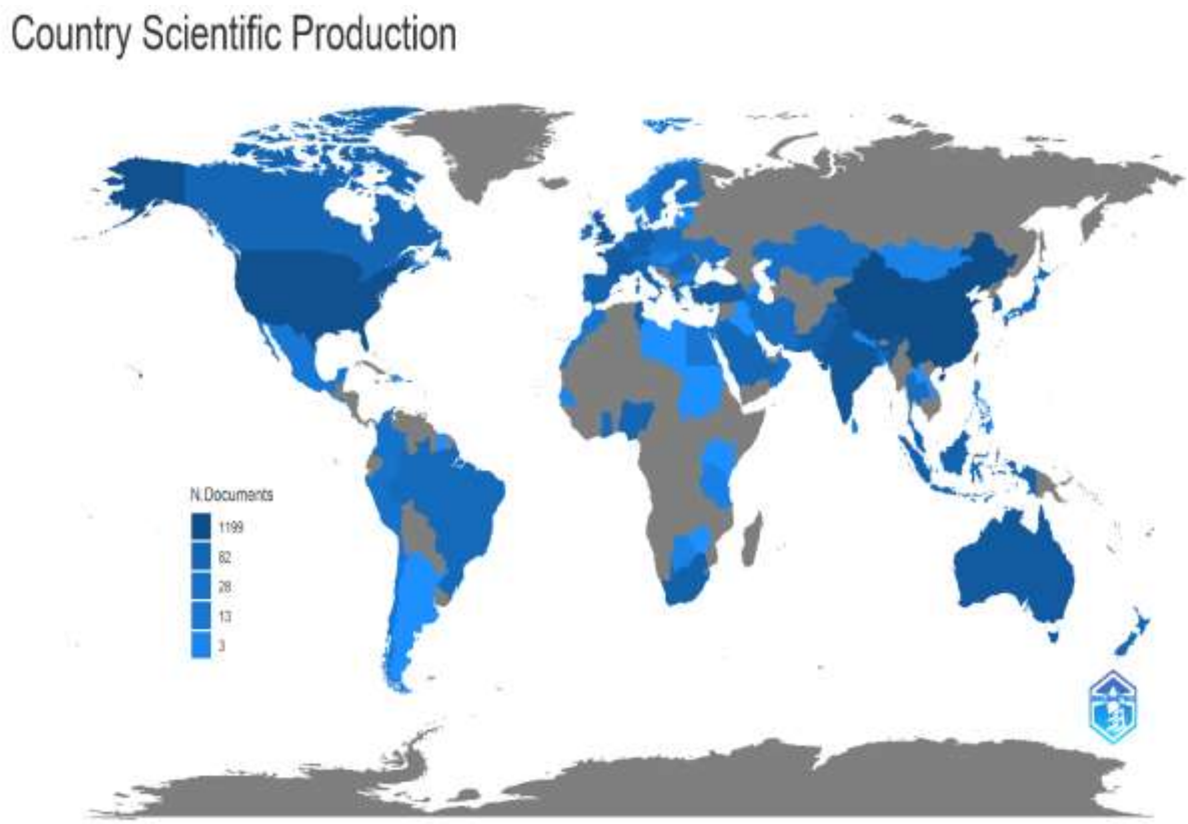


Figure 2.1 Countries Scientific Production

Table 2.3 Countries' Scientific Production

Region	Frequency
China	1199
USA	858
India	456
UK	382
Australia	287
France	195
Turkey	182
Malaysia	172
South Africa	148
Tunisia	145

The examination of the frequency distribution of regions contained in the dataset yields significant insights regarding the geographical dispersion of research emphasis. China is the most frequently examined region, accounting for approximately 29.9% of the total entries (1,199 occurrences). The United States closely follows with 858 instances, representing approximately 21.4% of the dataset. India is positioned third in terms of frequency, accounting for approximately 11.4% of the total with 456 instances. Following with 382 and 287 instances, respectively, the United Kingdom and Australia account for approximately 9.5% and 7.2% of the dataset. France, Turkey, and Malaysia demonstrate comparatively lower frequencies, comprising 195, 182, and 172 instances, respectively, which account for an estimated 4.9%, 4.5%, and 4.3% of the overall sample. The list is completed by South Africa and Tunisia, each having 148 and 145 instances, which account for roughly 3.7% and 3.6% of the dataset, respectively. This analysis highlights the prevalence of research emphasis on China and the United States, with studies from India, the United Kingdom, and Australia following suit. Furthermore, it underscores the varied geographic distribution of research interests, which includes France, Turkey, Malaysia, South Africa, and Tunisia.

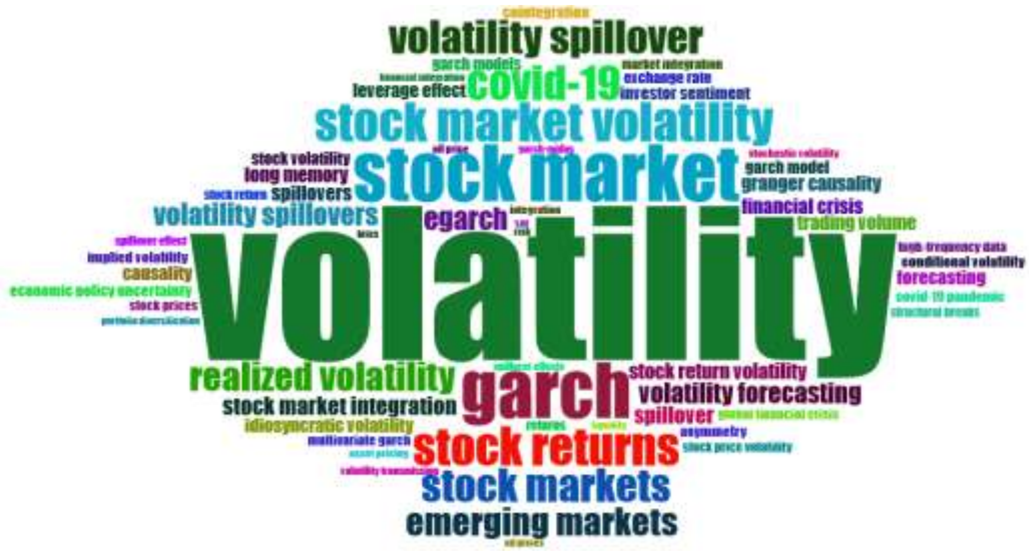


Figure 2.2 Word Cloud

Table 2.4 Word Cloud

Terms	Frequency
Volatility	406
Stock Markets	89
Volatility Spillover	88
Volatility Spillovers	59
Volatility Forecasting	54
Stock Market Integration	48
Spillover	46
Stock Return Volatility	42
Financial Crisis	41
Spillovers	41
Granger Causality	40
Long Memory	40
Causality	38

An examination of the term frequency distribution within the dataset yields significant insights pertaining to the fundamental concepts and focal points of finance research. The expression "volatility" appears the most frequently, comprising 406 occurrences or roughly 24.5% of the overall entries. 89 and 88 instances, representing approximately 5.4% and 5.3% of the dataset, are devoted to "Stock Markets" and "Volatility Spillover," respectively. Furthermore, "Stock Market Integration" and "Volatility Forecasting" appear frequently, comprising approximately 3.3% and 2.9% of the total, respectively, with 54 and 48 occurrences. Additional noteworthy terms include

"Causality," "Spillover," "Stock Return Volatility," "Financial Crisis," and "Granger Causality." With occurrences ranging from 38 to 41, these terms account for an estimated 2.3% to 2.5% of the dataset. The presence of discrepancies between the terms "Volatility Spillovers" and "Spillovers" suggests that there is a nuanced emphasis on the cross-market transmission of volatility. This analysis highlights the significance of concepts related to volatility and the wide range of subjects covered in finance research, including stock markets, volatility forecasting, integration, spillovers, and causal relationships. These findings illustrate the field's complexity and the researchers' varied areas of interest.

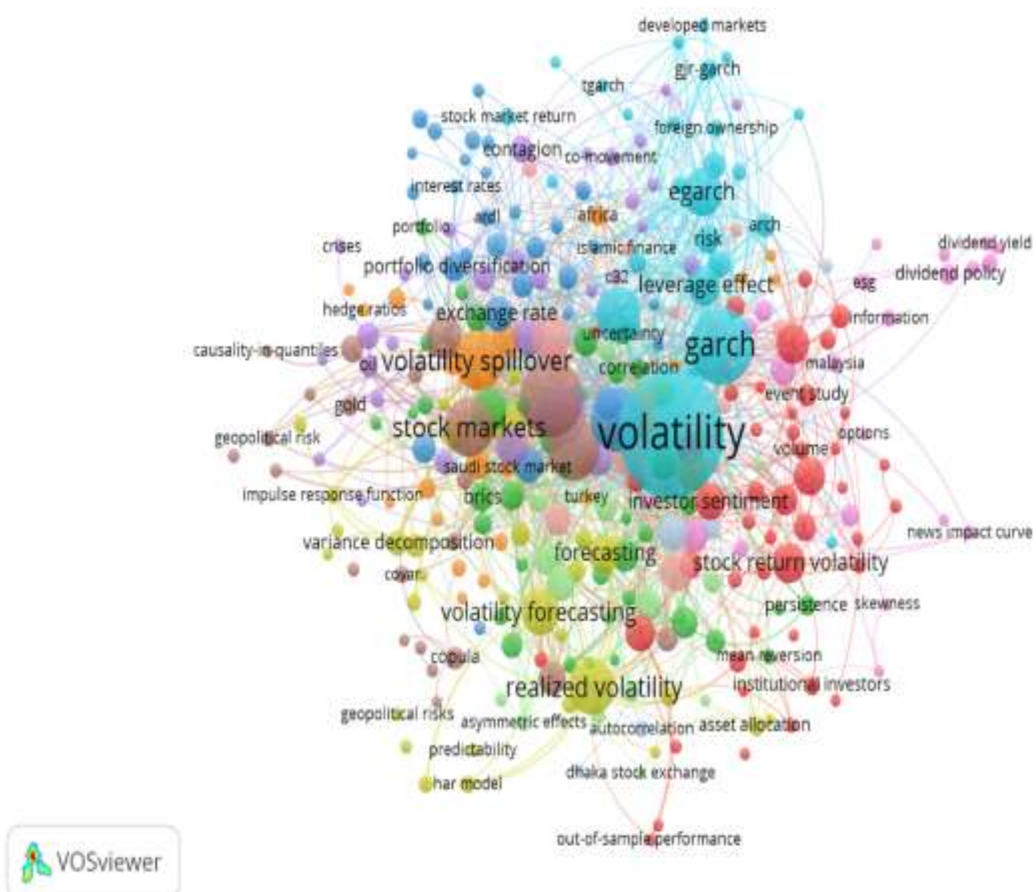
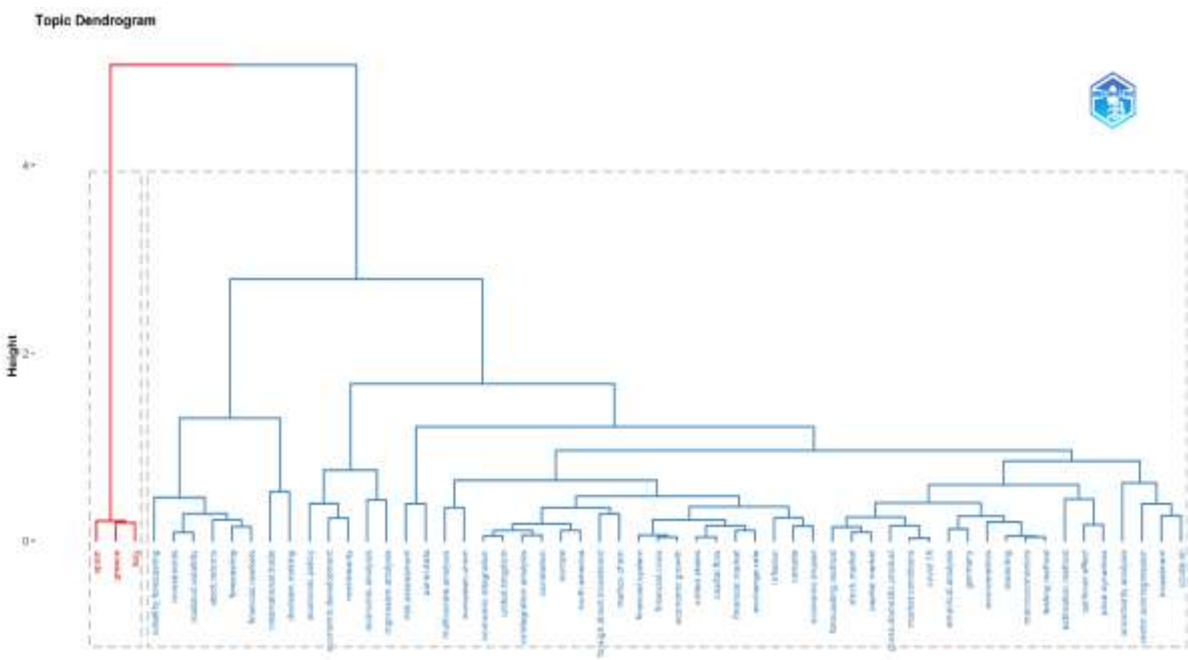


Figure 2.3 Keyword Co-Occurrence

Table 2.5 Keyword Co-occurrence

Keyword	Occurrences	Total Link Strength
Volatility	406	780
Stock Market	149	304
GARCH	147	352
Stock Market Volatility	103	138
Stock Returns	101	188
Covid-19	93	210
Stock Markets	89	151
Volatility Spillover	88	187
Realized Volatility	78	113
Emerging Markets	75	170
EGARCH	60	148
Volatility Spillovers	59	103
Volatility Forecasting	54	75
Stock Market Integration	48	62
Spillover	46	98

Table 2.6 Factorial Analysis



CHAPTER 3

Methodology

3.1 Introduction

Research involves not just reviewing current literature but also uncovering new details relevant to the process of dynamic societal changes. Methodology is a set of procedures, guidelines, and rules that enable data gathering and assessment. It consists of many actions that a researcher often does when examining a research problem. In addition to listing research techniques, research methodology takes into account the reasoning behind the researcher's choices within the framework of the study and clarifies the reason why certain techniques or methods were chosen over others in order to produce research results that can be assessed. Research methodology is therefore the most important component of a study. The research design is the first element of the accepted technique, followed by the sample design, statistical design, measurement and scaling, and data collection method. This chapter explains the need and research objectives of the study. The chapter produces information about the sources of data collection and the sample size taken. It also discusses the econometric tools used to examine the data.

3.2 Need of the study

There was need to explore the area of globalization of stock markets to investors across the world. So that the investors of different countries will invest their money in international stock markets under different investment strategies and having least risk factor. The international stock markets have caught a great attention from the investors around the globe and it looks like they will develop a new strong merged market in the near future (Hwahsin Cheng et.al. 2005). The investors must look for the trends to invest like foreign investors must look for a portfolio that has less risk capacity in Indian markets while as the domestic investors of India must look in foreign stocks matter for the BRICs (Sanjay k. Hansda et.al. 2002). Most of the studies are done on developed countries and there are few studies that has been done on Linkages between stock exchanges especially with emerging countries like BRICS, ASEAN, MENA and BIMSTEC. It has been found out that linkages between stock markets are increasing. And in some studies, constraints are implied on time scale and on number of stock exchanges to be taken under study. So, there is still need to explore more the linkages between different stock markets by increasing time scale, number of stock exchanges and variables. Therefore, this study is focused on the linkages between National Stock Exchange and selected International Stock Exchanges by taking into account market integration, price volatility, volatility spill overs and causality. This study will be enlightening for the International Investing Investors and investors-making portfolio formation to enhance the growth of investors in the stock markets and is also beneficial for policy makers, forecasters, researchers, finance ministry, SEBI and banks and helps them in their decision-making processes.

3.3 Research Objectives

The aim of this research is to analyse the linkages between NSE and International Stock exchanges. The main objective of this study was attained with the assistance of mentioned below sub objectives:

3.3.1 Objectives

1. To study the volatility of price indices between National Stock Exchange and selected International Stock Exchanges.
2. To study the impact of major spillovers between National Stock Exchange and selected International Stock Exchanges.
3. To explore the causality between National Stock Exchange and selected International Stock Exchanges.
4. To identify the integration between National Stock Exchange and selected International Stock Exchanges.

Objective 1: To study the volatility of price indices between National Stock exchange and selected International Stock Exchanges.

This study investigates the volatility of price indices between the National Stock Exchange (NSE) and selected International Stock Exchanges. This objective involves examining the characteristics of volatility, including persistence, conditional volatility, and sensitivity to news. The approach to achieving this objective encompasses the implementation and the application of VAR (1) GARCH (1,1) model applied to the closing price indices of the National Stock Exchange and selected International Stock Exchanges.

Objective 2: To study the impact of major spillovers between National Stock Exchange and selected International Stock Exchanges.

This objective involves investigating the influence of significant spillover effects on the financial markets. The methodology employed to achieve this objective utilizes the (Dynamic Conditional Correlation) DCC-GARCH model. To authorize the results of DCC-GARCH, BEKK-GARCH is employed. The analysis focuses on studying the interconnectedness and transmission of shocks between the NSE and selected International Stock Exchanges, providing insights into the cross-market dynamics and potential spillover effects.

Objective 3: To explore the causality between National Stock Exchange and selected International stock Exchange.

This objective entails investigating the directional relationships and connecting links among the NSE and chosen international stock exchanges. The chosen methodology for this exploration involves the application of the Granger Causality Test. Through this test, the study aims to discern the presence and direction of causality between the two markets, shedding light on the interdependencies and information flow between the National Stock Exchange and selected International Stock Exchanges.

Objective 4: To identify the integration between National Stock Exchange and selected International Stock Exchanges.

This objective involves assessing the degree of integration and long-term relationships between the NSE and selected International Stock Exchanges. The methodology employed for this purpose is the Johansen Cointegration Test. Through this test, the study seeks to analyze the presence of cointegration, indicating a shared long-term equilibrium relationship between the markets. The outcomes of the Johansen Cointegration Test offer insights into the extent of integration and the potential for sustained relationships between the NSE and selected International Stock Exchanges.

3.4 Research Approach

The research methodology utilized in this study is significantly influenced by a quantitative approach, with the primary focus being on the accomplishment of research objectives through the careful examination of the data the researchers have gathered. For the sake of this particular investigation, the research objective is accomplished by making use of secondary time series data that is derived from stock indexes that have been properly picked. The temporal dimension of these data is gathered on a daily basis, which provides a detailed perspective that enables a comprehensive investigation of patterns and trends within the financial markets.

The acquired dataset is subjected to a series of econometrics tests in a methodical manner in order to guarantee the reliability of the study. The study team is able to efficiently evaluate and understand the data thanks to these tests, which function as analytical instruments. Through the utilization of these quantitative methods, the research endeavours to arrive at results that are both valid and significant, thereby shining light on the complex dynamics of volatility that are present within the selected stock indices. The quantitative character of the research approach makes it easier to conduct a thorough investigation, which in turn contributes to a more in-depth comprehension of the complexity that are present in the financial markets that are being considered.

3.5 Research Design

A research design is a strategic strategy for the gathering, measurement, and analysis of data. The selection of a research design is determined by the level of knowledge that is already present regarding the research topic (Cooper et al., 2003; Kothari, 2004). A strategy that is both descriptive and causal is utilized in this particular research investigation. The nature of this study is descriptive, and its primary focus is on doing an in-depth analysis into the features of volatility within a number of different stock indexes that are selected from the National Stock Exchange and other worldwide stock exchanges. Furthermore, the study is causal since it investigates the linkages that are manifested as volatility spillover between the National Stock Exchange and selected international stock exchange indices. This is an important aspect of the study. The purpose of this endeavor is to gain an understanding of the nature of volatility and the correlations that exist between the National Stock Exchange and other stock exchanges around the world.

3.5.1 Sources of Data Collection

In this study, secondary data has been rigorously obtained, with a particular emphasis on the daily closing values of a variety of stock indexes that have been carefully selected from the National Stock Exchange (NSE) as well as selected international stock exchanges. The collection of this information was carried out by means of reliable sources, BLOOMBERG and the official website of NSE as nseindia.com. The intrinsic nature of the data is that it is a time series, which captures the evolution of various stock indices over the course of consecutive days. Due to the fact that this time series is updated on a daily basis, it is possible to conduct a detailed analysis of the fluctuations and patterns that occur within the financial markets. Following the conclusion of each trading day, the primary data points for the subsequent analysis are the daily closing values of the selected stock indices. These values provide a snapshot of the performance of the market at the end of each trading day.

An extensive amount of supplementary information that is necessary for this investigation has been obtained from a variety of sources, such as websites, journals, and books. Through the utilization of a wide range of trustworthy resources, the research endeavour intends to enhance both its analytical framework and its context. The use of this all-encompassing method for collecting data ensures a solid foundation for the future analysis and interpretation, which in turn contributes to the overall validity and depth of the findings of the research.

3.5.2 Study Period

A significant amount of time has been invested in the study endeavour, which spans a period of 21 years, beginning in April 2001 and continuing through March 2022. The recommendation made by Engle and Mezrich (1995), who suggested that a minimum of eight years of data is necessary for reliable GARCH estimation, was considered when selecting this timeframe. The decision to cover this extended period is a deliberate one since it enables a full investigation of the dynamics of the market and the patterns of volatility present in the market.

Over the course of these 21 years, the financial environment has been subject to major shifts, not just inside the National Stock Exchange but also within International Stock Exchanges. Throughout this period, there have been significant fluctuations, which reflect the dynamic character of the financial markets. The incorporation of such a wide variety of market conditions and events guarantees that the research will capture a comprehensive understanding of the development of volatility over time. To be more specific, the Indian stock market displayed a significant amount of volatility throughout this extended time, witnessing remarkable oscillations that have left an indelible mark on its trajectory. The temporal scope that was selected offers a substantial dataset that makes it possible to conduct an in-depth investigation of volatility patterns. This, in turn, makes it possible to conduct a more robust and nuanced examination of the Indian and international financial markets.

3.5.3 Sampling

This research aims to investigate and compare the linkages between the National Stock Exchange (NSE) and selected International Stock Exchanges over a comprehensive period spanning from April 2001 to March 2022. The study encompasses 14 prominent stock exchanges representing key countries contributing significantly to the global economy. China, Canada, France, the USA, Japan, India, Germany, Switzerland, South Korea, Taiwan, Australia, and the United Kingdom are some of the countries that fall under this category. The selected indices for analysis are SSE (Shanghai Stock Exchange), TSX (Toronto Stock Exchange), LSX (London Stock Exchange), NASDAQ, NIKKEI-225, NSE (National Stock Exchange), NYSE (New York Stock Exchange), HSI (Hang Seng Index), DAX (Frankfurt Stock Exchange/Deutscher Aktienindex), SWX (Six Swiss Exchange), KRX (Korea Exchange), TWSE (Taiwan Stock Exchange), ASX-200 (Australian Stock Exchange), and EURONEXT-100.

The daily stock closing values of the aforementioned 14 indices have been collected from global economic sources to carry out this study. The time frame that has been covered by this study spans a significant 21 years. The data for the National Stock Exchange (NSE) is obtained straight from the official website of the NSE, which can be found at www.nseindia.com. On the other hand, the data for other exchanges is obtained from Bloomberg, which is a well-known distributor of financial data.

To conduct an exhaustive investigation, the approach that was utilized in this study included the utilization of price indices as well as returns. Insights into the general performance of the market may be gained from the daily closing prices of the selected indices, while a more in-depth comprehension of the profits or losses suffered by investments over the defined period can be established through the examination of returns. The utilization of this dual technique guarantees a more nuanced examination of the links that exist between the National Stock Exchange (NSE) and chosen international stock exchanges. This evaluation takes into account not only the fluctuations in prices but also the real financial rewards that are linked with the selected indices. The research is expected to give useful insights into the evolving function of these stock exchanges in the interconnected environment of the international financial markets. This is because the selected countries have a significant economic impact on the global economy. It is the purpose of this study to contribute to a better understanding of the dynamics and relationships that have existed within the global stock market over the previous two decades. This will be accomplished by incorporating a broad range of indexes and applying a sophisticated approach. The list of exchanges is given in exhibit 3.5.3(a).

Table: 3.5.3(a) Stock Exchanges and Index of Stock Exchanges

S.NO.	Stock Exchanges	Index	Country
1	Shanghai Stock Exchange (SSE)	SSE Composite Index (SCI)	China
2	Toronto Stock Exchange (TSX)	S&P/TSX Composite Index (TCI)	Canada
3	London Stock Exchange (LSE)	FTSE 100 Index	London
4	NASDAQ	NASDAQ Composite Index	USA
5	Nikkei-225 (Tokyo Stock Exchange)	NIKKEI-225	Japan
6	National Stock Exchange (NSE)	Nifty 50	India
7	New York Stock Exchange (NYSE)	NYSE Composite Index	USA
8	Hang Seng Stock Exchange (HSI)	Hang Seng Index (HSI)	South Korea

9	Frankfurt Stock Exchange (DAX)	DAX Performance Index	Germany
10	Six Swiss Stock Exchange (SWX)	Swiss Market Index (SMI)	Switzerland
11	Korea Stock Exchange (KRX)	Korea Composite Stock Price Index (KOSPI)	South Korea
12	Taiwan Stock Exchange (TWSE)	Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX)	Taiwan
13	Australian Stock Exchange-200	S&P/ASX-200	Australia
14	Euronext-100	EURONEXT-100 Index	France

The sampling frame for this study encompasses the stock markets of selected international countries, serving as the population under investigation. These stock markets are selected because they are representative of important economies around the world and because they play an important part in the international financial scene. There is a defined time frame that constitutes the sampling period, and that time span is from April 2001 to March 2022. The daily data for the selected stock markets is collected over this time span.

3.5.4 Population: The stock marketplaces of the selected international states, which include the Shanghai Stock Exchange (SSE), the Toronto Stock Exchange (TSX), the London Stock Exchange (LSE), the National Stock Exchange (NSE), the New York Stock Exchange (NYSE), the Hang Seng Stock Exchange (HSI), the Frankfurt Stock Exchange (DAX), the Six Swiss Stock Exchange (SWX), the Korea Stock Exchange (KRX), the Taiwan Stock Exchange (TWSE), the Australian Stock Exchange-200 (ASX-200), and Euronext-100.

The target population unit consists of the daily closing prices and accompanying data of the specified stock markets from April 2001 to March 2022. A focused and comprehensive perspective of the performance of the stock market is provided by the specific time frame for data collection.

This enables a full study of the linkages and patterns that occurred within the worldwide financial markets over the period that was specified.

3.6 Data Analysis

Following the collection of the aforementioned data, a comprehensive analysis was conducted utilizing RATS, EVIEWS and RStudio software. The study employed various methods from the fields of econometrics and statistics to derive meaningful insights. The application of these analytical techniques is outlined below:

3.6.1 Descriptive statistics:

Descriptive statistics provides an in-depth narrative of the data employed in the model and enable to examine the data for any uncommon figures. The primary descriptive measurements include the mean, standard deviation, minimum and maximum values, skewness, kurtosis, and Jarque-Bera test results for the variables across the specified time period. Mean explains the average value of observations and standard deviation indicates change or deviation of data from mean. By these price movements are analyzed. By skewness, kurtosis and Jarque-Bera, normality of the data series is tested.

3.6.2 Unit Root Test:

It is a primary test employed before the application of other econometric tools or methods. First, it is important to check whether the collected data is stationary or not. Stationary of data means when the Mean and Variance of the time series data are constant over time and having no seasonal component (a non-repeating pattern over time). Non stationary of data means when the Mean and Variance of the time series data are not constant over a specified period of time and having a seasonal component (a repeating pattern over time). In stationary process, all the moments of probability distribution are in-variant over time and in non-stationary process, all moments of probability distribution are variant over time. To test the stationary of collected time series data and to find the presence of a unit root in a time series variable, Unit Root Test was used. In other terms, absence of a unit root denotes stability of time series data. The null hypothesis is commonly explained as the existence of unit root and the alternative hypothesis is stationary. The non-stationarity time series with a deterministic trend becomes stationary when the trend or de-trend is removed.

In Unit Root Test, Autoregressive models are used. Autoregressive ski model predicts the future values of the stock on the basis of past values. It has two types, Autoregressive ski (1) in which the current value depends on the immediately preceding value and Autoregressive ski (2) in which current value depends on previous two values. In this study, Augmented Dickey Fuller test (ADF) and Phillip Perron (PP) test was performed including intercept at level and level 1 for the time frame of 21 years from April 2001 to March 2022. For testing stationarity, let us assume an AR (1) model:

$$\boldsymbol{\gamma_t = p_1 \gamma_{t-1} + \varepsilon_t}$$

In the AR (1) model, often known as a random walk model, the series behaviour is important. If the absolute value of parameter p_1, which represents the coefficient of the lagged value, is less than 1, the series shows a stationary feature, maintaining consistency across time. When p_1=1, the unit root problem arises. In this case, the series shows non-stationarity, suggesting an absence of consistency or a persistent trend. This differentiation is essential for evaluating the behaviour and characteristics of time series data, especially in economic evaluations.

3.6.2.1 Augmented Dicker-Fuller Test

Augmented Dicker-Fuller Test was used to find the presence of a unit root in an Autoregressive Model. But if there is a presence of unit root, then methods of forecasting are used i.e., Autoregressive Integrated Moving Average Model (ARIMA) or Vector Error Correction Model/Vector Autoregression model. Both these methods assume that the time series is stationary. It tests the null hypothesis to find out that a unit root is present in an autoregressive model.

$$\boldsymbol{\Delta Yt = \mu_0 + \delta\, Y_{t-1} + \varepsilon_t}$$

Where, $\Delta Y_t = Y_t - Y_{t-1}$. Here the null hypothesis is the $\{Y_t\}$ process has a unit root, i.e., $H_0: \delta = \alpha - 1$. Since -1 ≤ α ≤ 0, it follows that -2 ≤ δ ≤0. Therefore, if the null hypothesis $H_0: \delta = \alpha - 1$ cannot be rejected, it provides evidence in support of the presence of a unit root in the autoregressive model, showing non-stationarity in the time series. This requires the use of forecasting techniques like the Autoregressive Integrated Moving Average (ARIMA) model or the Vector Error Correction Model/Vector Autoregression model, which are specifically created to address non-stationary data through the use of differencing to attain stationarity.

3.6.2.2 Phillips-Perron Test

The Phillips–Perron test, developed by Peter C. B. Phillips and Pierre Perron in 1988, is used as a unit root test in time series analysis to deal with serial correlation using a nonparametric approach. It assesses if a time series is integrated of order 1, which is crucial for understanding its behaviour.

$$\Delta yt = \delta y_{t-1} + \mu_t$$

The test evaluates the null hypothesis that a time series follows a model where the first difference of the series (Δyt) is equal to a constant (δ) times its lagged value y_{t-1}, plus an error term (μ). This methodology is similar to the standard Dickey-Fuller (DF) test but includes lagged differences of yt as regressors to address any autocorrelation problems.

The Phillips–Perron test addresses issues related to probable higher-order autocorrelation in the data-producing process for yt that may not be accounted for in the test equation, similar to the Augmented Dickey-Fuller (ADF) test. Not addressing this difference could make (y_{t-1}) endogenous. The Phillips-Perron test is strong against nonspecific autocorrelation and heteroscedasticity, making it a reliable tool for analyzing time series data. Researchers have utilized this strategy in their studies, highlighting its effectiveness in empirical research.

3.6.3 Structural Break Test

A structural break test is a statistical tool that is used to identify shifts or changes in the underlying structure of time series data. These shifts or changes indicate variations in the relationships between variables or shifts in the process of data generation. Common methods include the Chow test, which detects breaks in regression models by comparing residuals from segmented and unrestricted models; the CUSUM test, which examines cumulative deviations from a reference value to identify significant deviations signalling structural breaks; the Perron test, a parametric approach estimating regression models with break points to assess differences in coefficients before and after breaks; the Zivot-Andrews test, which allows for multiple breaks and selects the model maximising specified criteria; and the Quandt-Andrews test, which assesses differences in residual variances between segments. In addition to playing important roles in the interpretation and modelling of time series data, these tests also contribute to the identification of significant alterations that occur over time in economic, financial, or other structural systems.

3.6.3.1 Zivot-Andrew Test

In this study, Zivot-Andrew Test (ZA test) was used for estimating structural break point. The Zivot-Andrews (ZA) test is a technique utilized to identify structural changes in time series data, especially in the framework of unit root testing or trend analysis. This test is an expansion of the Augmented Dickey-Fuller (ADF) test, typically used to determine the existence of a unit root in a time series. A unit root indicates that a time series is non-stationary, showing a consistent pattern or trend across time. The ZA test allows for the possibility of the occurrence of one or more structural breaks in the data, which makes it possible to identify periods during which the fundamental dynamics of the time series may have undergone major changes. The ZA test process entails determining an upgraded Dickey-Fuller regression model with a possible breakpoint. The exact breakpoint is currently unidentified and must be established through empirical means. The model is represented by the equation:

$$\boldsymbol{\Delta yt = \alpha + \beta t + \gamma yt - 1 + \sum i = 1 p\delta i\Delta yt - i + \epsilon t}$$

Where:

- Δyt represents the differenced time series at time t,
- α is the intercept term,
- β is the coefficient of time trend,
- γ is the coefficient of the lagged dependent variable,
- δi are coefficients of lagged differences,
- ϵt is the error term.

The test searches for the best break point by maximizing a specific criterion, like the Schwarz information criterion (SIC) or the Akaike information criterion (AIC), using an iterative process. The model is calculated individually for each possible break point, and the one that produces the highest criterion value is chosen as the most probable break point. The ZA test evaluates the null hypothesis of a unit root against the alternative hypothesis of stationarity, considering the presence of a structural break in the data once the break point is identified. Reject the null hypothesis of a unit root if the test statistic is higher than the crucial value at the selected significance level. This suggests that the time series is stationary or trend stagnant with a structural break.

The Zivot-Andrews test is valuable in time series analysis for detecting potential changes in the underlying structure of the data over time. This may be caused by alterations in economic policy, fluctuations in market conditions, or external variables that impact the behaviour of the time series. The ZA test enables researchers to identify structural breaks, resulting in a more precise evaluation of the data's stationarity characteristics, which enhances model design and forecasting precision.

3.6.4 Cointegration Test

It is a renowned econometrics instrument primarily utilized in research investigations focused on time series data. Regression analysis is comparable to correlation analysis and it is specifically designed to identify long-term associations between endogenous and exogenous variables. Cointegration between two variables indicates a persistent and stable long-run association between them. In this research, the market integration was analysed by using the time series technique of Johnson Co-Integration Test (1988), Vector Error Correction Model (VECM) and Engle-Grangers Test. Johansen’s test comes in 2 main forces; Trace tests and Maximum Eigen value test.

3.6.4.1 Johansen co integration test

The Johansen cointegration test is a statistical technique employed to examine the long-term relationship between various time series variables. It assists in determining a stable relationship between multiple variables over time, which is crucial for developing relevant financial or economic models. When two or more-time series variables are individually non-stationary (that is, they have a unit root), but some linear combination of them is stationary, then the test is based on the idea that they are cointegrated. This is the concept that supports the test.

The Johansen cointegration test can be expressed in equation form as follows:

$$\boldsymbol{\Delta yt = \Pi yt - 1 + \Gamma 1 \Delta yt - 1 + \Gamma 2 \Delta yt - 2 + \cdots + \Gamma p - 1 \Delta yt - (p - 1) + \varepsilon t}$$

Where:

- Δyt is the differenced vector of time series variables at time t.
- Π is the matrix of cointegration parameters.
- Γi are matrices of adjustment coefficients capturing short-term dynamics.
- εt is the vector of error terms.
- p is the lag order of the model.

The Johansen Cointegration test assesses the rank of Π to identify the number of cointegrating links present in the variables. If the rank is lower than the total number of variables, it indicates the presence of cointegration, suggesting a long-term equilibrium relationship between the variables. If the variables are not cointegrated, then the rank Γ will not be significantly different from zero. If Γ= 0 it implies there is no co integration but there will be co integration if Γ=1

3.6.6 Granger Causality Test

Granger causality is a statistical concept that assesses the predictive association between two-time series variables. It was established by Nobel Prize-winning economist Clive Granger in the 1960s. Clive Granger first proposed the idea of Granger causality in his influential study "Investigating Causal Relations by Econometric Models and Cross-spectral Methods," published in 1969. Granger's research used time series analytic methods to analyze causal connections among economic variables. If a time series variable X "Granger-causes" another time series variable Y, it means that previous values of X provide better predictions for future values of Y compared to utilizing merely past values of Y itself.

Granger causality relies on the concept of predictability. If variable X Granger causes variable Y, it indicates that previous values of X provide valuable information for forecasting future values of Y. It is vital to reminder that Granger causality does not indicate actual causation in the philosophical sense, but simply statistical predictability. The Granger causality test entails generating autoregressive models for individual variables and then assessing the predictive performance of these models with and without lagged values of the possible causal variable. If incorporating past values of X enhances the prediction of Y more than just using past values of Y, then X is considered to be Granger-cause Y.

The Granger causality test is usually carried out using a Vector Autoregression (VAR) model. The equation for a VAR(p) model with two variables (X and Y) is as follows:

$$\boldsymbol{Y_t = \sum_{i=1}^{p} \alpha_i Y_{t-1} + \sum_{i=1}^{p} \beta_i X_{t-1} + \varepsilon_t}$$

$$\boldsymbol{X_t = \sum_{i=1}^{p} \gamma_i Y_{t-1} + \sum_{i=1}^{p} \delta_i X_{t-1} + \eta_t}$$

Where;

- $\boldsymbol{Y_t}$ and $\boldsymbol{X_t}$ are the dependent variables at time t.
- $\boldsymbol{X_t}$, $\boldsymbol{\beta_i}$, $\boldsymbol{\gamma_i}$ and $\boldsymbol{\delta_i}$ are the coefficients of lagged values of Y and X.
- $\boldsymbol{p}$ is the lag order of the VAR model
- $\boldsymbol{\varepsilon_t}$ and $\boldsymbol{\eta_t}$ are white noise error terms.

On comparing the fit of two VAR models, it determines whether or not Granger causality exists. One of the models includes lagged values of both X and Y (as seen above), while the other model only includes lagged values of Y. In the event that the incorporation of lagged X results in an enhancement of the forecasting ability of the model for Y, this implies that X is the Granger cause of Y.

Researchers can gain a better understanding of the dynamic interactions that occur across economic, financial, and other systems by using the Granger causality test, which is a statistical tool that gives them the opportunity to investigate probable causative linkages between variables in time series data.

3.6.7 GARCH Model:

The GARCH term was first introduced in 1982 by Robert F. Engle. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is an effective statistical framework that is largely utilized in the field of finance for modeling and forecasting the volatility of financial assets. GARCH extends the Autoregressive Conditional Heteroskedasticity (ARCH) model by incorporating the concept of volatility persistence, where previous conditional variances impact the current volatility. The GARCH process is an approach which is used to calculate the volatility of financial markets. It is used by financial institutions to calculate the return volatility of stocks, bonds and other securities. A GARCH model represents the conditional variance of the asset return by incorporating its own lagged squared residuals and lagged conditional variances, as well as presumably exogenous inputs. The dynamic specification of GARCH allows for the modeling of the changing volatility patterns often seen in financial time series data, including the clustering of big and small returns and fluctuations between high and low volatility periods. GARCH parameter estimation usually entails maximising the likelihood function by maximum likelihood estimation to determine the ideal parameter values that most accurately represent the observed data. GARCH models are commonly utilized in financial risk management, portfolio optimization, option pricing, and volatility forecasting to offer significant insights into the behavior and dynamics of financial markets. It is mathematically represented as:

$$\boldsymbol{\sigma^2{}_n = \alpha\, r^2{}_{n-1} + \beta\, \sigma^2{}_{n-1}}$$

Where, $r^2{}_{n-1}$ represents innovation, with α denoting the innovation factor. $\sigma^2{}_{n-1}$ represents lagged variance, showing persistence, whereas β acts as the persistence factor. The total of α and β is 1. The exponential weighted moving average diminishes weight exponentially as the lag value increases.

3.6.7.1 GARCH (1,1) Model

In the field of financial time series analysis, traditional regression techniques such as ordinary least squares (OLS) frequently fail because they are based on the assumption of continuous volatility, which is not the case for many financial datasets. The Autoregressive Conditional Heteroscedasticity (ARCH) model was developed by Engle (1982) to address this issue. This model made it possible to model time-varying volatility. This model was a huge step ahead; however, it was later revised by Bollerslev (1986) with the presentation of the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model, which offered a more streamlined and effective method. This model was a significant step forward. Numerous types of univariate and multivariate GARCH models have been utilized heavily throughout the body of research that has been conducted on volatility modeling and spillover effects. Before utilizing GARCH models, it is customary to do a Lagrange-Multiplier (LM-ARCH) test to determine whether or not the ARCH effect is present. GARCH (1,1) is mathematically represented as

$$\boldsymbol{\sigma^2{}_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2{}_{t-1}}$$

where $\omega = \gamma \times$ (long-term unconditional variance)

ω signifies the base level of volatility in the model (mean reversion) and γ is the weight assigned to the mean reversion factor, with $\alpha\varepsilon^2_{t-1}$ and $\beta\sigma^2{}_{t-1}$ representing the influence of previous shocks and past volatility on the current volatility. Parameter α influences the immediate effect of shocks on volatility, while parameter β determines the persistence of volatility, indicating volatility's tendency to return to its long-term average.

Utilizing only three limitations in the equation of conditional variance has been determined to be adequate for generating a convincing model suitable for everyday asset returns. Hansen and Lund (2004) found that it is tough to identify a volatility model that outclasses the meek GARCH (1,1) model. The GARCH (1,1) model is often considered the most suitable volatility model for daily returns in a variety of applications. The GARCH (1,1) model incorporates historical squared residuals and conditional variance data to estimate the parameters α and β. The historical data enables the model better to understand the changing levels of volatility over time and produce more dependable predictions of future volatility.

3.6.7.2 DCC-GARCH Model

The DCC-GARCH model is a multivariate extension of the GARCH model that incorporates changing correlations between assets over time. Robert Engle introduced it in 2002. The DCC-GARCH model comprises univariate GARCH models for individual asset return series and a dynamic correlation model. The DCC-GARCH model posits that the conditional covariance matrix of asset returns can be separated into the conditional variance of each asset return and the conditional correlation matrix among asset returns. Mathematically, the conditional covariance matrix H_t at time *t* is given by:

$$\boldsymbol{h_t = D_t R_t D_{t,}}$$

h_t is the estimator of conditional correlation.

$$\boldsymbol{D_t = diag\left\{h^{\frac{1}{2}}{}_{i,t}\right\}}$$

D_t is the diagonal matrix of the dynamic correlation matrix.

$$\boldsymbol{R_t = diag\left(q^{\frac{1}{2}}{}_{i,j,t}\right) Q_t diag\left(q^{\frac{1}{2}}{}_{i,j,t}\right)}$$

R_t is the dynamic correlation matrix, and Q_t is the positive definite matrix.

$$\boldsymbol{Q_t = c + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1}}$$

Where α and β are the ARCH and GARCH terms, respectively.

Dynamic condition correlation coefficient (ρijt) is represented as:

$$\boldsymbol{\rho_{ijt} = \frac{q_{ijt}}{(q_{iit} q_{jjt})^{\frac{1}{2}}}}$$

The mathematical presentation of the mean equation is as below

$$\boldsymbol{R_t = \mu + \epsilon_t}$$

Co- variance matrix equation is as follows:

$$\boldsymbol{H_t = D_t R_t D_t}$$

Where D_t is a diagonal matrix

R is a correlation matrix.

3.6.7.3 BEKK-GARCH Model

The GARCH-BEKK model, established by Engle and Kroner in 1995, is commonly employed to represent conditional variances, especially in research that examines the transmission of volatility among markets (Bala & Takimoto, 2017; Arouri et al., 2015; Olson et al., 2017). To evaluate the conditional covariance structure across commodity futures, for example, Chang (2009) used a tri-variate complete BEKK-GARCH model, which captures economic bonds. This model effectively incorporates the impact of previous variability on the relationship between different markets, which is essential for knowing cross-market dynamics (Soriano & Climent, 2005). It is crucial to incorporate the covariance factor in the equation for conditional variance to accurately represent these interactions.

The BEKK-GARCH Model is specified as:

$$\boldsymbol{H_{(t)} = C'C + A'u(t-1)u'(t-1)A + B'H(t-1)B}$$

C is the lower triangular matrices while A and B are general *n*x*n* matrices. Thus, every term is affirmative semi-definite by construction. This part of financial modelling explains how particular matrices, namely positive semi-definite and lower triangular, are utilized to conduct risk analysis in a scenario involving two assets. The model generates the conditional variance by considering previous shocks and previous conditional variances of each asset (which are represented by the matrices). This allows the model to anticipate future volatility based on historical data effectively.

3.7 VAR

Vector Autoregression, also known as VAR, is a proficient statistical technique that is widely utilized in the field of econometrics. Its purpose is to describe and analyze the dynamic interactions that occur between numerous time series variables. Its applicability can be recognized in various domains, such as macroeconomics, finance, and the social sciences, where it is essential to comprehend the connections between numerous variables over time to make decisions, formulate policies, and conduct academic research. Within the scope of this all-encompassing investigation, we delve into the complexities of VAR modeling, addressing its theoretical foundations, estimate methodologies, key assumptions, practical concerns, and applications in the real world. The idea of autoregression in VAR, which involves regressing each system variable on both its own and other variables' lagged values. Compared to univariate time series analysis, this multivariate approach allows researchers to capture the reciprocal dependencies among the variables, providing a more detailed understanding of their interrelationships. The VAR model is conveyed as:

$$\boldsymbol{Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t}$$

Here, Y_t represents a vector of *k* dependent variables at time *t*, *c* is a constant term, $A_1, A_2, \dots, A_p$ are coefficient matrices capturing the lagged effects, *p* denotes the order of the VAR model, and ε_t is a vector of white noise error terms.

In the VAR model, the number of lagged observations that are incorporated into the model is determined by the order of the model, denoted by *p*. Determining the right sequence is crucial and typically requires statistical methods like information criteria (e.g., AIC, BIC) or model selection algorithms (e.g., Akaike's FPE criterion) to find a balance between model complexity and fit quality. Under-fitting or over-fitting the model might result in biased parameter estimations and invalid inference, emphasizing the need for particular order selection. Estimating the coefficients of a VAR model usually requires methods like ordinary least squares (OLS) or maximum likelihood estimation (MLE). OLS estimation is commonly utilized for its simplicity and effectiveness, however it relies on the hypothesis that the error terms are autonomously and identically sprinkled (i.i.d.), which may not be valid in real-world scenarios, particularly for time series data that display autocorrelation and heteroscedasticity. MLE provides greater adaptability than other methods by loosening the condition of homoscedasticity and accommodating correlated error components, which allows for modelling intricate connections and capturing the complete covariance structure of the data.

VAR modelling is advantageous because it enables dynamic analysis using impulse response functions (IRFs) and forecast error variance decompositions (FEVDs). Impulse response functions (IRFs) measure the influence of a disturbance in one variable on the entire system across various time intervals, enabling policymakers and researchers to evaluate the immediate and prolonged consequences of economic disruptions. prediction error variance decompositions (FEVDs) analyze the contribution of individual variables' shocks and shocks from other variables to the prediction error variance, offering insights into the varying significance of different sources of uncertainty.

VAR models can be expanded to include exogenous variables, structural breaks, cointegration relationships, and time-varying parameters, which increases their adaptability and suitability for many empirical scenarios. Structural Vector Autoregressions (SVARs) impose constraints or identifying assumptions to establish causal connections between variables, allowing researchers to perform counterfactual analysis and assess the impact of policy initiatives.

Although VAR modeling has many benefits, it also presents limitations and obstacles. The curse of dimensionality creates challenges when working with numerous variables, resulting in computational complexity and sparse data problems. The assumption of linearity may limit the ability to capture nonlinearities and regime shifts in the data, requiring the adoption of alternate modeling techniques such as nonlinear VARs, threshold VARs, or state-space models. VARs are vulnerable to misspecification errors, measurement mistakes, and omitted variable bias, which can weaken the dependability of the outcomes and understanding of causal links.

3.7.1 VAR GARCH Model:

VAR-GARCH, short for Vector Autoregressive Generalized Autoregressive Conditional Heteroskedasticity, is a statistical model employed in the fields of econometrics and finance to examine the behavior of numerous time series variables while taking into consideration their changing volatility over time. VAR-GARCH enables multivariate modeling of the mean and volatility of multiple variables within the framework of volatility. The VAR component captures the linear relationship between the means of the variables, whereas the GARCH component models the conditional variance of each variable, taking into account volatility clustering and persistence over time. VAR-GARCH is a framework that combines both components to effectively analyze and predict the volatility of numerous time series variables at the same time. The model, initially introduced by Ling and McAleer (2003), is a VARMA GARCH model with constraints. But Athanasopoulos and Vahid (2008) have led a discussion against the restriction of the model to

VAR-GARCH. However, its restricted version has become popular because of its computational capacity and parameter efficiency, which makes it more attractive to analysts.

The mean equation of the VAR model in the VAR-GARCH structure is generally written as $Y_t = \mu + \Phi Y_{t-1} + \epsilon_t$, where Y_t represents the vector of the return series and ϵt represents the error terms. The error terms are specified as $\epsilon_t = D_t \eta_t$, where η_t is a series of random vectors that are exogenous and identically distributed, and $D_t = \text{diag}\left(h_t^{\,½}\right)$ denotes a diagonal matrix containing the square root of the conditional variances.

In the VAR-GARCH model, the following equation is used to estimate market variances:

$$\boldsymbol{h_t^i = \mu_i^2 + \beta_{i1}^2 h_{t-1}^i + \alpha_{c1}^2 \left(\varepsilon_{t-1}^i\right)^2 + \beta_{i2}^2 h_{t-1}^c + \alpha_{i2}^2 (\varepsilon_{t-1}^c)^2}$$

$$\boldsymbol{h_t^c = \mu_i^2 + \beta_{c1}^2 h_{t-1}^c + \alpha_{c1}^2 (\varepsilon_{t-1}^c)^2 + \beta_{c2}^2 h_{t-1}^i + \alpha_{c2}^2 \left(\varepsilon_{t-1}^i\right)^2}$$

where, the ARCH terms are denoted by the coefficients α, and the short-term effects of shock transmission between markets are represented by $\left(\boldsymbol{\varepsilon_{t-1}^i}\right)^{\boldsymbol{2}}$ and $(\boldsymbol{\varepsilon_{t-1}^c})^{\boldsymbol{2}}$. Similarly, the effects of past values of conditional variance at time $t-1$ are shown by h_{t-1}^c and h_{t-1}^i, where the associated coefficients β are called the GARCH terms. The VAR-GARCH model accurately predicts one market's present volatility by combining historical volatility and shock from both markets.

3.8 Justification for selected Econometric Techniques

a) The Vector Autoregression (VAR) model integrated with GARCH (1,1) serves as an optimal framework for analysing the volatility of price indices between the National Stock Exchange (NSE) and selected international stock exchanges. The VAR model clarifies the interrelationships among various time series by permitting each variable to depend on its own lagged values as well as the lagged values of other variables. This is especially beneficial for examining the impact of price indices in one market on those in another. The GARCH (1,1) component describes the conditional variance of price indices, accurately reflecting the clustering of volatility, a prevalent occurrence in financial markets when high volatility periods are succeeded by further high volatility, and conversely. The GARCH

(1,1) model is favoured over simpler models such as ARCH due to its ability to incorporate both short-term and long-term volatility impacts, hence offering a thorough comprehension of market dynamics. For Objective 1, which examines the volatility of price indices, the VAR (1)-GARCH (1,1) framework is the optimal selection since it integrates the advantages of both models to assess interdependencies and volatility patterns across markets. Alternative methodologies, such as univariate GARCH or EGARCH, fail to consider the interdependencies among markets, rendering them less appropriate for this purpose.

b) The DCC-GARCH model is explicitly formulated to capture the dynamic correlations across financial markets, rendering it an effective instrument for analysing the impact of volatility in one market on another. In contrast to conventional GARCH models, which presuppose constant correlations, DCC-GARCH facilitates dynamic correlations that fluctuate over time. This is essential for comprehending how disturbances in one market transmit to another during times of financial strain or stability. The model's capacity to estimate conditional correlations renders it superior to alternatives such as BEKK-GARCH, which, although proficient in assessing spillovers, are computationally demanding and less adaptable in capturing dynamic interdependencies.

c) The Granger Causality Test is a prevalent econometric method employed to ascertain if one time series may forecast another. It is especially effective for finding causal linkages between stock markets, as it determines if fluctuations in one market precede and affect fluctuations in another. This is essential for comprehending the influence dynamics between the NSE and specific international stock exchanges. Granger Causality is favoured above alternative causality tests, including the Sims Test and Transfer Entropy, due to its simplicity, interpretability, and broad acceptance in financial literature. It is also adept at analysing linear relationships, which are prevalent in stock market data. Although nonlinear causality tests are available, they are computationally intricate and typically necessitate larger datasets, rendering Granger Causality the most pragmatic and efficient option for fulfilling the third purpose.

d) The Johansen Cointegration Test is an effective instrument for analysing long-term equilibrium relationships among non-stationary time series, including stock market indices. In contrast to the Engle-Granger two-step method, which is limited to identifying cointegration between two variables, the Johansen Test accommodates numerous variables, rendering it suitable for analysing the integration between the NSE and selected international stock exchanges. The Johansen Test is favoured over alternative cointegration methods due to its superior reliability, particularly in multivariate contexts. It facilitates the detection of numerous cointegrating vectors, providing enhanced understanding of the long-term linkages among markets. Alternative approaches, including the Phillips-Ouliaris Test, are less robust and less appropriate for multivariate analysis. This study used the Johansen Cointegration Test to provide a thorough and precise analysis of long-term relationships, so achieving the fourth objective.

3.9 Statistical Software Used

Table 3.2 presents a collection of statistical software used for different statistical and econometric analyses.

Table 3.2: Statistical Software

S. No.	Test/Analysis	Software
1	Unit Root Test, Structural Break Test, Grangers Causality Test and, Cointegration Test (Johansen Cointegration Test)	EVIEWS
2	VAR (1) GARCH (1,1) and BEKK-GARCH	RATS (Ahn and Lee, 2006)
3	DCC-GARCH	RStudio

CHAPTER 4

VOLATILITY OF PRICE INDICES BETWEEN NATIONAL STOCK EXCHANGE AND SELECTED INTERNATIONAL STOCK EXCHANGES

This chapter presents the findings obtained from the statistical and economic analysis conducted on the secondary time series data acquired from the NSE and Selected International Stock Exchanges included in the study. The current chapter is partitioned into six distinct sections. Section 4.1 provides an overview of the theoretical foundation and several analytical methods, such as Descriptive Statistics and Unit Root Test, that are relevant to the study. Section 4.2 also addresses the findings of the first objective set in the study. This purpose centres on analysing the characteristics of volatility in terms of its persistence, conditional volatility, and sensitivity to news, among other factors. The objective is accomplished by utilizing the VAR (1) GARCH (1,1) model on the indices of the NSE and chosen International Stock Exchanges.

4.1 Volatility of Price Indices - NSE and International Stock Exchanges

The studies differentiate between advanced and emerging stock markets based on their distinct features. Developed stock markets are mostly considered to have higher levels of liquidity and competence when compared to stock markets in emerging economies. Investment theory states that the greater volatility commonly connected with emerging stock market returns leads to correspondingly greater expected returns in those markets. During the past decade, numerous stock markets have experienced significant changes. However, emerging markets, in particular, have witnessed exponential growth in means of trading volume, the volume of businesses listed, and market cap. The appealing conditions in these zones have significantly changed the perception of universal investors in current years. There is confirmation to imply that numerous emerging markets are increasingly becoming assimilated into the international financial market. When allocating assets to a globally differentiated portfolio, a stakeholder wants to assess returns and risk across several nations. The advantage of having a universally differentiated portfolio can only be realized when there is a low correlation between worldwide stock markets. In addition, when building an internationally diversified portfolio of securities, it is necessary to take into account the correlation in the returns of stocks from two distinct economies. Several studies have found evidence suggesting that there is a lower level of interdependence among a specific group of countries, including selected international nations, European nations, and BRICs nations. Indian and worldwide countries are regarded to have strong long-term correlations, resulting in limited portfolio diversification prospects for overseas investors. This chapter specifically examines the fluctuation and instability of the NSE (National Stock Exchange) as well as certain chosen international stock exchanges. In order to achieve this objective, NSE and thirteen other stock exchanges are examined over a span of twenty-one years, from April 2001 to March 2022. The United States, South Korea, Japan, India, China, Russia, France, Germany, other European countries, and London are collectively assuming a progressively significant position in the global economy. The following stock exchanges are included in the list: SSE (Shanghai Stock Exchange), TSX (Toronto Stock Exchange), LSX (London Stock Exchange), NASDAQ, NIKKEI-225, NSE (National Stock Exchange), NYSE (New York Stock Exchange), HSI (Hang Seng Index), DAX (Frankfurt Stock Exchange/Deutscher Aktienindex), SWX (Six Swiss Exchange), KRX (Korea Exchange), TWSE (Taiwan Stock Exchange), ASX-200 (Australian Stock Exchange), and EURONEXT-100. The IMF report classifies the stock markets of the USA, UK, Australia, Japan, Germany, Hong Kong, and Singapore as advanced economies, along with 29 other nations. The NSE data was obtained from the official website of the National Stock Exchange, which is www.nse.com. The data for other selected international stock exchanges was gathered from the Bloomberg database.

4.2 Normality Test

A normality test is a statistical procedure used to conclude if a given data series or sample is normally distributed. Normal distribution is a statistical term that describes a pattern where the greater part of data values is clustered around the mean, with fewer values farther away from the mean in either direction. In a normally distributed data series, the mean, median, and mode are all equal. Normality tests are important because many statistical analyses assume that the data are normally distributed. If the data are not normally distributed, these analyses may not be appropriate or may produce misleading results. Therefore, it is important to test for normality before performing any statistical analysis that assumes normal distribution.

4.3 Descriptive Statistics:

It is a set of procedures used to condense and describe the main structures of a dataset, such as its dispersion, central tendency, shape, and relationship between variables. Descriptive statistics are used to provide a basic understanding of the data and to identify patterns, trends, and relationships in the data.

Table 4.1: Descriptive Statistics of Stock Exchanges

	ASX-200	DAX	EURONEXT-100	Hang Seng	KOREA	LSX	NASDAQ	NIKKEI-225	NSE	NYSE	SSE	SWX	TSX	TWSE
Mean	0.0002	0.0002	0.0001	0.0001	0.0003	0.0006	0.0004	0.0001	0.0005	0.0002	0.0001	0.0001	0.0002	0.0002
Median	0.0006	0.0008	0.0006	0.0006	0.0007	0.0000	0.0008	0.0006	0.0007	0.0005	0.0006	0.0006	0.0007	0.0007
Maximum	0.0541	0.1080	0.1032	0.1018	0.0721	0.2667	0.1116	0.0949	0.1633	0.1153	0.0940	0.1133	0.0696	0.0652
Minimum	-0.0761	-0.0887	-0.0895	-0.0929	-0.1280	-0.1853	-0.0959	-0.1211	-0.1305	-0.1023	-0.0926	-0.1140	-0.1083	-0.0691
Std. Dev.	0.0092	0.0138	0.0126	0.0131	0.0125	0.0210	0.0132	0.0139	0.0128	0.0110	0.0149	0.0115	0.0092	0.0117
Skewness	-0.5530	-0.1544	-0.1473	-0.1161	-0.6174	0.6614	-0.0782	-0.5713	-0.3385	-0.5153	-0.3282	-0.2857	-0.8374	-0.2864
Kurtosis	8.5466	8.5917	9.1750	8.5488	9.0693	20.5553	8.7682	9.4084	15.3826	13.0769	8.2720	14.0812	13.1558	6.7973
Jarque-Bera	7301.3510	7158.5480	8723.2360	7039.9510	8755.8330	70743.7800	7600.0570	9671.6870	35101.7100	23419.6100	6442.3360	28101.8600	24182.1700	3366.0830
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Author's Calculations

In table 4.1, the normal distribution is a symmetric distribution with well-behaved tails. The skewness measures the degree of asymmetry of the data series. Data are considered fairly symmetrical if the skewness falls within the range of -0.5 to 0.5. Data is considered to be significantly skewed if its skewness falls between the range of -1 to -0.5 or 0.5 to 1. Data with a skewness value less than -1 or greater than 1 exhibit a high degree of skewness. In the provided table, the skewness value is less than -1 and greater than 1, indicating that the data is significantly skewed.

If the kurtosis is approximately 0, it is commonly considered that the distribution follows a normal distribution (mesokurtic). If the kurtosis is negative, then the distribution is characterized by light tails, often known as platykurtic or negatively kurtosis. If the Kurtosis is bigger than zero, then it has heavier tails (leptokurtic or Positively Kurtosis). The data showed that the Kurtosis is greater than 0, which means the distribution has heavier tails. The data series are Leptokurtic or Positively Kurtosis.

A normal distribution exhibits zero skewness, indicating perfect symmetry around the mean. It also has a kurtosis of 0, which provides information about the amount of data in the tails and the level of peakedness in the distribution. Prior knowledge of the mean or standard deviation of the data is not required to conduct the test.

The Jarque-Bera Test is a Lagrange multiplier test used to assess the normality of a distribution. Normality is a prerequisite for several statistical tests, such as the t test or F test. To verify normality, the Jarque-Bera test is typically conducted before to these tests. Typically, it is employed for extensive data sets, as other tests for normalcy lack reliability when the sample size is big (e.g., Shapiro-Wilk test is unreliable for sample sizes beyond 2,000). The Jarque-Bera test is used to assess whether a distribution is normal or not. The null hypothesis (H0) states that the distribution is normal, whereas the alternative hypothesis (H1) states that the distribution is not normal.

If the P-values are less than 0.05 %, the null hypothesis is rejected. In the above descriptive statistics table, the p-values are less than 0.05%. The null hypothesis posits that the data follows a normal distribution, while the alternative hypothesis suggests that the data does not conform to a normal distribution. Therefore, the alternate hypothesis, which is the data series is not normal is accepted.

4.4 Stationarity Test

The purpose of conducting a stationarity test is to ascertain the presence or absence of stationarity in a particular time series. There are several tests that can be used for this purpose, including the Augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test, and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. In order to support the ADF results, PP test was executed as shown in below table.

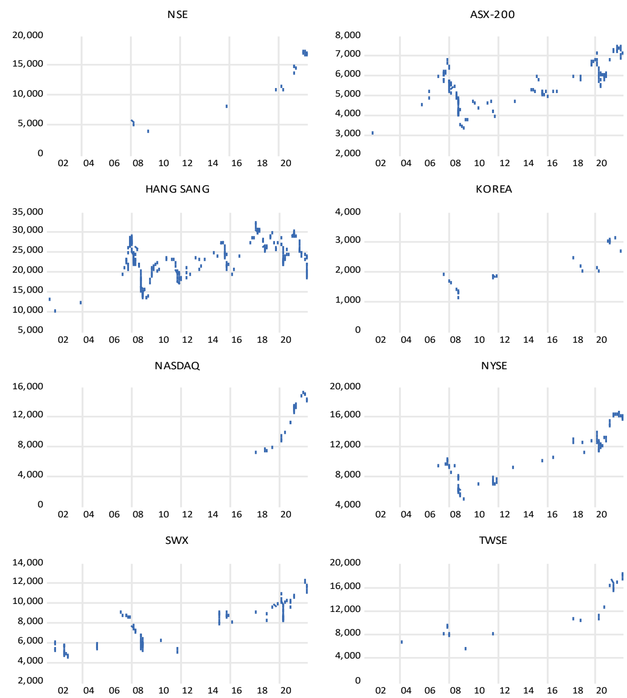


Figure 4.1: Daily Price Time Series Plot of Stock Exchanges

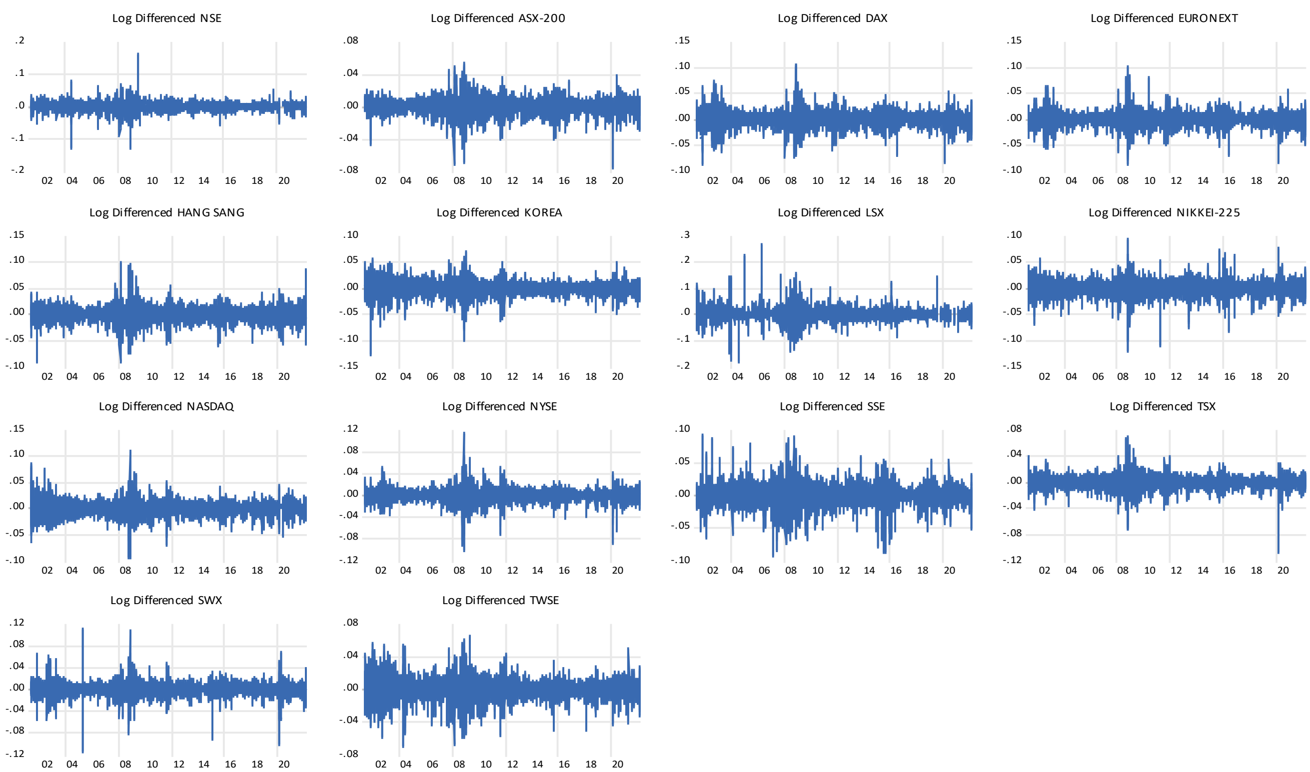


Figure 4.2: Log Returns Plot of Stock Exchanges

4.5 Unit Root Test:

To check whether there is presence of unit root in the data series or not, ADF was operate at the log of difference 1 [log (-1)]. At level, the level of significance was more than 0.05. But at difference 1 the level of significance remains below 0.05. As shown in table above, the p-values are "0.0000". The null hypothesis which is, there is a presence of unit root present in the data series is rejected and alternate hypothesis which is, there is no unit root present in the data series is accepted

Table 4.2 ADF Test at Level and Level 1:

Particulars	NYSE	NASDAQ	SSE	EURONEXT	NIKKEI 225	HANG SENG	NSE	LSE	TSX	ASX 200	SWX	KOREA	DAX	TWSE
ADF at level (t-statistic)	-2.187754	0.271725	-2.477246	-2.570737	-2.105622	-2.886121	-0.961753	-1.067424	-2.188276	-2.408953	-2.583461	-2.863692	-3.408246	-1.320114
P-values	0.4958	0.9985	0.3396	0.2939	0.5420	0.1670	0.9473	0.9328	0.4955	0.3747	0.2880	0.1746	0.0503	0.8827
ADF at Level 1 (t-statistic)	-76.8305	-78.9377	-33.84229	-73.8561	-75.7492	-73.5900	-44.4804	-80.3004	-72.9741	-73.6705	-73.43691	-71.6832	-72.7815	-69.6231
P-values	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0000	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000

Table 4.3 PP Test at Level and Level 1:

Particulars	NYSE	NASDAQ	SSE	EURONEXT	NIKKEI 225	HANG SENG	NSE	LSE	TSX	ASX 200	SWX	KOREA	DAX	TWSE
PP at Level (Adj. t-statistic)	-2.026015	0.432374	-2.448374	-2.507455	-2.084143	-2.894103	-1.061366	-1.105961	-2.219371	-2.370732	-2.415882	-2.942429	-3.433816	-1.295906
P-values	0.5863	0.9991	0.3542	0.3245	0.5540	0.1644	0.9337	0.9266	0.4781	0.3950	0.3711	0.1491	0.0470	0.8886
PP at level 1 (Adj. t-statistic)	-76.9476	-79.5804	-71.9325	-73.8947	-75.7387	-73.5888	-67.7176	-80.1651	-72.9673	-73.6846	-73.6755	-71.6598	-72.7724	-69.6231
P-values	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000

Source: Author's Calculations

The Augmented Dickey-Fuller (ADF) test is frequently employed to assess stationarity in a time series by determining the series' autocorrelations at various delays with the related t-statistics. The Augmented Dickey-Fuller (ADF) test null hypothesis asserts that the series under consideration is not stationary, whereas the alternative hypothesis suggests that the series is stationary.

On the other hand, KPSS Test tests the null hypothesis that a time series is stationary contrary to the alternative hypothesis that the series has a unit root, meaning that it is non-stationary. The test is based on the idea that if a time series is stationary, its difference should persist constant over time.

The KPSS test differs from the ADF test in that it tests the null hypothesis of stationarity for the series. Essentially, the analysis of the p-value is the inverse of one another. If the p-value is less than the significance level (0.05), then the series is considered to be non-stationary. In the ADF test, a stationary tested series would be indicated.

A test for determining the unit root is known as the Phillips–Perron test, which was named after Pierre Perron and Peter C. B. Phillips. For the purpose of testing the null hypothesis that a time series is integrated of order, it is utilised in the field of time series analysis. The ADF test and the Phillips-Perron test are comparable, although the Phillips-Perron exam is a little bit more sophisticated. It examines the data points to determine whether or not they are in a manner that can be predicted. Therefore, the time series is said to be stationary if the data points are changing in a manner that can be predicted. In the event that the data points are undergoing changes that are not expected, the time series is considered to be non-stationary. In other words, the ADF test determines whether or not the mean of the time series remains unchanged over time, while the PP test determines whether or not the variance of the time series remains unchanged over time.

In the above table, in case of ADF test at level, the p-values revealed that the level of significance is above 5% and at level 1, the p-values showed that the level of significance is below 0.05%. At level the data series is not stationary i.e., there is occurrence of unit root in the data series and at level 1 the series is stationary. To support the results of ADF test, PP test was performed at level and level 1, which also shows that the p- values are above 0.05% at level, showing presence of unit root in the data series and below 0.05% at level 1 showing no presence of unit. Hence, the results showed that the data series are non-stationary at level and stationary at level 1.

4.6 Structural Breakeven Test:

A structural break is a sudden and significant fluctuation in the statistical attributes or features of a financial time series, such as the prices of stocks or the returns of the stock exchange. These structural breaks signify a fundamental change in the conduct of the market or a particular stock, typically arising from diverse sources such as economic developments, policy modifications, financial crises, or other external shocks. Alterations in statistical characteristics such as the average, variability, autocorrelation, or distribution of stock returns commonly detect structural breaks. The statistical features of the data may exhibit significant differences before and after a structural break. Structural fractures can significantly influence investing strategies and the management of risks. Traders and investors must modify their methods to accommodate these alterations. After a structural disruption, models or techniques that were previously effective may become ineffective. Identifying structural changes in stock market data typically requires the application of statistical methods such as the Chow test, CUSUM tests (cumulative sum tests), or time series analysis. These strategies aid in determining the specific moment when a structural break takes place. Structural disruptions can have enduring impacts on the stock market. They have the potential to cause alterations in investor sentiment, market dynamics, and overall market performance for prolonged durations.

Understanding and responding to structural breaks is essential for investors and financial professionals since it can impact the performance of portfolios and the management of risks. It emphasises the significance of continuous monitoring and study of market conditions to adjust to evolving circumstances and make well-informed investment choices.

The Zivot-Andrews (ZA) unit root test is a usually used technique for examining the existence of a unit root in time series data. The Zivot-Andrews test is a statistical test employed in econometrics to ascertain the stationarity of a time series. The Zivot-Andrews test is specifically designed to consider potential structural discontinuities in the time series data, a factor that the ADF test does not consider. This test identifies the break in the time series that has the most substantial influence, out of all the breaks present.

Features that make it advantageous over other unit root tests:

- **Allows for a single structural break:** The ZA test differs from standard unit root tests by accommodating a single structural break, which can occur in either the level or the trend of the series. Unlike these traditional tests, which assume a constant mean and variance across time, the ZA test allows for this flexibility. This is significant because empirical data in the actual world frequently displays structural discontinuities caused by events such as policy alterations, economic disturbances, and so on. Neglecting to consider such interruptions can result in inaccurate deductions regarding the existence of a unit root.
- **Robust to nuisance parameters:** The ZA test is resistant to the influence of external variables such as the autoregressive order and the presence of heteroscedasticity. This indicates that the test results remain dependable even if certain particular characteristics of the data are not precisely defined.

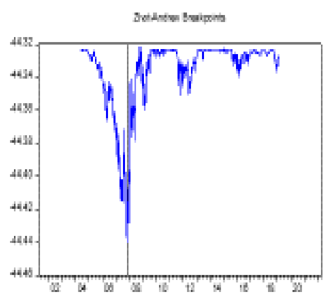
Table 4.4 The structural break test was calculated by using EVIEWS software, it shows the following results:

S.No.	Stock Exchange	t-statistic	Prob.
1.	ASX-200	-44.43973	0.004663
2.	DAX	-34.78298	0.023430
3.	EURONEXT-100	-35.91694	0.022932
4.	HSI	-73.66986	0.027469
5.	KSX	-37.46769	0.022136
6.	LSX	-77.45799	0.017518
7.	NASDAQ	-55.75967	0.002731
8.	NIKKEI-225	-44.37836	0.033837
9.	NSE	-36.30504	0.003775
10.	NYSE	-54.85421	0.012807
11.	SSE	-34.92632	0.000543

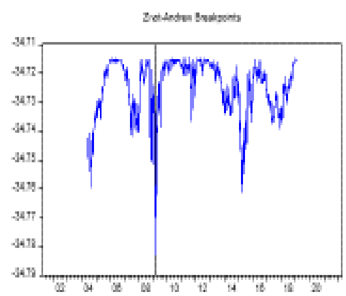
12.	SWX	-35.35892	0.027153
13.	TSX	-33.90135	0.031907
14.	TWSE	-36.74576	0.044020

Source: Author's Calculations

The Test shows that all the series are stationary at level 1. The test also shows that the significant break for all the variables is US financial crises.



ASX-200



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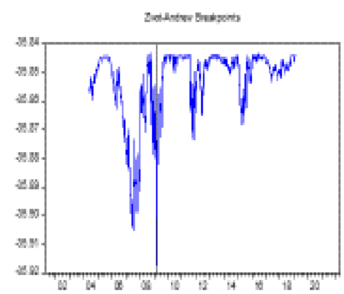
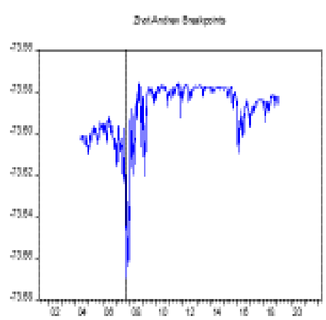
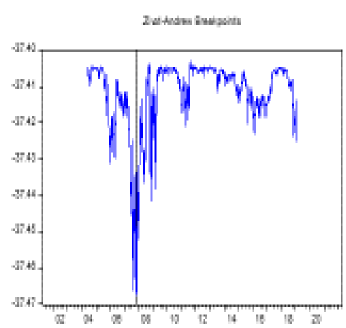


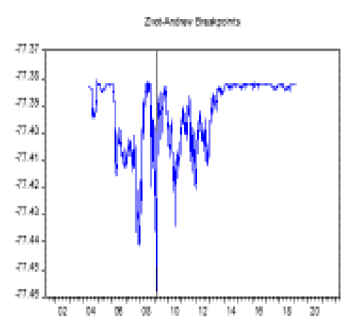
EURONEXT-100



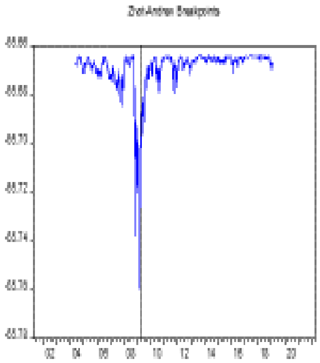
HANG SENG

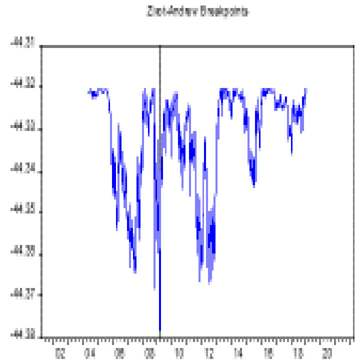


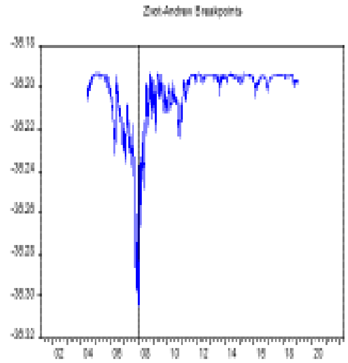
KOREA



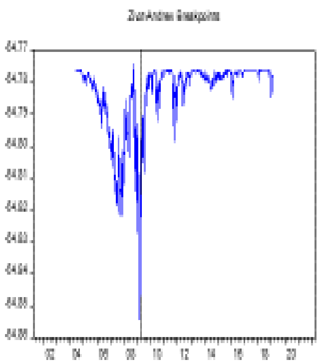
LSX

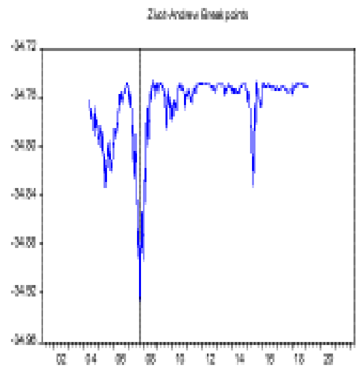


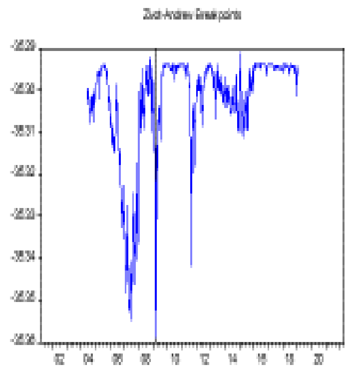




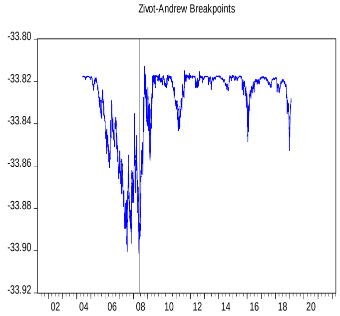
NASDAQ **NIKKEI-225** **NSE**







NYSE **SSE** **SWX**



TSX **TWSE**

Figures 5.1 Structural Breaks

4.7 Volatility Spillover between NSE and Selected International stock exchanges (SISE)

To analyse the volatility spillover between NSE and Selected International stock Exchanges, thirteen bivariate VAR (1) GARCH (1,1) model has been assessed.

Table 4.5 Results of VAR (1)-GARCH (1,1) between NSE and SISE

		NSE/SWX		NSE/SSE		NSE/EURONEXT-100	
		NSE	**SWX**	**NSE**	**SSE**	**NSE**	**EURONEXT-100**
Mean Equation	**X (-1)**	0.0583	0.0767	0.0948	-0.0228	0.0522	0.0947
	Y (-1)	1.3232e-03	-3.5406e-03	0.0600	-9.8786e-03	5.3914e-03	-0.0281
	C	2.5539e-06	5.0124e-06	1.5773e-06	1.5098e-06	3.3612e-06	2.8856e-06
Variance Equation	$(\varepsilon_{t-1}^{x})^2$	0.1083	0.0115	0.1175	6.8573e-03	0.1195	0.0166
	$(\varepsilon_{t-1}^{y})^2$	0.0216	0.1319	4.7031e-03	0.0827	8.3951e-03	0.1144
	(h_{t-1}^{x})	-0.8840	-0.0170	0.8688	3.5565e-04	0.8656	-0.0196
	(h_{t-1}^{y})	0.0106	0.8117	3.2483e-03	0.9092	-6.2470e-03	0.8650

Source: Author's Calculations

In Table 7.1, the dynamics of conditional variance and long-term persistence in the specified markets are indicated by the findings of the VAR (1)-GARCH (1,1) model of the relationship between the NSE and SWX, the NSE and SSE, and the NSE and Euronext-100. With the conditional variance equation, the sensitivity of the conditional variance to previous shocks $(\varepsilon_{t-1}^{x})^2$ and previous variance (h_{t-1}^{x}) is brought to light for the National Stock Exchange (NSE) and the markets that correspond to it. The coefficients of $(\varepsilon_{t-1}^{x})^2$ are shown to be substantial across pairs, with the NSE-SWX being 0.1083, the NSE-SSE being 0.1175, and the NSE-Euronext-100 being 0.1195. This suggests that previous unexpected shocks in the NSE have a considerable impact on its conditional variance. In a similar vein, the coefficients of $\left(\varepsilon_{t-1}^{y}\right)^2$, which include 0.1319 for the SWX and 0.1144 for the Euronext-100, indicate that unanticipated shocks in these markets also play a major role in contributing to the volatility of the NSE. In markets such as NSE-SWX and NSE-Euronext-100, the persistence of variance, which is calculated by the sum of (h_{t-1}^{x}) and $\left(h_{t-1}^{y}\right)$, is high. This indicates that the impact of previous volatilities continues to affect the market. The responsiveness of the variance structure to prior periods is reflected by parameters such as -0.8840 for NSE-SWX (h_{t-1}^{x}) and 0.8117 $\left(h_{t-1}^{y}\right)$ for SWX. These parameters indicate that the variance structure may exhibit a mean-reverting behavior. For the most part, the connection between the National Stock Exchange (NSE) and the International markets that were investigated demonstrates strong cross-market volatility transmission as well as persistent effects of past volatility.

Table 4.5 Results of VAR (1)-GARCH (1,1) between NSE and SISE

		NSE/ASX-200		NSE/DAX		NSE/HSI	
		NSE	**ASX-200**	**NSE**	**DAX**	**NSE**	**HSI**
Mean Equation	**X (-1)**	0.0789	0.0199	0.0484	0.0992	0.0919	-5.7770e-03
	Y (-1)	0.0741	-0.0313	0.0102	-0.0133	0.0912	-0.0135
	C	3.3188e-06	1.7001e-06	2.6799e-06	3.2522e-06	2.2482e-06	1.7792e-06
Variance Equation	$(\boldsymbol{\varepsilon}_{t-1}^{x})^2$	0.1084	0.0459	0.1162	0.0127	0.1333	5.3399e-04
	$(\boldsymbol{\varepsilon}_{t-1}^{y})^2$	7.8805e-03	0.0924	0.0109	0.0995	0.0155	0.0491
	$(\boldsymbol{h}_{t-1}^{x})$	0.8781	-0.0546	0.8710	-0.0129	0.8730	-8.4887e-03
	$(\boldsymbol{h}_{t-1}^{y})$	-6.5056e-03	0.8833	-8.5594e-03	0.8805	-0.0103	0.9345

Source; Author's Calculations

In Table 7.1, the interactions in conditional variance and long-term persistence across various markets are revealed by the findings of the VAR (1)-GARCH (1,1) model that was applied between the NSE and the ASX-200, the NSE and the DAX, and the NSE and the Historical Stock Index. An equation known as the conditional variance equation illustrates the impact of previous shocks $(\varepsilon_{t-1}^{x})^2$ and previous variances (h_{t-1}^{x}) on the NSE and its relationship with foreign markets. According to the coefficients for $(\varepsilon_{t-1}^{x})^2$, which include 0.1084 for the NSE-ASX-200, 0.1162 for the NSE-DAX, and 0.1333 for the NSE-HSI, it can be observed that the conditional variance of the NSE is considerably effected by the unexpected shocks that occurred in the past. The coefficients for $\left(\varepsilon_{t-1}^{y}\right)^2$, namely 0.0924 for DAX and 0.0491 for HSI, indicate that unforeseen disturbances in major global markets also have a role in the conditional volatility of NSE.

The enduring presence of variability is shown by the addition of (h_{t-1}^{x}) and (h_{t-1}^{y}). Significantly, the pairs NSE-DAX and NSE-HSI exhibit high coefficients of 0.8833 and 0.9345, respectively, for the variable (h_{t-1}^{y}). This indicates a substantial long-term persistence of prior variances. The values of 0.8781 for NSE-ASX-200 (h_{t-1}^{x}) and 0.8710 for NSE-DAX (h_{t-1}^{x}) indicate that the NSE's variance is strongly influenced by its own previous variances, demonstrating a significant level of inertia in the volatility process. To summarize, the data shows that the NSE is greatly influenced by its own previous shocks as well as those from the ASX-200, DAX, and HSI. There is a substantial and lasting connection between the volatility of these markets over the long run.

Table 4.5 Results of VAR (1)-GARCH (1,1) between NSE and SISE

		NSE/KRX		NSE/LSX		NSE/NASDAQ	
		NSE	KRX	NSE	LSX	NSE	NASDAQ
Mean Equation	**X (-1)**	0.0855	6.6063e-03	0.0847	0.0212	0.0535	0.1951
	Y (-1)	0.1197	-0.0236	0.0356	-0.0115	1.7372e-04	-0.0421
	C	2.2495e-06	1.2426e-06	2.3295e-06	1.0389e-05	1.9737e-06	3.2770e-06
Variance Equation	$(\boldsymbol{\varepsilon}_{t-1}^{x})^2$	0.1142	6.1377e-03	0.1222	2.9863e-03	0.1013	0.0332
	$(\boldsymbol{\varepsilon}_{t-1}^{y})^2$	0.0249	0.0548	0.0438	0.2823	0.0153	0.1260
	$(\boldsymbol{h}_{t-1}^{x})$	0.8718	-1.8147e-03	0.8625	-4.8316e-04	0.8847	-0.0280
	$(\boldsymbol{h}_{t-1}^{y})$	-0.0242	0.9373	-0.0275	0.7637	-5.1065e-03	0.8455

Source: Author's Calculations

The values of 0.8781 for NSE-ASX-200 (h_{t-1}^{x}) and 0.8710 for NSE-DAX (h_{t-1}^{x}) indicate that the NSE's variance is strongly influenced by its own previous variances, demonstrating a significant level of inertia in the volatility process. To summarize, the data shows that the NSE is greatly influenced by its own previous shocks as well as those from the ASX-200, DAX, and HSI. There is a substantial and lasting connection between the volatility of these markets over the long run. It may be deduced from this that the conditional variance of the NSE is considerably influenced by the unexpected shocks that have occurred in the past. Similar to the previous example, the coefficients for $(\varepsilon_{t-1}^{y})^2$ provide light on the impact of unforeseen shocks from the global markets on the volatility of the National Stock Exchange (NSE), with a notable value of 0.0548 for the LSX and 0.1260 for the NASDAQ.

The evaluation of long-term persistence is determined by the addition of (h_{t-1}^{x}) and $\left(h_{t-1}^{y}\right)$. For instance, the elevated values of $\left(h_{t-1}^{y}\right)$, such as 0.9373 for LSX and 0.8455 for NASDAQ, suggest a substantial level of persistence in volatility within these markets. The parameters 0.8718 for (h_{t-1}^{x}) in NSE-KRX and 0.8847 for (h_{t-1}^{x}) in NSE-NASDAQ indicate that NSE's conditional variance. The presence of negative coefficients for (h_{t-1}^{x}) in NSE-LSX (-4.8316e-04) and for $\left(h_{t-1}^{y}\right)$ in NSE-KRX (-0.0242) indicates a tendency for mean-reversion. However, the volatility of NSE is greatly influenced by its own historical shocks as well as those from KRX, LSX, and NASDAQ. This phenomenon demonstrates a strong correlation and transfer of volatility between various markets significantly affected by its own previous variances, demonstrating significant inertia.

Table 4.5 Results of VAR (1)-GARCH (1,1) between NSE and SISE

		NSE/NIKKEI_225		NSE/NYSE		NSE/TWSE	
		NSE	**NIKKEI-225**	**NSE**	**NYSE**	**NSE**	**TWSE**
Mean Equation	**X (-1)**	0.0869	-6.5635e-03	0.0385	0.2515	0.0808	0.0148
	Y (-1)	0.1259	-0.0438	6.2368e-03	-0.0315	0.1331	7.3060e-03
	C	2.9961e-06	3.7621e-06	2.1781e-06	2.7802e-06	2.0393e-06	1.0054e-06
Variance Equation	$(\varepsilon_{t-1}^{x})^2$	0.1153	1.5154e-03	0.0927	0.0519	0.1100	0.0131
	$(\varepsilon_{t-1}^{y})^2$	8.5250e-03	0.0996	0.0103	0.1439	0.0156	0.0663
	$(\boldsymbol{h_{t-1}^{x}})$	0.8793	-8.5572e-03	0.8929	-0.0485	0.8760	-6.5124e-03
	$(\boldsymbol{h_{t-1}^{y}})$	2.5829e-04	0.8739	-5.2347e-04	0.8183	-0.0102	0.9212

Source: Author's Calculations

The VAR (1)-GARCH (1,1) model yields insights into the conditional variances and long-term persistence of the interactions between NSE and NIKKEI-225, NSE and NYSE, and NSE and TWSE. The squared coefficients of the previous shocks (ε_{t-1}^{x}) for NSE are statistically significant for all pairs, with values such as 0.1153 for NSE-NIKKEI-225, 0.0927 for NSE-NYSE, and 0.1100 for NSE-TWSE. This suggests that unexpected shocks in the past have a notable impact on the conditional variance of NSE. The coefficients $\left(\varepsilon_{t-1}^{y}\right)^2$ are also significant for the shocks that occur in overseas markets. For example, the coefficients for the New York Stock Exchange (NYSE) are 0.0996, and the coefficient for the Taiwan Stock Exchange (TWSE) is 0.0663. These coefficients demonstrate that unexpected shocks in these markets have an effect on the volatility of the NYSE. The long-term persistence in variance is defined by the coefficients of (h_{t-1}^{x}) and $\left(h_{t-1}^{y}\right)$. For example, the values of (h_{t-1}^{x}), such as 0.8793 for NSE-NIKKEI-225 and 0.8929 for NSE-NYSE, indicate that NSE's conditional variance is strongly affected by its own previous variances, demonstrating a substantial level of inertia. The coefficients for $\left(h_{t-1}^{y}\right)$, namely 0.8739 for NYSE and 0.9212 for TWSE, demonstrate a significant level of persistence in volatility within these markets as well. The analysis indicates that the NSE is greatly influenced by its own previous shocks as well as those from NIKKEI-225, NYSE, and TWSE. These influences have a lasting impact on the volatility connections in the long term. This relationship emphasises the interdependence and magnitude of volatility between the NSE and global markets. The presence of negative coefficients for (h_{t-1}^{x}) in pairs such as NSE-NYSE (-0.0485) and $\left(h_{t-1}^{y}\right)$ in pairs such as NSE-NIKKEI-225 (2.5829e-04) indicates a tendency towards mean reversion. However, the overall influence of prior shocks and variances remains strong in these market interactions.

Table 4.5 Results of VAR (1)-GARCH (1,1) between NSE and SISE

		NSE/TSX	
		NSE	**TSX**
Mean Equation	**X (-1)**	0.0486	0.2312
	Y (-1)	7.9486e-03	8.8077e-03
	C	2.3412e-06	1.0669e-06
Variance Equation	$(\boldsymbol{\varepsilon_{t-1}^{x}})^2$	0.0926	0.0549
	$(\boldsymbol{\varepsilon_{t-1}^{y}})^2$	7.3253e-03	0.0884
	$(\boldsymbol{h_{t-1}^{x}})$	0.8820	-0.0332
	$(\boldsymbol{h_{t-1}^{y}})$	-8.5253e-03	0.9041

Source: Author's Calculations

The results of the VAR (1)-GARCH (1,1) model comparing NSE and TSX offer valuable information on their conditional variances and the long-term persistence of volatility. The mean equation demonstrates that previous values of both NSE (X (-1) = 0.0486) and TSX (X (-1) = 0.2312) have a significant impact on their respective current values, demonstrating an effective autoregressive component. The variance equation reveals that the squared coefficients of past shocks $(\varepsilon_{t-1}^{x})^2$ are statistically significant for both NSE (0.0926) and TSX (0.0549), showing that previous unexpected shocks in each market have a large impact on their respective conditional variance. The cross-market shock coefficients, such as $\left(\varepsilon_{t-1}^{y}\right)^2$, indicate that unexpected shocks in TSX have an impact on NSE's volatility, though to a smaller degree (0.0073). The enduring nature of anything is demonstrated by the coefficients associated with previous variances (h_{t-1}^{x}) and $\left(h_{t-1}^{y}\right)$. The NSE (0.8820) and TSX (0.9041) have high values, indicating a substantial level of inertia in their volatility. This means that historical levels of volatility have a big influence on future volatility. The presence of negative coefficients, such as -0.0332 for TSX (h_{t-1}^{x}), indicates the occurrence of mean-reverting behaviour. However, the impact of previous variances on the total outcome remains significant. This analysis emphasises the interdependence and strong transmission of volatility between the NSE and TSX stock exchanges. It shows that both prior shocks and variations within each market, as well as across markets, have had a substantial impact.

Conclusion

The analysis of the VAR (1)-GARCH (1,1) model between the variable shows that there are mixed short-term dynamics with different coefficients in the mean and variance equations. The lagged values of X and Y demonstrate weak short-term correlations, as most of the coefficients are weak and some are insignificant. The variance equation shows that there is a strong persistence of volatility, which signifies that there is strong evidence of a long-term relationship between the variables. in short, the results reveal that there is a strong long term volatility persistence between the variable.

CHAPTER 5

TO STUDY THE IMPACT OF MAJOR SPILLOVERS BETWEEN NATIONAL STOCK EXCHANGE AND SELECTED INTERNATIONAL STOCK EXCHANGES

5.1 DCC-GARCH Model

For the purpose of estimating the conditional volatility and correlation of financial time series data, the DCC-GARCH model, also identified as the Dynamic Conditional Correlation GARCH model, is a statistical and econometric model that is extensively used in the field of finance. It is a multivariate model. The GARCH model and the idea of dynamic conditional correlations come together to form the basis of the DCC-GARCH model. These two fundamental components are the foundation of the model. Through the combination of the GARCH framework and a dynamic model for the conditional correlation matrix, the DCC-GARCH model is able to incorporate these two concepts inside its framework. Because of this, the model is able to assess not only the time-varying volatilities of individual assets (by means of the GARCH model), but also the time-varying correlations between these assets (by means of the DCC framework). The GARCH model, which Robert Engle established in the 1980s, is one that is intended to internment the time-varying volatility that is present in the financial markets. Volatility clustering is the assumption that the variance of a financial time series is not constant but rather varies over time and is reliant on previous squared observations. This is the assumption that is made. It was specifically built in order to manage numerous time series at the same time. When modelling the behaviour of many assets, where the returns and volatilities of one item may be related to those of other assets, this is an important consideration to take into account.

Assumptions:

- It is important to evaluate the values of alpha1 and beta1 separately. If the values are affirmative and substantial, this directs that volatility is still present.
- Examine the total of the alpha1 and beta1 values for both series: If the value is less than one, this indicates that the volatility persistence has decreased over time. Determine which of the series is rapidly deteriorating.
- In the event that dcca1 and dccb1 are both positive and substantial, the extent of spillover is both short-term and long-term. [correlations that are close to one percent are strong, close to five percent are moderate, and below five percent are low]
- If the total of dcca1 and dccb1 is less than 1, it indicates that the DCC values are time varying.

Justification for Assumptions

Evaluating alpha1 and beta1 Separately

Alpha1 denotes the immediate effect of historical shocks on volatility, whereas Beta1 reflects the enduring persistence of volatility across time. If these values are positive and significant, it signifies that volatility is affected by both recent shocks and historical trends, hence affirming the existence of volatility clustering. This is crucial for understanding the mechanics of financial markets, where volatility frequently demonstrates persistence.

Sum of Alpha1 and Beta1

The aggregate of Alpha1 and Beta1 quantifies the total persistence of volatility. If this sum is below one, it implies that volatility shocks diminish over time, signifying decreased volatility persistence. This facilitates the identification of the series exhibiting more rapid decay, offering information into the stability and risk profile of the investigated markets.

DCCA1 and DCCB1 Importance

DCCA1 assesses short-term spillover effects, while DCCB1 evaluates long-term spillover effects. If both are positive and substantial, it signifies the existence of spillovers over both time frames. The magnitude of these correlations (about 1% = strong, 5% = moderate, below 5% = weak) quantifies the degree of dependency between the series, which is essential for comprehending market linkages.

Sum of DCCA1 and DCCB1:

If this sum is less than one, it indicates that the dynamic conditional correlations (DCC) are time-varying. This is essential for understanding the dynamic nature of market interactions, as financial markets frequently undergo varying levels of dependency over time due to economic events or policy alterations.

These assumptions combined provide a comprehensive investigation of volatility persistence, spillover effects, and time-varying correlations, which are essential for fulfilling the study's aims.

The data presented in Table 5.1 displays the estimates and corresponding p-values for different parameters associated with financial time series data. These parameters are related to various returns, NSE/SWX, NSE/SSE, NSE/EURONEXT-100, NSE/ASX-200, NSE/DAX, NSE/HSI, NSE/KSX, NSE/LSX, NSE/NASDAQ, NSE/NIKKEI-225, NSE/NYSE, NSE/TWSE, and NSE/TSX. The estimates consist of parameters represented as [A]α1, [A]β1, [B]α1, [B]β1, [Joint]dccα1, and [Joint]dccβ1, along with their respective p-values. The variables α1 and β1 reflect the measures of conditional volatility and conditional correlation, respectively. [joint]dccα1 denotes the conditional volatility between variables. The term [Joint]dccβ1 denotes the measure of the conditional correlation between variables. The sum of [Joint]dccα1 and [Joint]dccβ1 should be less than one. If the value is less than one, then the conditional correlation between variables are dynamic i.e. it is time varying. These estimations refer to statistical and economic measurements concerning the conditional volatility, correlation, and joint dynamics of these stock indices.

The DCC GARCH model is designed to incorporate two parameters, primarily (α) and (β), to consider the vigorous nature of correlations in the volatility of the asset market. Each of these characteristics is time-dependent and reflects the changing linkages that exist between asset values over the course of time. A precise quantification of the short-term persistence of volatility shocks is provided by the coefficient (α), which indicates the extent to which the unexpected price movements that occurred yesterday influenced the volatility that occurred today. The coefficient β, which is a component of the DCC GARCH model, serves to quantify the residual impact of previous volatility shocks on the conditional correlations that exist between asset prices. This parameter indicates the length of time that the effects of previous events continue to have an influence on the correlation dynamics that are now being observed. It depicts the persistence of shocks in the correlation dynamics. A constraint that ensures the stability of the model is that the sum of (α) and (β) be less than one. This constraint prevents correlations from becoming permanently set at previous values, which enables dynamic modifications to be made over time. There appears to be a significant correlation in volatility among the various assets, as seen in Table 5.1. The spillover effect, which was detected across all variables and pairings of variables over the course of the long run, is proof of this observation. The fact that the individual values of alpha and beta are both positive and substantial lends credibility to the persistence volatility. Moreover, the sum of alpha and beta for all of the series is less than 1, which indicates that the volatility persistence has decreased over the course of time. For all pairs in the DCC model, the Joint β coefficient is greater than 0.9, which suggests that the shock impact has a very strong and persistent effect on the conditional correlations between the variables. It may be deduced from this that shocks to one variable have a considerable and long-lasting impact on the correlations with another one. In addition, the study emphasizes the fact that volatility continues to exist throughout time. Also, it has been suggested that the implementation of structural breaks can assist in the reduction of this persistent behavior. In the course of the financial crisis that occurred in the United States, a consistent pattern of dynamic correlations emerged across all variables. This pattern was visible in the DCC graphs (Figure 5.1) as well. All of the factors appear to be interconnected in a way that is both strong and long-lasting after considering this.

Table 5.1 DCC-GARCH Results of NSE and selected International Stock Exchanges

		NSE/SWX		NSE/SSE		NSE/EURONEXT-100		NSE/ASX200		NSE/DAX	
S. No.		Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
1.	**[A]α1**	0.124787	0.000318	0.124787	0.000334	0.124787	0.000315	0.124787	0.000328	0.124787	0.000314
2.	**[A]β1**	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000
3.	**[B]α1**	0.141943	0.000000	0.081307	0.199269	0.118396	0.000000	0.098920	0.552425	0.100146	0.000000
4.	**[B]β1**	0.811987	0.000000	0.916112	0.000000	0.866356	0.000000	0.887312	0.000002	0.883137	0.000000
5.	**[Joint]dccα1**	0.021497	0.004863	0.003509	0.057283	0.016342	0.004781	0.017860	0.058909	0.017029	0.011623
6.	**[Joint]dccβ1**	0.951230	0.000000	0.994933	0.000000	0.966652	0.000000	0.954808	0.000000	0.966810	0.000000

Table 5.1 DCC-GARCH Results of NSE and selected International Stock Exchanges

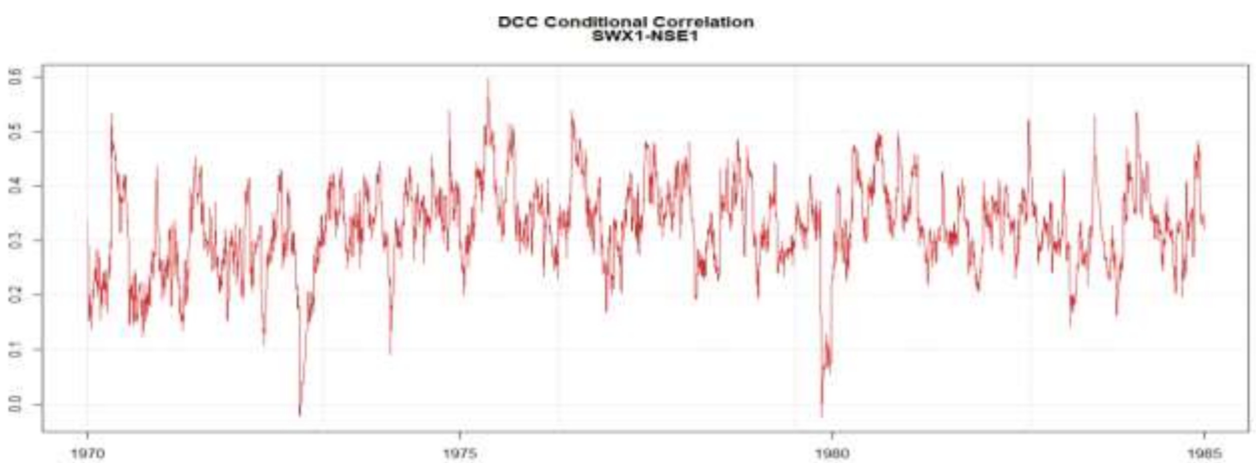
		NSE/LSX		NSE/NASDAQ		NSE/NIKKEI225		NSE/NYSE		NSE/TWSE	
S. No.		Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
1.	**[A]α1**	0.124787	0.000329	0.124787	0.000330	0.124787	0.000332	0.124787	0.000327	0.124787	0.000321
2.	**[A]β1**	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000	0.869228	0.000000
3.	**[B]α1**	0.216661	0.007028	0.125546	0.000000	0.111870	0.000000	0.129129	0.000333	0.080494	0.235334

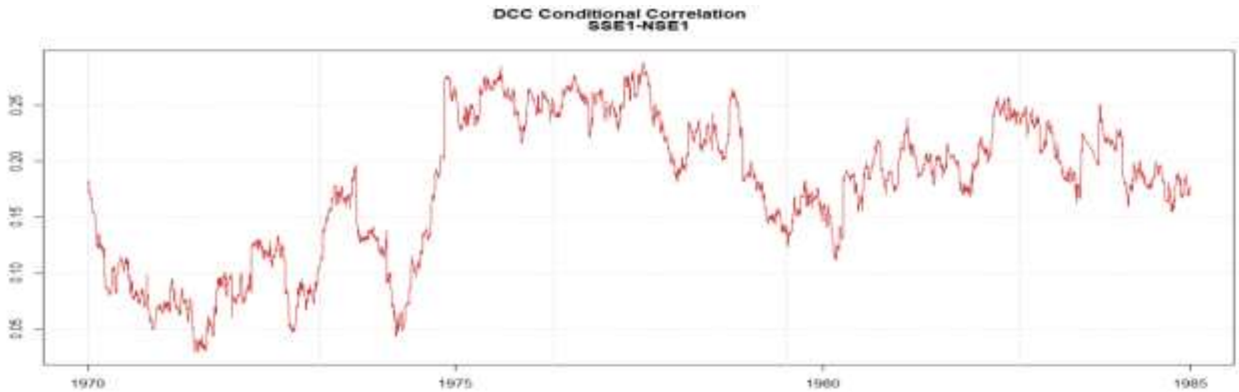
4.	**[B]β1**	0.782339	0.054118	0.852310	0.000000	0.868081	0.000000	0.849067	0.000000	0.912065	0.000000
5.	**[Joint]dccα1**	0.015394	0.006646	0.002597	0.001818	0.013109	0.008628	0.002405	0.014656	0.016131	0.004302
6.	**[Joint]dccβ1**	0.969471	0.000000	0.996973	0.000000	0.950400	0.000000	0.997350	0.000000	0.944526	0.000000

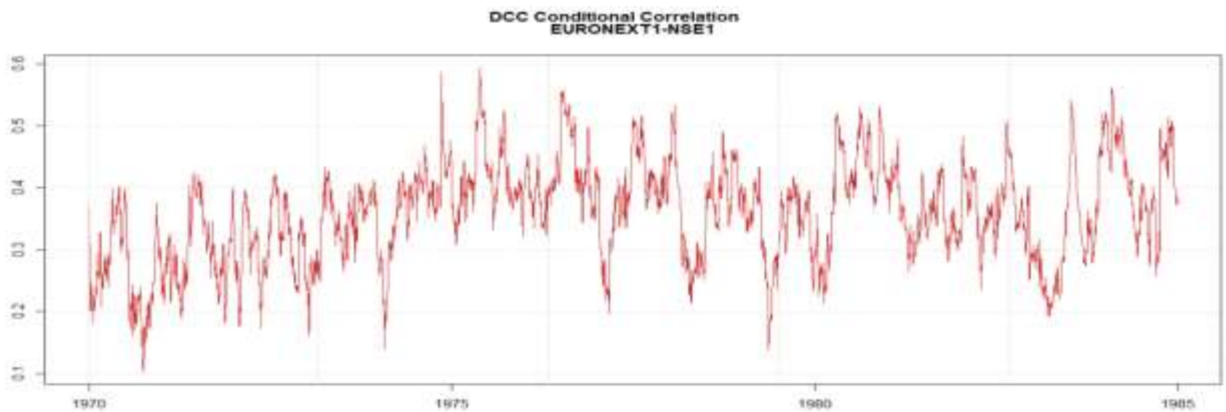
Table 5.1 DCC-GARCH Results of NSE and selected International Stock Exchanges

		NSE/TSX		**NSE/HSI**		**NSE/KSX**	
S. No.		Estimate	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Pr(>|t|)
1.	**[A]α1**	0.124787	0.124787	0.000331	0.124787	0.000327	0.000332
2.	**[A]β1**	0.869228	0.869228	0.000000	0.869228	0.000000	0.000000
3.	**[B]α1**	0.113775	0.062372	0.930369	0.075788	0.004550	0.011391
4.	**[B]β1**	0.873326	0.927625	0.243533	0.918839	0.000000	0.000000
5.	**[Joint]dccα1**	0.004663	0.015536	0.043956	0.020433	0.000026	0.339877
6.	**[Joint]dccβ1**	0.985469	0.000000	0.966013	0.000000	0.951150	0.000000

Source: Author's Calculations

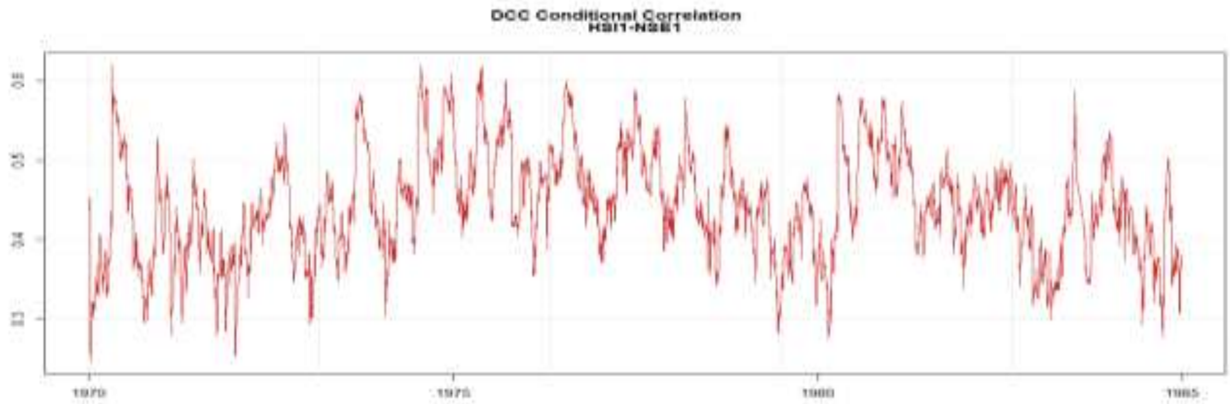



DCC Conditional Correlation
SSE1-NSE1
0.25
0.20
0.15
0.10
0.05
1970
1975
1980
1985


DCC Conditional Correlation
EURONEXT1-NSE1
0.6
0.5
0.4
0.3
0.2
0.1
1970
1975
1980
1985

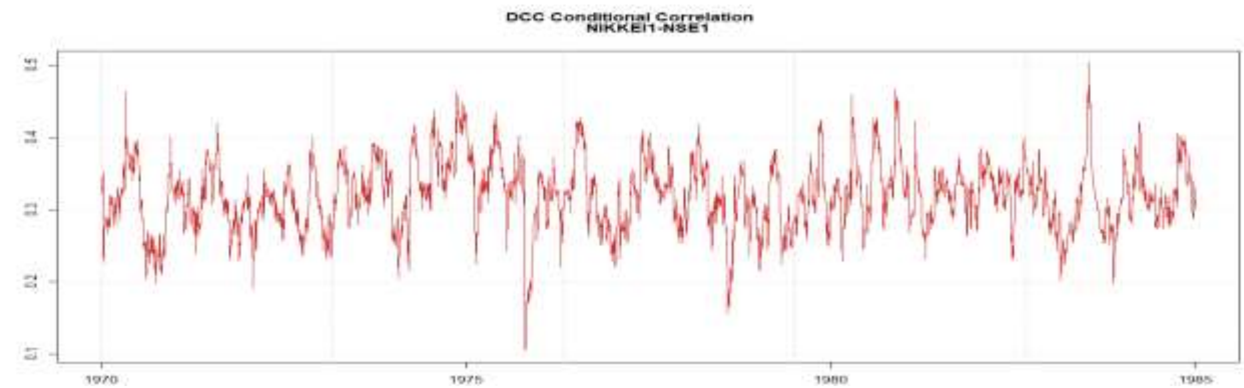

DCC Conditional Correlation
ASX1-NSE1
0.6
0.5
0.4
0.3
0.2
0.1
1970
1975
1980
1985

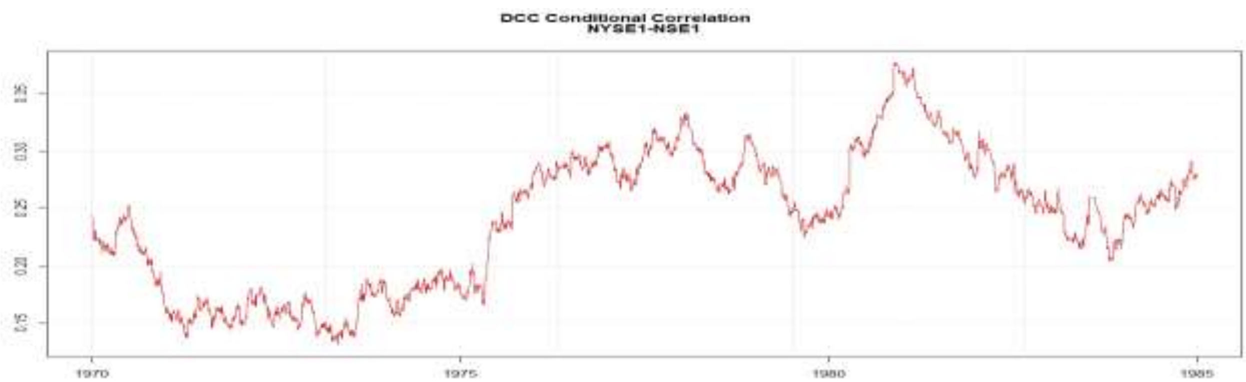

DCC Conditional Correlation
DAX1-NSE1
1970
1975
1980
1985

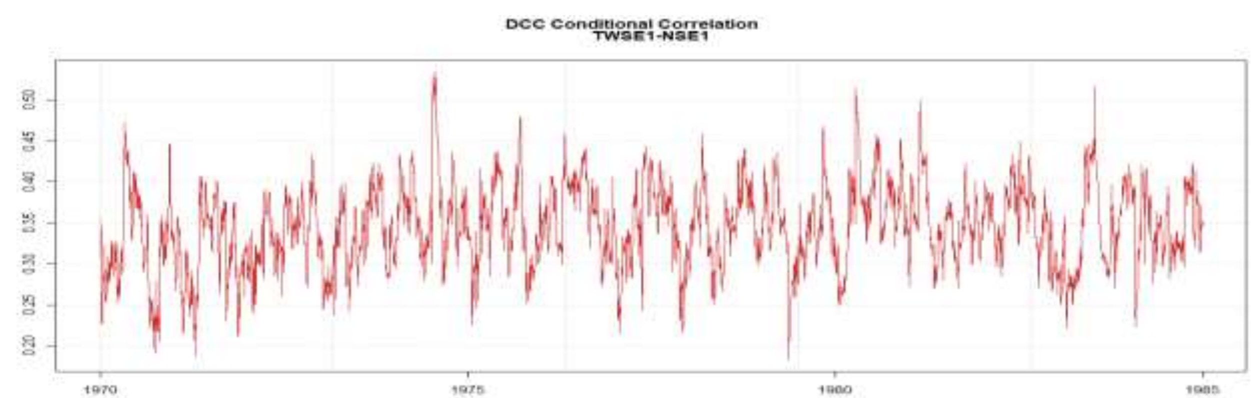

DCC Conditional Correlation
HSI1-NSE1
1970
1975
1980
1985

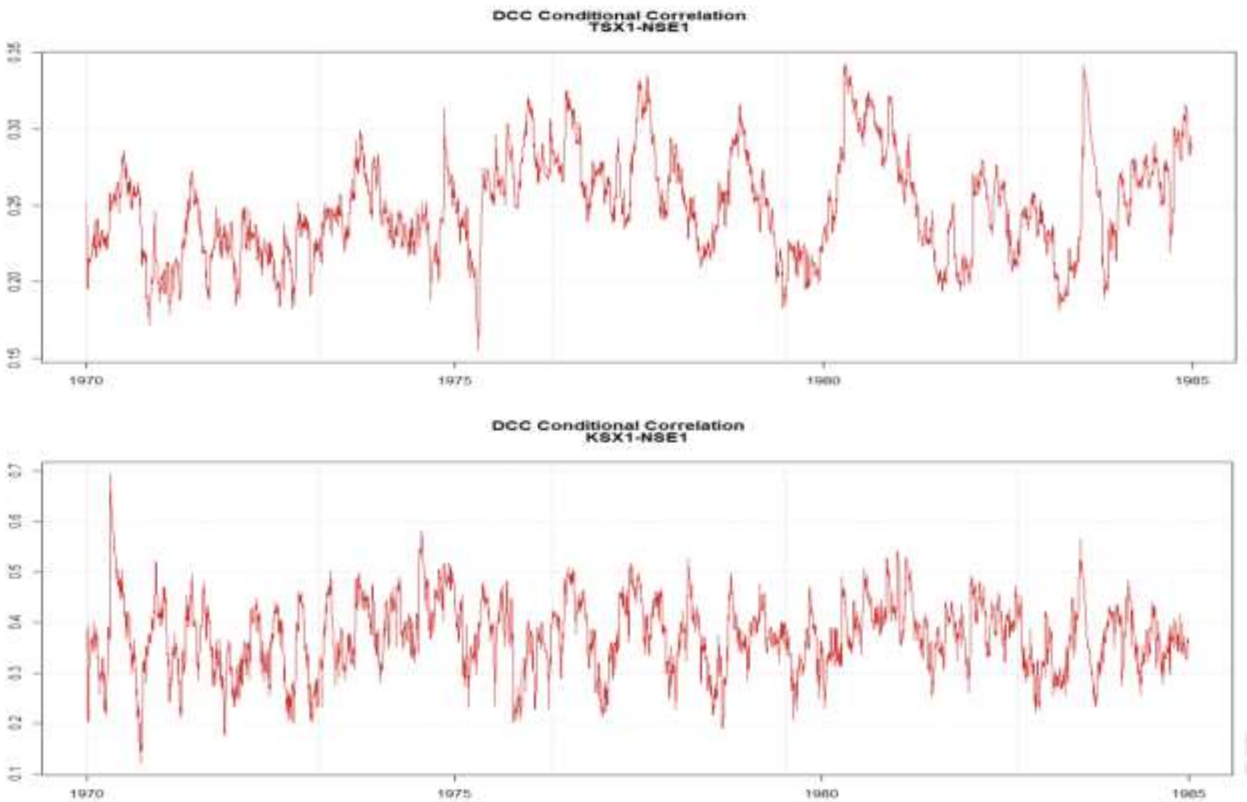

DCC Conditional Correlation
LSX1-NSE1
1970
1975
1980
1985


DCC Conditional Correlation
NASDAQ1-NSE1
1970
1975
1980
1985


DCC Conditional Correlation
NIKKEI1-NSE1
1970
1975
1980
1985


DCC Conditional Correlation
NYSE1-NSE1
1970
1975
1980
1985


DCC Conditional Correlation
TWSE1-NSE1
1970
1975
1980
1985



Figures 5.1 Conditional Correlation Between Stock Exchanges

5.2 BEKK-GARCH Model

In order to authorize the above results calculated by employing DCC-GARCH, BEKK-GARCH is used:

Table 5.2 BEKK-GARCH Results of NSE and selected International Stock Exchanges

Variable	SWX	SSE	EURONEXT100	ASX-200	DAX	HSI	KRX
Mean	0.0004	0.0001*	0.0005	0.0004	0.0006	0.0004	0.0004
Mean (NSE)	0.0007	0.0007	0.0007	0.0007	0.0008	0.0007	0.0007
C(1,1)	0.0014	0.0016	0.0014	0.0012	0.0014	0.0015	0.0015
C(2,1)	0.0008	0.0004	0.0005	0.0005	0.0005	0.0006	0.0006
C(2,2)	0.0020	0.0011	0.0014	0.0009	0.0016	0.0009	0.0005
A(1,1)	0.3078	0.3187	0.3164	0.2816	0.3126	0.3327	0.3345
A(1,2)	0.0125*	0.0168*	0.0239	0.0139	0.0252*	0.0509	0.0578
A(2,1)	-0.0096*	0.0117*	0.0080*	0.0650	-0.0306	0.0115*	0.0250*
A(2,2)	0.3455	0.2471	0.2954	0.2712	0.2799	0.2074	0.1976
B(1,1)	0.9479	0.9409	0.9450	0.9557	0.9449	0.9365	0.9350
B(1,2)	-0.0015*	-0.0091*	-0.0045*	-0.0039*	-0.0069*	-0.0162	-0.0208
B(2,1)	-0.0002*	-0.0011*	-0.0044*	-0.0213	0.0088*	-0.0006*	-0.0032*
B(2,2)	0.9154	0.9680	0.9473	0.9560	0.9516	0.9759	0.9799

Table 5.2 BEKK-GARCH Results of NSE and selected International Stock Exchanges

Variable	LSX	NASDAQ	NIKKEI225	NYSE	TWSE	TSX
Mean	0.0009	0.0006	0.0004	0.0004	0.0005	0.0004
Mean (NSE)	0.0006	0.0007	0.0008	0.0007	0.0008	0.0008
C(1,1)	0.0012	0.0013	0.0014	0.0014	0.0015	0.0015
C(2,1)	0.0002*	-0.0001*	0.0009	0.0001*	0.0007	0.0002
C(2,2)	0.0035	0.0018	0.0016	0.0014	-0.0007	0.0008
A(1,1)	0.2576	0.2957	0.3117	0.3024	0.3253	0.3190
A(1,2)	0.0150*	0.0170*	0.0675	0.0220	0.0574	0.0353
A(2,1)	0.0105*	-0.0432	-0.0037*	0.0001*	0.0401	0.0195*
A(2,2)	0.5131	0.3094	0.2715	0.3155	0.2231	0.2636
B(1,1)	0.9603	0.9490	0.9480	0.9489	0.9382	0.9434
B(1,2)	-0.0077*	-0.0022*	-0.0159	-0.0041*	-0.0206	-0.0093
B(2,1)	0.0020*	0.0165	-0.0047*	0.0010*	-0.0080	-0.0075
B(2,2)	0.8811	0.9395	0.9514	0.9382	0.9724	0.9601

Author's Calculations

In Table 5.2, the results B (2,2) also show that there is long run spillover or volatility dynamics between the variables, all the variables show the long run spillover as their p-values are significant. They also show that there is a strong affirmative correlation amongst variables as their GARCH coefficients **(0.915, 0.9680, 0.9473, 0.9560, 0.9516, 0.9759, 0.9799, 0.8811, 0.9395, 0.9514, 0.9382, 0.9724, 0.9601)** are near to 1. These BEKK-GARCH results in Table 5.2 authorize the results shown by DCC-GARCH in Table 5.1.

In conclusion, the results showed that:

- The [Joint]dccα1 shows the short run spillover between variables, all the variables had significant p values which indicate the short run spillover except SSE, ASX-200 and TSX, where p-values are insignificant.
- The [Joint]dccβ1 shows the long run spillover between variables, all the variables show the long run spillover as their p-values are significant. They also show strong positive correlation between variables as the coefficients are near to 1. The results also show that the DCC is mean reverting.

The DCC-GARCH model revealed a strong positive correlation between variables. This means that the variables tend to move in the same direction: When one variable increases, the other variable also tends to increase. When one variable decreases, the other variable also tends to decreases.

CHAPTER 6

GRANGER CAUSALITY BETWEEN NATIONAL STOCK EXCHANGE AND SELECTED INTERNATIONAL STOCK EXCHANGES

Granger causality is a concept that was first introduced by Clive Granger in 1969 and has since become an essential component of the toolkit utilized by researchers and analysts in a wide range of fields. The core premise of this approach is to determine if one variable in a time series may be deemed to have a causal influence on another variable. Granger causality theory states that if the addition of past values of one variable considerably improves the ability to forecast another variable, then the former is considered to be the "Granger cause" of the latter. In simple terms, if knowing the previous values of variable X improves the accuracy of forecasting the future values of variable Y, in addition to considering Y's prior values, then X is considered to have a Granger causality on Y. This indicates that X possesses information that is not already included in Y's existing historical data, so making it crucial for predicting Y's future course. For example, the correlation between economic indices like inflation and unemployment. Granger causality analysis can be used to assess whether incorporating previous inflation rates, together with historical unemployment data, enhances the precision of predicting future levels of unemployment. If this is the case, it implies that inflation has a Granger causality effect on unemployment, demonstrating a predicted association between the two variables. Maziarz (2015) emphasizes the importance of Granger causality when the connection between variables is not well-established theoretically or when conducting controlled trials is impossible. Granger causality is a useful technique for deducing causal linkages solely from observational data in such instances. Granger causality tests generally produce one of three results: unidirectional, bidirectional, or no significant Granger causality between the examined variables. Unidirectional causality refers to a situation where one variable has an influence on another variable, but the reverse is not true. For example, if X Granger causes Y, it indicates that alterations in X occur before and have an impact on changes in Y, but the opposite is not the case. This scenario implies a causal relationship between the variables, in which one variable serves as a predictive signal for the other. Bidirectional causality refers to a mutual relationship in which both variables have an impact on the future values of each other. This indicates a more detailed relationship between the variables, where alterations in one variable not only impact the other but are also reciprocally influenced by it. However, the lack of substantial Granger causality indicates that the variables do not exhibit a causal relationship in either direction. This does not imply that the variables are necessarily independent or unrelated; instead, it suggests that the apparent connections between them can be accounted for by other factors or mechanisms.

It is of utmost importance to differentiate Granger causality from a direct cause-and-effect relationship. Establishing Granger causality does not indicate that one variable is the direct cause of another in the conventional sense. Instead, it indicates the order in which events occur and the ability to predict future changes - specifically, one variable comes before another and helps in forecasting changes in the latter. For instance, if X Granger induces Y, it does not necessarily imply that alterations in X directly result in modifications in Y. Alternatively, it proposes that knowing X's previous values can assist in predicting future changes in Y, even if the exact connection between X and Y is not fully understood. The data is segregated into 3 parts, pre break, during break and post break. The pre break period is 2001-2006. During break period is 2007-2008 and post break period is 2009-2022.

Hypothesis:

H01: International stock exchanges does not Granger cause the NSE.

H02: NSE does not Granger cause International stock exchanges

H11: International stock exchanges does Granger cause the NSE.

H12: NSE does Granger cause the international stock exchanges.

If, the P-value is < or = 0.05 %, then the alternate hypothesis is accepted.

The result of Granger Causality test of all fourteen indices of stock exchanges under research for the time period of twenty-one years from April 2001 to March 2022 is shown in Table 6.1, 6.2, and 6.3.

Table 6.1: Grangers Causality Test of NSE and selected International Stock Exchanges Pre-US financial crises (01-04-2001 to 30-03-2007)

Null Hypothesis	Observations	F-Statistic	Prob.	Significance
NIKKEI-225 does not Granger Cause NSE	1563	0.15891	0.8531	Accepted
NSE does not Granger Cause NIKKEI-225		14.7511	5.E-07	Rejected
NASDAQ does not Granger Cause NSE	1563	27.0650	3.E-12	Rejected
NSE does not Granger Cause NASDAQ		1.78482	0.1682	Accepted

LSX does not Granger Cause NSE	1563	0.67987	0.5068	Accepted
NSE does not Granger Cause LSX		5.70397	0.0034	Rejected
KOREA does not Granger Cause NSE	1563	1.86314	0.1555	Accepted
NSE does not Granger Cause KOREA		6.93423	0.0010	Rejected
HANG SENG does not Granger Cause NSE	1563	1.04905	0.3505	Accepted
NSE does not Granger Cause HANG SENG		9.90466	5.E-05	Rejected
EURONEXT-100 does not Granger Cause NSE	1563	8.27905	0.0003	Rejected
NSE does not Granger Cause EURONEXT-100		3.40593	0.0334	Rejected
DAX does not Granger Cause NSE	1563	13.5670	1.E-06	Rejected
NSE does not Granger Cause DAX		3.78894	0.0228	Rejected
ASX-200 does not Granger Cause NSE	1563	0.54563	0.5796	Accepted
NSE does not Granger Cause ASX-200		10.5211	3.E-05	Rejected
NYSE does not Granger Cause NSE	1563	44.5936	1.E-19	Rejected
NSE does not Granger Cause NYSE		3.27681	0.0380	Rejected
SSE does not Granger Cause NSE	1563	4.00814	0.0184	Rejected
NSE does not Granger Cause SSE		10.8903	2.E-05	Rejected
SWX does not Granger Cause NSE	1563	7.69651	0.0005	Rejected
NSE does not Granger Cause SWX		3.38473	0.0341	Rejected
TSX does not Granger Cause NSE	1563	56.7659	2.E-24	Rejected
NSE does not Granger Cause TSX		2.39816	0.0912	Accepted
TWSE does not Granger Cause NSE	1563	0.80347	0.4480	Accepted
NSE does not Granger Cause TWSE		12.9654	3.E-06	Rejected

Note: The results are based on AIC (Akaike Information Criterion)

Source: Author's calculations.

The findings of the Granger Causality Test in Table 6.1 showed that the NSE (National Stock Exchange) is affected by several international stock exchanges. This is supported by the rejection of the null hypothesis that the international stock exchanges do not have a causal influence on the NSE. In particular, the stock exchanges NASDAQ, EURONEXT-100, DAX, NYSE, SSE, SWX, and TSX indexes all show a strong Granger causality relationship with the NSE. This suggests that the past values of these stock exchange offer important forecasting information for the NSE. In simpler terms, these stock exchanges do influence the NSE. Conversely, the null hypothesis that the NSE does not have a causal relationship with these international stock exchanges is rejected in some stock exchanges, indicating that there is an inverse causality between the NSE and these exchanges. NSE Granger cause NIKKEI-225, LSX, KOREA, HANG SENG, EURONEXT-100, DAX, ASX-200, NYSE, SSE, SWX, TSX and TWSE. Even so, the null hypothesis is upheld for the NASDAQ and TSX exchanges, suggesting that the NSE does not have a Granger causality effect on the NASDAQ and TSX. However, they do have such an effect on the NSE. These results showed that there is the presence of both the unilateral and bilateral relationships between the NSE and these selected international stock exchanges. There is bilateral relationship between NSE and EURONEXT-100, DAX, NYSE, SSE and SWX. These findings indicate that there are intricate connections between the NSE and worldwide stock markets, emphasizing the significance of taking foreign issues into account when analyzing the behaviour of the NSE.

Table 6.2: Grangers Causality Test of NSE and selected International Stock Exchanges During US financial crises (01-04-2007 to 31-03-2009)

Null Hypothesis:	Observat-ions	F-Statistic	Prob.	Signific-ance
NIKKEI-225 does not Granger Cause NSE	520	2.83207	0.0598	Accepted
NSE does not Granger Cause NIKKEI-225		14.3315	9.E-07	Rejected
NASDAQ does not Granger Cause NSE	520	26.2809	1.E-11	Rejected
NSE does not Granger Cause NASDAQ		0.64042	0.5275	Accepted
LSX does not Granger Cause NSE	520	10.6306	3.E-05	Rejected
NSE does not Granger Cause LSX		1.49880	0.2244	Accepted
KOREA does not Granger Cause NSE	520	3.49975	0.0309	Rejected
NSE does not Granger Cause KOREA		8.14785	0.0003	Rejected
HANG SENG does not Granger Cause NSE	520	13.4234	2.E-06	Rejected
NSE does not Granger Cause HANG SENG		7.18103	0.0008	Rejected
EURONEXT-100 does not Granger Cause NSE	520	9.86058	6.E-05	Rejected
NSE does not Granger Cause EURONEXT-100		2.56648	0.0778	Accepted

DAX does not Granger Cause NSE	520	10.2810	4.E-05	Rejected
NSE does not Granger Cause DAX		3.02042	0.0496	Rejected
ASX-200 does not Granger Cause NSE	520	3.78315	0.0234	Rejected
NSE does not Granger Cause ASX-200		8.67801	0.0002	Rejected
NYSE does not Granger Cause NSE	520	22.6792	4.E-10	Rejected
NSE does not Granger Cause NYSE		1.19874	0.3024	Rejected
SSE does not Granger Cause NSE	520	8.67711	0.0002	Rejected
NSE does not Granger Cause SSE		8.66974	0.0002	Rejected
SWX does not Granger Cause NSE	520	9.80405	7.E-05	Rejected
NSE does not Granger Cause SWX		0.63866	0.5284	Accepted
TSX does not Granger Cause NSE	520	11.0709	2.E-05	Rejected
NSE does not Granger Cause TSX		0.05544	0.9461	Accepted
TWSE does not Granger Cause NSE	520	3.82903	0.0224	Rejected
NSE does not Granger Cause TWSE		12.5784	5.E-06	Rejected

Note: The results are based on AIC (Akaike Information Criterion)

Source: Author's Calculations

The findings of the Granger Causality Test in Table 6.2 showed that the NSE (National Stock Exchange) is affected by several international stock exchanges. This is supported by the rejection of the null hypothesis that the international stock exchanges do not have a causal influence on the NSE. In particular, the stock exchanges NASDAQ, LSX, KOREA, HANG SENG, EURONEXT-100, DAX, ASX-200, NYSE, SSE, SWX, TSX and TWSE indexes all show a strong Granger causality relationship with the NSE. This suggests that the past values of these stock exchange offer important forecasting information for the NSE. In simpler terms, these stock exchanges do influence the NSE. Conversely, the null hypothesis that the NSE does not have a causal relationship with these international stock exchanges is rejected in some stock exchanges, indicating that there is an inverse causality between the NSE and these exchanges. NSE Granger cause NIKKEI-225, LSX, KOREA, HANG SENG, DAX, ASX-200, NYSE, SSE, and TWSE. Even so, the null hypothesis is upheld for the NASDAQ, LSX, EURONEXT-100, SWX and TSX exchanges, suggesting that the NSE does not have a Granger causality effect on the NASDAQ, LSX, EURONEXT-100, SWX and TSX. However, they do have such an effect on the NSE. These results showed that there is the presence of both the unilateral and bilateral relationships between the NSE and these selected international stock exchanges. There is bilateral relationship between NSE, KOREA, HANG SENG, DAX, ASX-200, NYSE, SSE and TWSE. These findings indicate that there are intricate connections between the NSE and worldwide stock markets during the crises period as compared to the pre-crises period, emphasizing the significance of taking foreign issues into account when analysing the behaviour of the NSE.

Table 6.3: Grangers Causality Test of NSE and selected International Stock Exchanges Post-US financial crises (01-04-2009 to 31-03-2022)

Null Hypothesis:	Observa-tions	F-Statistic	Prob.	Signific-ance
NIKKEI-225 does not Granger Cause NSE	3390	0.34271	0.7099	Accepted
NSE does not Granger Cause NIKKEI-225		26.9943	2.E-12	Rejected
NASDAQ does not Granger Cause NSE	3390	96.3150	2.E-41	Rejected
NSE does not Granger Cause NASDAQ		1.08512	0.3380	Accepted
LSX does not Granger Cause NSE	3390	3.65270	0.0260	Rejected
NSE does not Granger Cause LSX		1.47412	0.2291	Accepted
HANG SENG does not Granger Cause NSE	3390	2.95631	0.0521	Rejected
NSE does not Granger Cause HANG SENG		13.4302	2.E-06	Rejected
KOREA does not Granger Cause NSE	3390	0.29852	0.7419	Accepted
NSE does not Granger Cause KOREA		37.2148	1.E-16	Rejected
EURONEXT-100 does not Granger Cause NSE	3390	29.3229	2.E-13	Rejected
NSE does not Granger Cause EURONEXT-100		7.48889	0.0006	Rejected
DAX does not Granger Cause NSE	3390	27.8454	1.E-12	Rejected
NSE does not Granger Cause DAX		1.78431	0.1681	Accepted
ASX-200 does not Granger Cause NSE	3390	3.46658	0.0313	Rejected
NSE does not Granger Cause ASX-200		39.7900	8.E-18	Rejected
NYSE does not Granger Cause NSE	3390	105.271	4.E-45	Rejected
NSE does not Granger Cause NYSE		4.13547	0.0161	Rejected

SSE does not Granger Cause NSE	3390	1.17221	0.3098	Accepted
NSE does not Granger Cause SSE		5.63112	0.0036	Rejected
SWX does not Granger Cause NSE	3390	12.8428	3.E-06	Rejected
NSE does not Granger Cause SWX		5.11977	0.0060	Rejected
TSX does not Granger Cause NSE	3390	58.9713	7.E-26	Rejected
NSE does not Granger Cause TSX		8.32743	0.0002	Rejected
TWSE does not Granger Cause NSE	3390	2.88927	0.0558	Accepted
NSE does not Granger Cause TWSE		35.7333	4.E-16	Rejected

Note: The results are based on AIC (Akaike Information Criterion)

Source: Author's Calculations

The findings of the Granger Causality Test in Table 6.3 showed that the NSE (National Stock Exchange) is affected by International Stock Exchanges. This is supported by the rejection of the null hypothesis that the international stock exchanges do not have a causal influence on the NSE. In particular, the stock exchanges NASDAQ, LSX, HANG SENG, EURONEXT-100, DAX, ASX-200, NYSE, SWX, and TSX all show a strong Granger causality relationship with the NSE. This suggests that the past values of these stock exchanges offer important forecasting information for the NSE. In simpler terms, these stock exchanges do influence the NSE. Conversely, the null hypothesis that the NSE does not have a causal relationship with these international stock exchanges is rejected in some stock exchanges, indicating that there is an inverse causality between the NSE and these exchanges. NSE Granger cause NIKKEI-225, KOREA, HANG SENG, EURONEXT-100, ASX-200, NYSE, SSE, and TWSE. Even so, the null hypothesis is upheld for the NASDAQ, LSX, EURONEXT-100, SWX, TSX and TWSE, suggesting that the NSE does not have a Granger causality effect on the NASDAQ, LSX, and DAX. However, they do have such an effect on the NSE. These results showed that there is the presence of both the unilateral and bilateral relationships between the NSE and these Selected International Stock Exchanges. There is bilateral relationship between HANG SENG, EURONEXT-100, ASX-200, NYSE, SWX and TSX. These findings indicate that there are intricate connections between the NSE and SISE during the post-crises emphasizing the significance of taking foreign issues into account when analyzing the behaviour of the NSE. The stock exchanges showed an insignificant relationship but after the

2008 US financial crises, the outcomes display that the association between the NSE and international stock exchanges have enhanced to a greater extent.

CHAPTER 7

COINTEGRATION BETWEEN NATIONAL STOCK EXCHANGE AND SELECTED INTERNATIONAL STOCK EXCHANGES

7.1 Cointegration Analysis

The application of cointegration theory has greatly revolutionized the examination of financial time series data, enhancing comprehension of the connections between variables and establishing a more resilient framework for evaluating market effectiveness. Cointegration, which was first introduced by Granger in 1986 and later expanded upon by Abadir and Taylor in 1999, has emerged as a fundamental concept in the fields of econometrics and finance. In the pre-cointegration theory era, financial time series were commonly regarded as integrated of order 1 or I (1), signifying their non-stationary characteristics. This implies that the series displayed unpredictable variations and did not possess a sustained equilibrium connection. However, they noted that specific combinations of I (1) time series could demonstrate a consistent, enduring correlation, despite their non-stationary nature. Granger coined the word "cointegration" to describe this occurrence, which indicates the presence of a common random pattern that limits the combination of variables across time. Cointegration is important because it may differentiate between spurious relationships and true long-term connections between variables. The presence of spurious regression in classical regression analysis can lead to misleading results when non-stationary variables are regressed against each other. On the other hand, cointegration approaches aid in identifying such interactions by examining the stationarity of a linear combination of non-stationary variables. The observation of stationarity in the combination implies the existence of cointegration and indicates the presence of a significant long-term association between the variables.

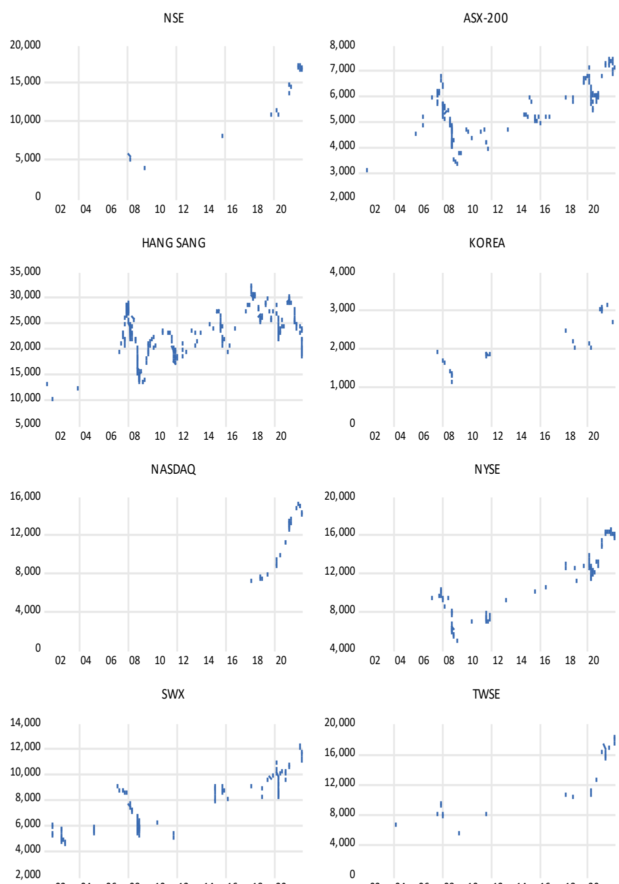
The notion of "cointegration" has experienced a transformation, shifting from "co-integration" to "cointegration," which signifies the development and broad recognition of this phrase in scholarly works. The evolution as mentioned earlier paralleled the growing acknowledgment of the significance of cointegration in knowing financial markets and economic events. The significance of cointegration analysis in reducing the intrinsic non-stationarity of financial time series has been emphasized by Chowdhury (1991). Researchers can enhance the accuracy of their estimations of long-term correlations between variables by recognizing and considering non-stationarity, thus avoiding the drawbacks of spurious regression. These advancements boosted the dependability of empirical investigations and increased the credibility of the inferences derived from them.

The significance of cointegration to market efficiency is a significant implication. The presence of cointegration between two price series of an asset indicates the efficiency of their respective markets. In a market characterized by efficiency, prices promptly adapt to novel information, and any deviations from the long-term equilibrium are of brief duration. Thus, cointegration indicates that market forces are successfully influencing prices to approach their equilibrium levels over some time (Schroeder and Goodwin, 1991).

The lack of cointegration may suggest market inefficiencies or the existence of unrelated price series. Persistent deviations from equilibrium in inefficient markets might present profitable possibilities for trading techniques that exploit these inefficiencies. Moreover, it is crucial to differentiate between true linkages and spurious ones in financial analysis, as unconnected price series might emerge due to various variables such as disparate asset classes or marketplaces. Cointegration approaches have been expanded to incorporate entire markets and asset classes, going beyond the analysis of individual assets. To examine the efficient market hypothesis across a array of investment instruments such as stocks, bonds, currencies, and commodities, scholars have employed cointegration analysis. Through the analysis of enduring correlations among prices, researchers can evaluate the extent to which markets accurately incorporate all accessible information and adapt effectively to novel information. Moreover, the utilization of cointegration has portrayed an essential role in the advancement of quantitative trading strategies and risk management procedures. Investors can develop trading techniques that capitalize on mean-reverting behavior in prices by recognizing cointegrated pairs or portfolios of assets. To potentially generate rewards while limiting risk, these techniques aim to exploit deviations from long-term equilibrium. Cointegration analysis plays a crucial role in the realm of international trade by facilitating the identification of equilibrium linkages among exchange rates, interest rates, and trade balances.

The long-term behavior of two-time series can also be used to understand cointegration. It is said that two series are cointegrated when, despite short-term deviations, they can move together over long periods. Many academics have looked into the relationships between stock exchanges in developed and emerging nations using the theory of cointegration. Palamalai et al., (2013) employed cointegration technique to examine the persistent linkages between stock markets across emerging economies in the Asia-Pacific zone. Sachdeva et al., (2021) also employed cointegration technique for understanding the long-term links between Indian stock markets and global stock markets. To understand the long-term connection between global stock markets of both developing and developed economies was followed by researchers like Endri (2020), David et al. (2021), Rizwanullah et al. (2020), and Caporale et al. (2022). Different studies have provided evidence of an increasing level of interconnectedness between Indian stock markets and their worldwide equivalents. Indian markets have been thoroughly analyzed by researchers to evaluate their interconnections with other nations (Joshi et al., 2021). In this study, the interconnections between Indian and worldwide stock exchanges were examined by utilizing cointegration theory. The findings are explained in detail below:

It is crucial to reflect the probability of structural breaks within the variables under investigation,



while performing analysis on time-series data that covers a long duration.

Figure 7.1: Daily Price Time Series Plot of Stock Exchanges

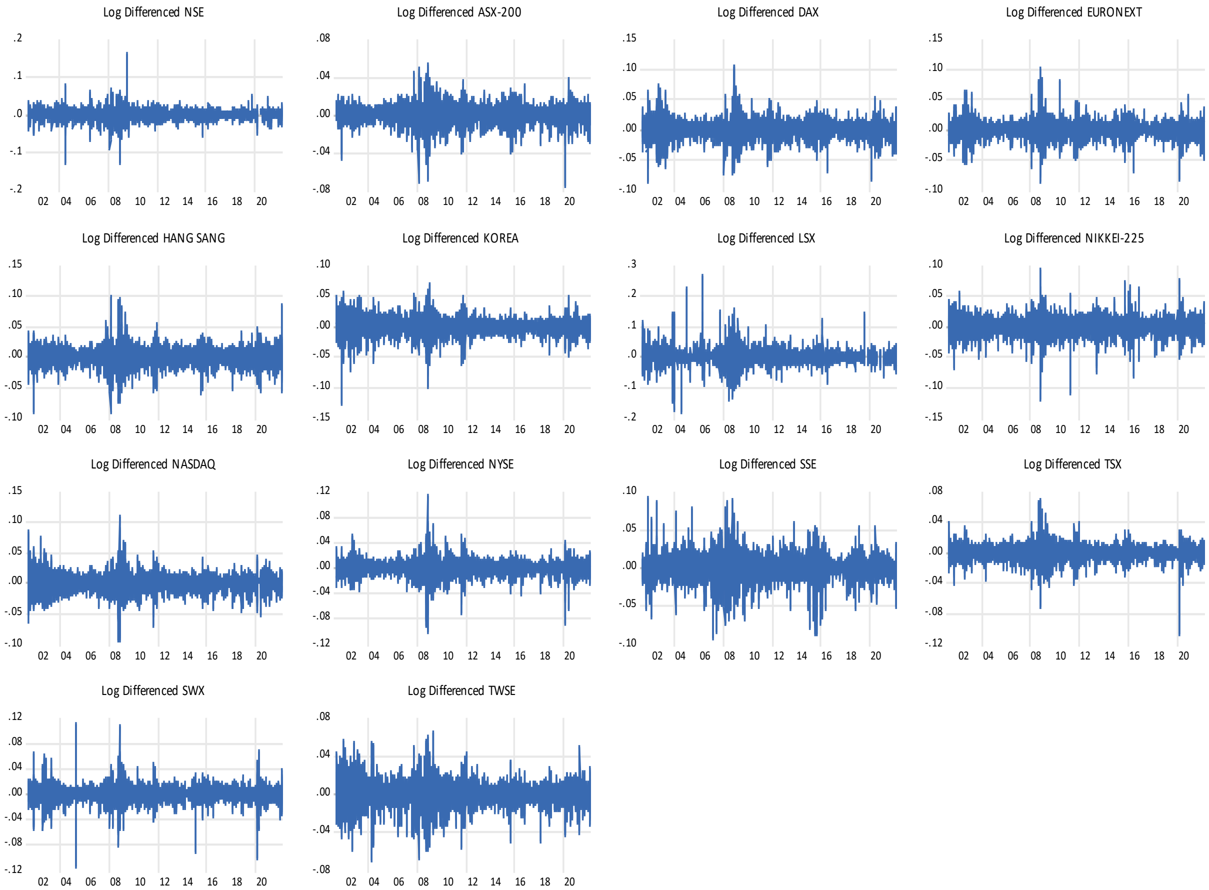


Figure 7.2: Log Returns Plot of Stock Exchanges

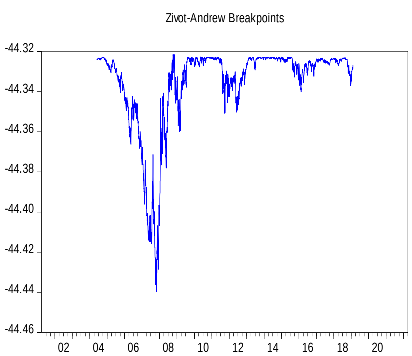
Prior to exploring the analysis of the long-term connection between the variables, it is common to visually represent the time series data to identify any structural patterns. The time series plots of the variables are presented in Figure 4.1 to enhance understanding. Figure 4.2 clearly shows the existence of structural changes in the series. To determine the most significant and common break across all stock exchanges, the Zivot-Andrew Test proposed by Gregory Zivot and Allen W. Andrew in their research “Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis" published in the Journal of Business & Economic Statistics in 1992 was utilized.

Table 7.1: Zivot-Andrew Test for Structural Breaks

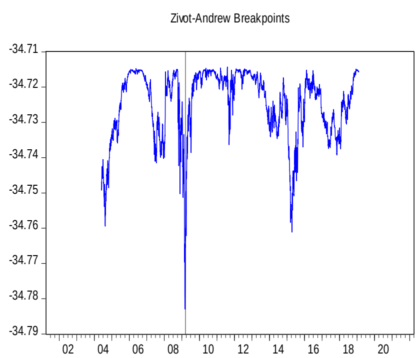
S. No.	Stock Exchange	t-statistic	Prob.
1.	ASX-200	-44.43973	0.004663
2.	DAX	-34.78298	0.023430

3.	EURONEXT-100	-35.91694	0.022932
4.	HSI	-73.66986	0.027469
5.	KSX	-37.46769	0.022136
6.	LSX	-77.45799	0.017518
7.	NASDAQ	-55.75967	0.002731
8.	NIKKEI-225	-44.37836	0.033837
9.	NSE	-36.30504	0.003775
10.	NYSE	-54.85421	0.012807
11.	SSE	-34.92632	0.000543
12.	SWX	-35.35892	0.027153
13.	TSX	-33.90135	0.031907
14.	TWSE	-36.74576	0.044020

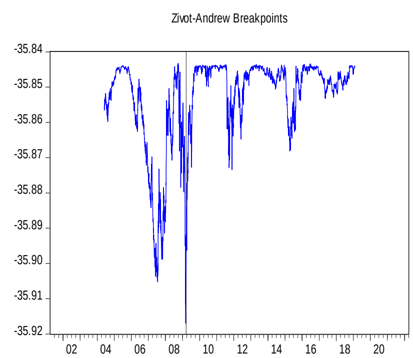
Source: Author's Calculations



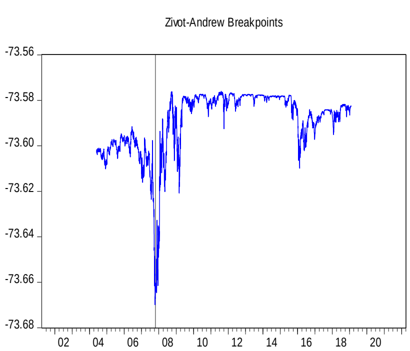
ASX-200



DAX



EURONEXT-100



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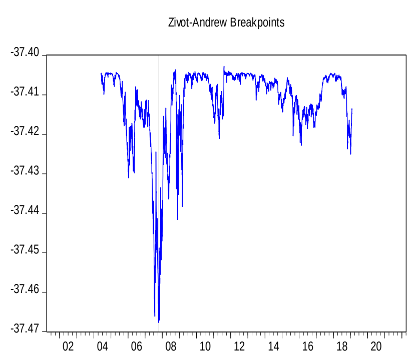
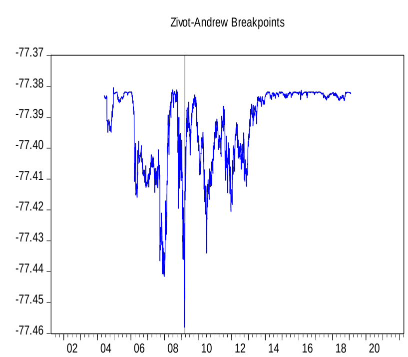
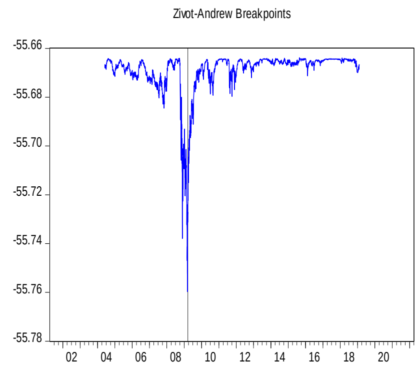


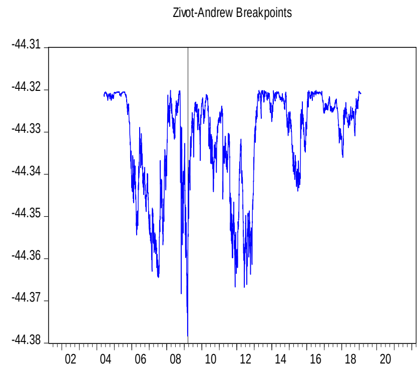
KRX



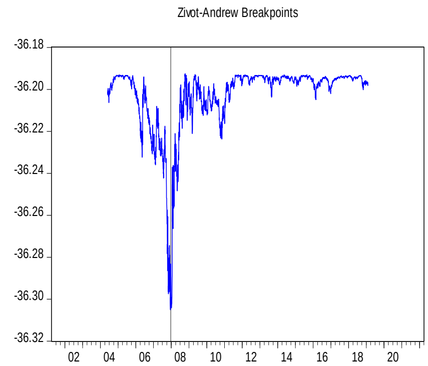
LSX



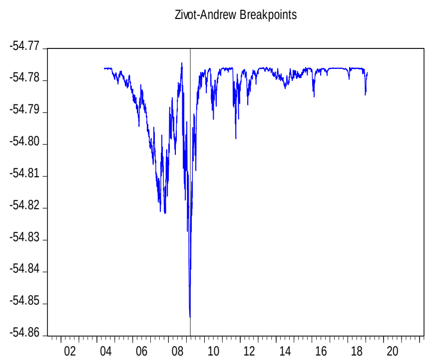
NASDAQ



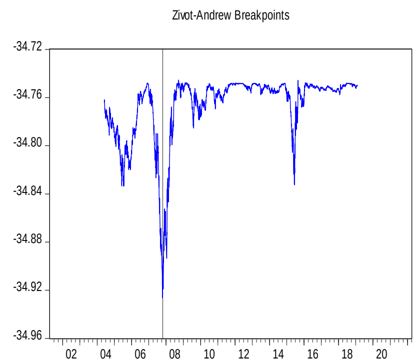
NIKKEI-225



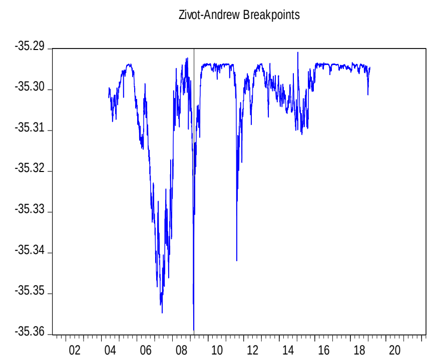
NSE



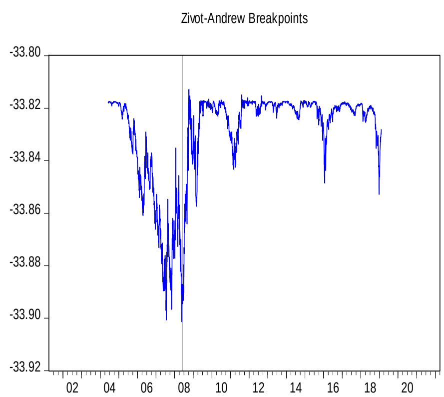
NYSE



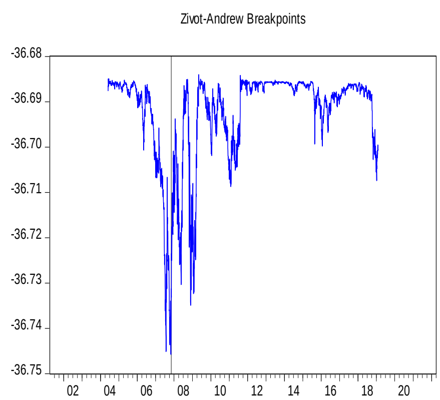
SSE



SWX



TSX



TWSE

Figure 7.3: Significant Structural Break in Price Returns of Stock Exchanges by ZA Test

Source: Author's calculations

Table 7.2: Cointegration Test Analysis Pre-Break Period (10-04-2001 to 30-03-2007)

	Hypothesized No. of CE(s)	Trace Statistics	0.05 Critical Value	Prob.**	Max-Eigen Statistics	0.05 Critical Value	Prob.**
ASX-200	None	10.43783	18.39771	0.4392	9.460413	17.14769	0.4489
	At most 1	0.977422	3.841466	0.3228	0.977422	3.841466	0.3228
DAX	None	14.23053	18.39771	0.1738	12.06752	17.14769	0.2357
	At most 1	2.163011	3.841466	0.1414	2.163011	3.841466	0.1414
EURONEXT-100	None	14.67511	18.39771	0.1537	12.22922	17.14769	0.2256
	At most 1	2.445894	3.841466	0.1178	2.445894	3.841466	0.1178
HSI	None	13.16511	18.39771	0.2311	9.437567	17.14769	0.4511
	At most 1	3.727546	3.841466	0.0535	3.727546	3.841466	0.0535
KSX	None	10.454971	15.49471	0.2471	10.10239	14.2646	0.2053
	At most 1	0.356082	3.841466	0.5507	0.356082	3.841466	0.5507
LSX	None	18.85678	18.39771	0.0431*	16.56666	17.14769	0.0606
	At most 1	2.290116	3.841466	0.1302	2.290116	3.841466	0.1302
NASDAQ	None	14.23267	25.87211	0.6384	9.699714	19.38704	0.6509
	At most 1	4.532957	12.51798	0.6642	4.532957	12.51798	0.6642
NIKKEI-225	None	16.24447	18.39771	0.0975	11.93578	17.14769	0.2442
	At most 1	4.308687	3.841466	0.0379*	4.308687	3.841466	0.0379*
NYSE	None	11.52688	18.39771	0.3455	8.415744	17.14769	0.5575
	At most 1	3.111141	3.841466	0.0778	3.111141	3.841466	0.0778
SSE	None	17.84024	18.39771	0.0597	17.24578	17.14769	0.0484*
	At most 1	0.594463	3.841466	0.4407	0.594463	3.841466	0.4407
SWX	None	19.85627	18.39771	0.0311*	17.38983	17.14769	0.0461*
	At most 1	2.466448	3.841466	0.1163	2.466448	3.841466	0.1163
TSX	None	13.65975	18.39771	0.2029	10.25564	17.14769	0.3741
	At most 1	3.404109	3.841466	0.0650	3.404109	3.841466	0.0650
TWSE	None	10.83008	15.49471	0.2221	10.62967	14.26460	0.1738
	At most 1	0.200412	3.841466	0.6544	0.200412	3.841466	0.6544

*Significant at 0.05 **

Source: Author's Calculations

The Co-Integration test was conducted on all fourteen stock exchanges for a span of six years, from April 2001 to March 2007. The results (Table: 7.2.) determined that NSE is integrated with LSX, NIKKEI-225, and SWX based on the trace value, which is statistically significant at a 5%. Therefore, null hypothesis is rejected that these series are not integrated with NSE. According to the Max-Eigen Value test, NSE is integrated with NIKKEI-225, SSE, and SWX since their values are statistically significant at a 5% level. Therefore, null hypothesis is rejected that these series are not integrated with the NSE.

In general, the study revealed that NSE is interconnected with both NIKKEI-225 and SWX, as determined by both Trace and Max-Eigen values.

Table 7.3: Cointegration Test Analysis During-Break Period (10-04-2007 to 31-03-2009)

	Hypothesized No. of CE(s)	Trace Statistics	0.05 Critical Value	Prob.**	Max-Eigen Statistics	0.05 Critical Value	Prob.**
ASX-200	None	18.39160	25.87211	0.3182	11.60308	19.38704	0.4530
	At most 1	6.788524	12.51798	0.3671	6.788524	12.51798	0.3671
DAX	None	14.20839	18.39771	0.1749	10.84717	17.14769	0.3239
	At most 1	3.361222	3.84466	0.0667	3.361222	3.841466	0.0667
EURONEXT-100	None	14.44896	18.39771	0.1636	10.88825	17.14769	0.3206
	At most 1	3.560712	3.841466	0.0592	3.560712	3.841466	0.0592
HSI	None	27.34723	12.32090	0.0001*	26.6328	11.2248	0.0001*
	At most 1	0.714427	4.129906	0.4567	0.714427	4.129906	0.4567
KRX	None	6.517579	12.32090	0.3758	6.235021	11.22480	0.3237
	At most 1	0.282558	4.129906	0.6559	0.282558	4.129906	0.6559
LSX	None	12.39869	20.26184	0.4138	11.00230	15.89210	0.2516
	At most 1	1.396394	9.164546	0.8916	1.396394	9.164546	0.8916
NASDAQ	None	10.27246	12.32090	0.1077	8.720596	11.22480	0.1334
	At most 1	1.551867	4.129906	0.2497	1.551867	4.129906	0.2497
NIKKEI-225	None	12.72484	20.26184	0.3862	7.659584	15.89210	0.5888
	At most 1	5.065255	9.164546	0.2764	5.065255	9.164546	0.2764

NYSE	None	11.47467	12.3209	0.0690	8.662846	11.22480	0.1364
	At most 1	2.811819	4.129906	0.1107	2.811819	4.129906	0.1107
SSE	None	13.69483	20.26184	0.3110	11.94911	15.89210	0.1889
	At most 1	1.745726	9.164546	0.8276	1.745726	9.164546	0.8276
SWX	None	17.44674	18.39771	0.0675	14.08734	17.14769	0.1322
	At most 1	3.359399	3.841466	0.0668	3.359399	3.841466	0.668
TSX	None	6.336477	12.32090	0.3962	5.039031	11.22480	0.4718
	At most 1	1.297227	4.129906	0.2975	1.297447	4.129906	0.2975
TWSE	None	9.824741	12.32090	0.1265	8.476294	11.22480	0.1462
	At most 1	1.348446	4.129906	0.2872	1.348446	4.129906	0.2872

*Significant at 0.05 **

Source: Author's Calculations

The Co-Integration test was conducted on all fourteen stock exchanges for a span of 2 years, from April 2007 to March 2009. The results (Table: 7.3.) determined that NSE is only integrated with HSI based on both the Trace and Max-Eigen values.

Table 7.4: Cointegration Test Analysis Post-Break Period (01-04-2009 to 31-03-2022)

	Hypothesized No. of CE(s)	**Trace Statistics**	**0.05 Critical Value**	**Prob.****	**Max-Eigen Statistics**	**0.05 Critical Value**	**Prob.****
ASX-200	None	18.36170	15.49471	0.0180*	17.73668	14.26460	0.0136*
	At most 1	0.625017	3.841466	0.4292	0.625017	3.841466	0.4292
DAX	None	16.70449	25.87211	0.4373	13.70562	19.38704	0.2745
	At most 1	2.998876	12.51798	0.8767	2.998876	12.51798	0.8767
EURONEXT-100	None	21.13927	25.87211	0.1736	18.05546	19.38704	0.0772
	At most 1	3.083815	12.51798	0.8664	3.083815	12.51798	0.8664
HSI	None	14.48844	18.39771	0.1619	14.48438	17.14769	0.1172
	At most 1	0.004054	3.841466	0.9479	0.004054	3.841466	0.9479
KRX	None	12.62230	15.49471	0.1294	12.53260	14.26460	0.0922
	At most 1	0.089704	3.841466	0.7645	0.089704	3.841466	0.7645
LSX	None	14.28337	25.87211	0.6342	9.179850	19.38704	0.7058
	At most 1	5.103517	12.51798	0.5816	5.103517	12.51798	0.5816

NASDAQ	None	18.62297	15.49471	0.0163*	17.23154	14.26460	0.0165*
	At most 1	1.391430	3.841466	0.2382	1.391430	3.841466	0.2382
NIKKEI-225	None	14.75304	25.87211	0.5951	12.13022	19.38704	0.4032
	At most 1	2.622829	12.51798	0.9180	2.622829	12.51798	0.9180
NYSE	None	21.08397	25.87211	0.1759	18.20805	19.38704	0.0735
	At most 1	2.875917	12.51789	0.8909	2.875917	12.51798	0.8909
SSE	None	8.353347	15.49471	0.4284	7.720934	14.26460	0.4078
	At most 1	0.632413	3.841466	0.4265	0.632413	3.841466	0.4265
SWX	None	17.90348	25.87211	0.3504	15.11314	19.38704	0.1876
	At most 1	2.790346	12.51798	0.9004	2.790346	12.51798	0.9004
TSX	None	20.95031	15.49471	0.0068*	20.41858	14.26460	0.0047*
	At most 1	0.531732	3.841466	0.4659	0.531732	3.841466	0.4659
TWSE	None	20.58400	25.87211	0.1978	18.53563	19.38704	0.0661
	At most 1	2.048369	12.51798	0.9657	2.048369	12.51798	0.9657

*Significant at 0.05 **

Source: Author's Calculations

The Co-Integration test was conducted on all fourteen stock exchanges for a span of twelve years, from April 2009 to March 2022. The results (Table: 7.4.) determined that NSE is integrated with ASX-200, NASDAQ and TSX based on the trace value, which is statistically significant at a 5% level. Therefore, null hypothesis is rejected that these series are not integrated with NSE. According to the Max-Eigen Value test, NSE is integrated with ASX-200, NASDAQ and TSX since their values are statistically significant at a 5% level. Therefore, null hypothesis is rejected that these series are not integrated with the NSE.

CHAPTER 8

SUMMARY OF FINDINGS, CONCLUSION AND SUGGESTIONS

The purpose of this study is to determine the linkages between the NSE and Selected International Stock Exchanges. There are objectives in place to help reach the overall objective.

It is discovered that the cointegration and Granger causal relationships know the long-run and short-run links between the markets. DCC-GARCH model determines the time-varying correlation over the sample period. Regression analysis is performed using the VAR (1) GARCH (1, 1) model to determine the short and long-term persistence of cross-market shocks.

8.1 Summary of Findings

8.1.1 Volatility of price indices between NSE and Selected International Stock Exchanges

An analysis of price volatility over the last 21 years between the National Stock Exchange (NSE) and selected International Stock Exchanges shows significant interdependence and transmission of volatility throughout global financial markets. Using the VAR (1)-GARCH (1,1) model reveals a number of important insights into how price volatility behaves:

- The data demonstrates that previous disturbances and fluctuations in both the NSE and foreign markets have a substantial impact on the current level of price volatility. The coefficients of past shocks for NSE are continuously significant, suggesting that unforeseen shocks inside NSE have a substantial influence on its volatility. Furthermore, NSE's volatility is significantly impacted by cross-market shocks originating from international markets like SWX, SSE, EURONEXT-100, and other similar exchanges.
- Long-term persistence is seen in the substantial volatility transmission between the NSE and selected International Stock Exchanges, as indicated by the high values of historical variances. This persistence indicates that previous fluctuations in both the NSE and international markets still affect future fluctuations, demonstrating a lasting influence over time.
- Dynamics that are specific to the market: the investigation reveals various patterns in the transmission of volatility. As an illustration, markets such as the NYSE and the TWSE display high coefficients, which indicates a strong and long-lasting link with the National Stock Exchange (NSE). Because of this, the crucial role that these markets play in affecting the volatility of the NSE is highlighted.

- Mean-reversion tendencies can be inferred from the existence of negative coefficients in specific models, indicating a propensity for volatility to return to its average level. Unlike these interests, the collective impact of previous disturbances and fluctuations remains substantial, underscoring the intricacy of volatility dynamics amongst the NSE and global markets.
- The study affirms the presence of notable volatility spillovers between the NSE and the chosen overseas stock exchanges. This suggests that volatility originating in one market might spread to others, impacting their stability and behavior. Understanding the global propagation of financial market shocks relies heavily on knowing the importance of these spillovers.
- The analysis recognizes the 2007-2009 US financial crisis as a significant event that caused a structural rupture and affected the patterns of volatility in the financial markets. During times of crisis, there are varying degrees of integration and the transfer of volatility between different markets. This reflects the increased interconnection and vulnerability of global markets during financial instability.

Ultimately, the examination of price volatility between NSE and Selected International Stock Exchanges highlights the substantial and complex connections among global capital markets. It is imperative for financial institutions, portfolio managers, and regulators to include global market dynamics in their risk management and strategic decision-making processes due to the ongoing existence of volatility, the influence of prior shocks, and the occurrence of volatility Spillovers. Gaining a comprehensive understanding of these patterns of volatility is crucial for minimizing risks and taking advantage of opportunities in a progressively linked financial landscape.

7.1.2 Return Spillover between NSE and Selected International Stock Exchanges

Due to the fact that economies are dependent on one another, the stock markets of different countries all over the world are influenced by one another. It is generally acknowledged in the academic literature that the phenomena of international stock market integration are a phenomenon. The universal integration and transmission of stock markets, as well as the spillover effects of stock returns and volatilities among international stock indexes, are now also in the process of being investigated by researchers from all over the world. Numerous scholars are interested in and conducting study on a variety of themes, one of which is the direction of the spillover from advanced markets to developing and emerging economies. Additionally, the volatility spillover that occurs between the National Stock Exchange and SISE is investigated in this research. Within the scope of this assessment, the researcher endeavors to consider the existence of volatility spill over as well as dynamic conditional correlation between the stock exchanges. Twenty-one years, beginning in April 2001 and ending in March 2022, are the time span for which the daily data is collected. For the purpose of the study, the DCC GARCH model is utilized in order to investigate the volatility spillover involved. Initially, the DCC model framework is constructed by fitting the univariate GARCH specifications that are the best appropriate for each of the specified series. The selected univariate GARCH specifications are anticipated to provide the most accurate explanation for the behaviour of the index return. The p value of the t statistics of the joint DCC coefficient was determined to be less than the 5 percent level of significance, as demonstrated by the findings of the DCC GARCH model that was utilized in the research study. It is possible that linear reliance is the result of some kind of market incompetence. DCC-GARCH estimates indicate the conditional correlation between the NSE and the selected international stock exchanges is very dynamic and varies over time. This is the importance of the estimates. Based on the findings of the study, it is possible to draw the conclusion that there is a substantial link between the conditional heteroscedastity estimates of the NSE indices and chosen international stock indexes. There was support for the findings from Gupta and Mollik (2008), Xiao and Dhesi (2010), AL-Zeaud and ALshbiel (2012), and Baumohl and Lyocsa (2013) for the findings.

7.1.3 Co-integration and Causality between NSE and Selected International Stock Exchanges

The cointegration analysis, done from April 2001 to March 2022, examines the long-term equilibrium linkages between the National Stock Exchange (NSE) and Selected International Stock Exchanges, yielding valuable insights. The study period was divided into pre-break, during-break, and post-break periods to completely analyze the impact of key events, such as the 2007-2009 US Capital crisis, on these associations. The main findings derived from the cointegration analysis can be summarized as follows:

Pre-Break Period (April 2001 - March 2007):

During this time frame, the NSE displayed a statistical relationship known as cointegration with both the NIKKEI-225 and SWX indices. This suggests the existence of a firm and composed link over a long duration of time between NSE and these two International Stock Exchanges. It implies that, despite temporary variations, the markets tend to move in sync in the long run. This link advocates that any imbalance between NSE and these markets is transient, and that corrections take place gradually to bring back a state of equilibrium.

During-Break Period (April 2007 - March 2009):

The financial crisis period showed a more limited set of cointegrated relationships, with NSE being cointegrated only with HSI. This indicates that the global financial turmoil disrupted long-term relationships with most other international stock exchanges, except for HSI. The strong linkage with HSI during this period suggests that the NSE and HSI markets were closely aligned, possibly due to similar impacts and responses to the financial crisis, leading to a maintained equilibrium relationship.

Post-Break Period (April 2009 - March 2022):

During the period following the crisis, the NSE exhibited cointegration with the ASX-200, NASDAQ, and TSX. The formation of enduring partnerships with these markets signifies a resurgence and restoration of balanced links following the crisis. The partnership with NASDAQ indicates a strong connection with one of the world's largest and most powerful stock markets, emphasizing the global integration of NSE in the period following the financial crisis.

Throughout the three time periods, the analysis demonstrates that there are differing degrees of long-term integration between the NSE and Selected International Stock Exchanges. The dynamic nature of international stock market linkages is demonstrated by the presence of cointegration prior to the crisis, the minimal cointegration that occurred during the crisis, and the re-establishment of relationships following the crisis. Additionally, the findings indicate that the National Stock Exchange's (NSE) long-term ties with overseas markets are susceptible to being strongly influenced by global financial events, which have the potential to temporarily disturb equilibrium relationships. The post-crisis era, on the other hand, demonstrates that these relationships have a tendency to recover and re-establish themselves over the course of time.

To summarise, the cointegration research highlights the substantial and changing long-term connections between the NSE and Selected International Stock Exchanges. The findings emphasize the influence of global financial events, such as the 2007-2009 financial crisis, on these links. These events can disrupt and subsequently alter the equilibrium connections. Financial institutions, portfolio managers, and regulators must comprehend these cointegration processes to make well-informed judgments about foreign investments, risk management, and strategic planning. The capacity of markets to restore balance following disturbances demonstrates the durability and interdependence of global financial institutions, demonstrating the significance of ongoing surveillance and examination of these enduring connections.

Causality between NSE and Selected Stock Exchanges

An analysis of Granger causality between the National Stock Exchange (NSE) and chosen global stock exchanges provides valuable insights into the immediate connections and the flow of influence among these markets. Through an analysis of the time span spanning from April 2001 to March 2022, and categorizing it into three distinct eras - pre-break, during-break, and post-break with reference to the 2007-2009 US financial crisis, several significant findings can be inferred:

Pre-Break Period (April 2001 - March 2007):

The results suggest that several global stock exchanges have a significant causal impact on the NSE. Exchanges like NASDAQ, EURONEXT-100, DAX, NYSE, SSE, SWX, and TSX offer useful forecasting information for NSE, indicating a robust short-term correlation.

In contrast, the NSE displays Granger causality with Selected International Stock Exchanges such as NIKKEI-225, LSX, KRX, HSI, EURONEXT-100, DAX, ASX-200, NYSE, SSE, SWX, TSX, and TWSE, suggesting a two-way relationship with these markets.

During-Break Period (April 2007 - March 2009):

The US financial crisis period exhibits an effective Granger causation connection between the NSE and SISE, including NASDAQ, LSX, HSI, EURONEXT-100, DAX, ASX-200, NYSE, SWX, and TSX. This indicates that the historical values of these exchanges accurately predict the movements of NSE during the crisis.

Similarly, NSE Granger causally affects NIKKEI-225, KRX, HSI, EURONEXT-100, ASX-200, NYSE, SSE, and TWSE during this era, emphasizing the impact of NSE on these global markets throughout the financial crisis.

Post-Break Period (April 2009 - March 2022):

During the post-crisis time, the previously discovered significant Granger causality links continue to persist. Exchanges such as NASDAQ, LSX, HSI, EURONEXT-100, DAX, ASX-200, NYSE, SWX, and TSX maintain their influence on NSE.

The NSE continues to exert its Granger causal influence on markets such as NIKKEI-225, KRX, HSI, EURONEXT-100, ASX-200, NYSE, SSE, and TWSE, showing a continuous two-way interaction with these exchanges.

To summarise, the Granger causality analysis highlights the complex and ever-changing connections between NSE and SISE. The strong reciprocal causality seen with major global markets such as EURONEXT-100, DAX, NYSE, SSE, and SWX demonstrates a solid interconnection, while the one-sided affects from markets like NASDAQ and TSX indicate distinct directional dependencies. These findings emphasize the crucial influence of global market trends on the behaviour of NSE, and vice versa. This offers useful insights for financial institutions, portfolio managers, and policymakers in their strategic decision-making and risk management endeavours. Gaining a comprehensive understanding of these cause-and-effect interactions is crucial for effectively navigating the intricate nature of global financial markets and maximising investing strategies.

7.2 Comparative Analysis

This study investigated the relationships between the National Stock Exchange (NSE) and Selected International Stock Exchanges by analysing Volatility Spillover, Return Spillovers, Granger Causality, and Cointegration. The results indicated substantial interdependencies between the NSE and Selected International Stock Exchanges, displaying differing levels of influence over distinct timeframes.

7.2.1 To study the volatility of price indices between National Stock Exchange and selected International Stock Exchanges.

The study was to examine the volatility spillover effects between the NSE and Selected International Stock Exchanges. The study, employed VAR (1)-GARCH (1,1) model, revealed that the NSE displays significant volatility transmission with Selected International Stock Exchanges, including the NYSE, TWSE, and HSI. The results indicate that prior volatilities and shocks in both the NSE and selected International Stock Exchanges significantly impact current volatility patterns, demonstrating a robust information transmission mechanism across international stock markets. The study emphasized that cross-market shocks are statistically significant, underscoring that external financial disturbances—stemming from economic crises, policy alterations, or macroeconomic variations—substantially affect the NSE. The study revealed that NYSE and TWSE demonstrate a consistent and enduring volatility correlation with NSE, indicating that prominent global financial hubs significantly impact the NSE. This information is essential for portfolio managers and institutional investors, since comprehending volatility spillover patterns can aid in improving asset allocation and alleviating risks linked to international market changes.

7.2.2 To study the impact of major spillovers between National Stock Exchange and selected International Stock Exchanges.

The study was to analyse the dynamic conditional correlation between the NSE and selected International Stock Exchanges employing the DCC-GARCH model. The results indicated that NSE's correlation with global stock markets is both highly dynamic and long-term, adapting to economic conditions. The findings indicated that although the NSE consistently demonstrated correlations with selected International Stock Exchanges, the intensity of these correlations fluctuates over time due to external shocks, policy alterations, and investor mood. Also, the study indicated that linear dependencies in conditional correlations arise from market inefficiencies, regulatory disparities, or liquidity limitations, which influence the absorption of financial information across various stock exchanges. A key discovery is the emergence of substantial changes in correlation patterns after 2009, indicating that globalization, technology-fueled financial integration, and cross-border investment flows have enhanced inter-market interconnections. The findings of this aim have significant implications for risk management and hedging techniques, as comprehending time-varying correlations enables investors to make more educated decisions about portfolio diversification and market timing strategies.

7.2.3 To explore the causality between National Stock Exchange and selected International Stock Exchanges.

The study focused on the short-term relationships between NSE and selected International Stock Exchanges by employing Granger Causality Test. The findings indicated the presence of both unilateral and bilateral causal linkages, demonstrated a two-way information flow between the NSE and selected International Stock Exchanges. The study revealed that during the pre-crisis period, NASDAQ, EURONEXT-100, DAX, NYSE, SSE, SWX, and TSX exhibited a robust Granger causation effect on NSE, indicating that NSE was substantially affected by trends in developed markets. NSE exerted a causal influence on markets, NIKKEI-225, LSX, KRX, HSI, and ASX-200, demonstrating that India's expanding financial impact enabled it to affect regional markets. During the financial crisis, the causal influence of selected international stock exchanges on the NSE diminished, indicating decreased investor confidence and increased risk aversion. Following the crisis, NSE demonstrated bilateral links with EURONEXT-100, DAX, NYSE, SSE, and SWX, signifying that emerging markets such as India are now more interconnected inside the global financial system than ever. The findings underscored the significance of foreign factors in influencing NSE's behavior, stressing the necessity for investors to observe global macroeconomic developments, regulatory changes, and international capital movements while making investment decisions.

7.2.4 To identify the Integration between National Stock Exchange and selected International Stock Exchanges.

The focus was to evaluate the impact of financial crises on the cointegration and connections between the NSE and selected International Stock Exchanges. The research divided the dataset into three periods: pre-crisis (2001–2007), crisis (2007–2009), and post-crisis (2009–2022). The data revealed that prior to the financial crisis, NSE was primarily connected with NIKKEI-225 and SWX, demonstrating a regional focus on Asian and European financial markets. During the 2007–2009 financial crisis, NSE's integration considerably deteriorated, with only HSI sustaining a robust connection. This indicated that financial concern prompted capital withdrawal and heightened market segmentation, as investors pursued safer assets, hence diminishing international stock market co-movements. Post-crisis, the NSE exhibited enhanced correlations with the ASX-200, NASDAQ, and TSX, indicating a transformation in global dependencies, wherein Western financial centres increasingly influence the Indian stock market. These findings corroborate prior research, highlighting that financial crises transform the global financial framework by modifying market dynamics and investor risk assessments. This understanding is especially beneficial for regulators and policymakers, since it highlights the significance of financial stability policies to preserve market integration during times of economic turmoil.

In conclusion, the study offers an extensive analysis of the interactions between the National Stock Exchange (NSE) and selected International Stock Exchanges, highlighting the increasing interdependence of stock exchanges in the context of financial globalization. The results are especially important for financial institutions, governments, and investors, as they underscore the dynamic and developing characteristics of stock market connections. The study employed sophisticated econometric models such as VAR (1) GARCH (1,1), DCC-GARCH and BEKK-GARCH, Granger Causality and Cointegration, provided a significant insight into the influence of volatility, return spillovers, and financial crises on market dynamics. As global markets expand, ongoing surveillance of these connections will be crucial for forecasting financial risks, formulating investment strategies, and securing long-term financial stability.

7.3 Suggestions

I. For Financial Institutions and Portfolio Managers

- **Diversification Strategy:** Due to the ever-changing nature of the long-term connections between NSE and foreign stock exchanges, it is crucial to spread investments across several markets in order to reduce risk and maximize earnings. Implementing diversification strategies can effectively reduce the negative effects of market-specific shocks and maximize the advantages of international market integration.
- **Risk Management:** Utilize sophisticated risk management methods, such as VAR-GARCH models, to predict and control the transmission of volatility from global markets. Gaining insight into the fluctuations in volatility can assist in formulating tactics to safeguard portfolios during moments of intense market instability.
- **Market Analysis:** Conduct ongoing surveillance and examination of the cointegration and causality connections between worldwide stock markets

in order to detect developing patterns and potential prospects. This will enable prompt modifications to investment plans in reaction to changing market conditions.

II. **For Policymakers and Regulators**

- **International Cooperation**: Promote international collaboration and facilitate information exchange among regulatory authorities to enhance comprehension and control of the interdependence of global markets. Cooperative endeavours can improve the efficiency of actions taken to reduce systemic hazards.

III. **For Multinational Corporations**

- **Investment planning:** Investment strategy involves utilizing insights from cointegration and volatility spillover assessments to make well-informed decisions regarding foreign investments and expansions. Gaining insight into market connections can aid in finding secure markets and potential avenues for expansion.
- **Strategic Alliances**: It is advisable to establish strategic alliances or partnerships with companies in other areas to utilize their expertise in local markets and strengthen resilience against fluctuations in the global market.

7.3 Limitations of the Study

- This limitations of the econometric analysis of time series data is applicable in this study.
- The futures prices have been sourced from various official exchanges of respective
- countries, are subject to accuracy.
- There are other stock exchanges like Shenzhen Stock Exchange, Singapore Stock Exchange and so on which are not considered in this study.
- The time frame considered is limited to twenty-one years in the study. It can be considered more to get more desired results.

7.4 Implications of the Study

Implications of the Study for Investors, Financial Institutions, Policy Makers, and Government

The findings of the study on the linkages between the National Stock Exchange (NSE) of India and selected international stock exchanges have significant implications for various stakeholders, including investors, financial institutions, policy makers, and government authorities.

Investors

- **Informed Decision-Making:** Investors can leverage the insights from this study to make more informed decisions about their portfolio diversification strategies. Understanding the volatility spillover and Granger causality relationships between the NSE and international markets enables investors to predict potential risks and returns more accurately. This is particularly useful for those investing in global markets, as the study identifies the interconnectedness and the impact of international stock exchanges on the NSE.
- **Risk Management:** The identification of significant volatility transmission between the NSE and selected global markets helps investors to better manage their risk exposure. For instance, knowing that certain international markets have a stronger influence on the NSE can prompt investors to hedge their positions during periods of anticipated market turbulence.
- **Market Timing:** Investors can use the findings on the short-term causal relationships to time their market entries and exits. If certain international markets are shown to Granger-cause movements in the NSE, investors can monitor these markets for early signs of potential changes in the NSE.

Financial Institutions

- **Portfolio Management:** Financial institutions, including mutual funds, hedge funds, and pension funds, can utilize the study's findings to optimize their portfolio management strategies. The knowledge of cointegration and causality between the NSE and international markets allows these institutions to construct portfolios that are better aligned with global market trends, enhancing overall portfolio performance.
- **Strategic Asset Allocation:** The study's insights into long-term cointegration between the NSE and certain international markets provide financial institutions with a basis for

strategic asset allocation. This can be particularly useful for those institutions aiming to achieve long-term growth by investing in correlated markets.

- **Stress Testing and Scenario Analysis:** Financial institutions can use the study's findings to improve their stress testing and scenario analysis processes. By incorporating the identified linkages into their models, they can better anticipate how global financial shocks might affect their portfolios and prepare appropriate contingency plans.

Policy Makers

- **Regulatory Framework:** Policy makers can use the findings to design a regulatory framework that takes into account the interconnectedness of the NSE with global markets. Understanding the spillover effects and causality relationships can help in developing policies that mitigate systemic risks and prevent contagion from international market disruptions.
- **Financial Market Stability:** The study's results highlight the importance of maintaining financial stability by monitoring global market trends and their potential impact on domestic markets. Policy makers can use this information to implement measures that enhance the resilience of the NSE against external shocks, such as enhancing liquidity provision or adjusting interest rates in response to global economic conditions.
- **International Cooperation:** The identified linkages between the NSE and international markets underscore the need for greater international cooperation in financial regulation and supervision. Policy makers can collaborate with their counterparts in other countries to ensure that cross-border financial flows are managed effectively, reducing the risk of global financial instability.

Government

- **Economic Policy Formulation:** The government can use the study's findings to inform the formulation of economic policies, particularly those related to international trade and investment. Understanding the interdependence between the NSE and global markets can help in designing policies that promote sustainable economic growth while minimizing exposure to global financial risks.

- **Foreign Investment Policies:** The study provides insights into the impact of international stock markets on the NSE, which can guide the government in shaping foreign investment policies. By identifying which foreign markets have a significant influence on the NSE, the government can tailor its policies to attract or regulate foreign investments in a way that aligns with national economic goals.
- **Crisis Management:** The findings on the transmission of volatility and shocks between the NSE and global markets can aid the government in developing effective crisis management strategies. In the event of a global financial crisis, the government can take preemptive actions based on the study's insights to protect the domestic economy from severe adverse effects.

In summary, this study offers valuable guidance to investors, financial institutions, policy makers, and the government in navigating the complexities of global financial markets. By understanding the dynamic linkages between the NSE and international stock exchanges, these stakeholders can make more informed decisions, manage risks more effectively, and contribute to the stability and growth of the financial system.

7.5 Future Scope of the Study

The future scope of this study involves expanding the dataset beyond 2022 to encompass recent market advancements, integrating other emerging and developed markets to facilitate a thorough analysis, and undertaking studies focused on specific sectors. Additionally, it entails analyzing the influence of technology progress, macroeconomic variables, political occurrences, and ESG considerations on market connections. Utilizing sophisticated econometric models and analyzing real-time data can yield more precise and timely insights. Conducting comparative research between the eras before and after the pandemic will provide insights into the lasting impacts of global crises on the integration of stock markets. These outlets will bolster investment strategies and provide valuable insights for making informed policy decisions to ensure the stability of financial markets.

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PAPER PUBLICATION DETAILS

S.no.	Title of papers with author names	Name of journal / conference	Published date	Issn no/ vol no, issue no
1.	Study on Causality between NSE and Selected International Stock exchanges DCC GARCH and Wavelet Approach - Syed Mohd Khalid & Dr. Babli Dhiman	Finance: Theory and Practice	June 2024 (Accepted)	-
2.	Co-integration of National Stock Exchange India with Global Stock Markets: An Empirical Analysis- Syed Mohd Khalid& Dr. Babli Dhiman	Indian Journal of Economics and Business	June 2021	Vol 20, Issue no. 1
3.	Has COVID-19 affected the Global economy?-Syed Mohd Khalid and Dr. Babli Dhiman	Positive School of Psychology	August 2022	1445-1448
4.	Cryptocurrencies and Blockchain Technology Augmentation Identification in Decentralized Finance- Syed Mohd Khalid and Dr. Babli Dhiman	Emerald Publishing- Augmenting Retail Reality: Blockchain, AR, VR and Beyond	Dec 2023	Book Chapter

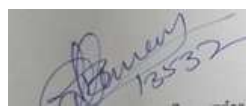
5.	Volatility of Price Indices Between National Stock Exchange and Selected International Stock Exchanges: A Thematic Analysis-Syed Mohd Khalid and Dr. Babli Dhiman	Roadmap towards Sustainability: A Multidimensional View.	July 2021	1St Edition

LIST OF CONFERENCES

S. No.	Name of The Conference	Date
1	3rd International Conference on Social Science, Management and Technology In Covid Era	28th of August, 2022
2	International Conference on Qualitative Research Design Organized By Eudoxia Research University USA, In Collaboration with Eudoxia Research Centre India.	24th and 25th of September

SYED MOHD KHALID

Date: 06/02/2025



Dr. BABLI DHIMAN

Date: 06/02/2025